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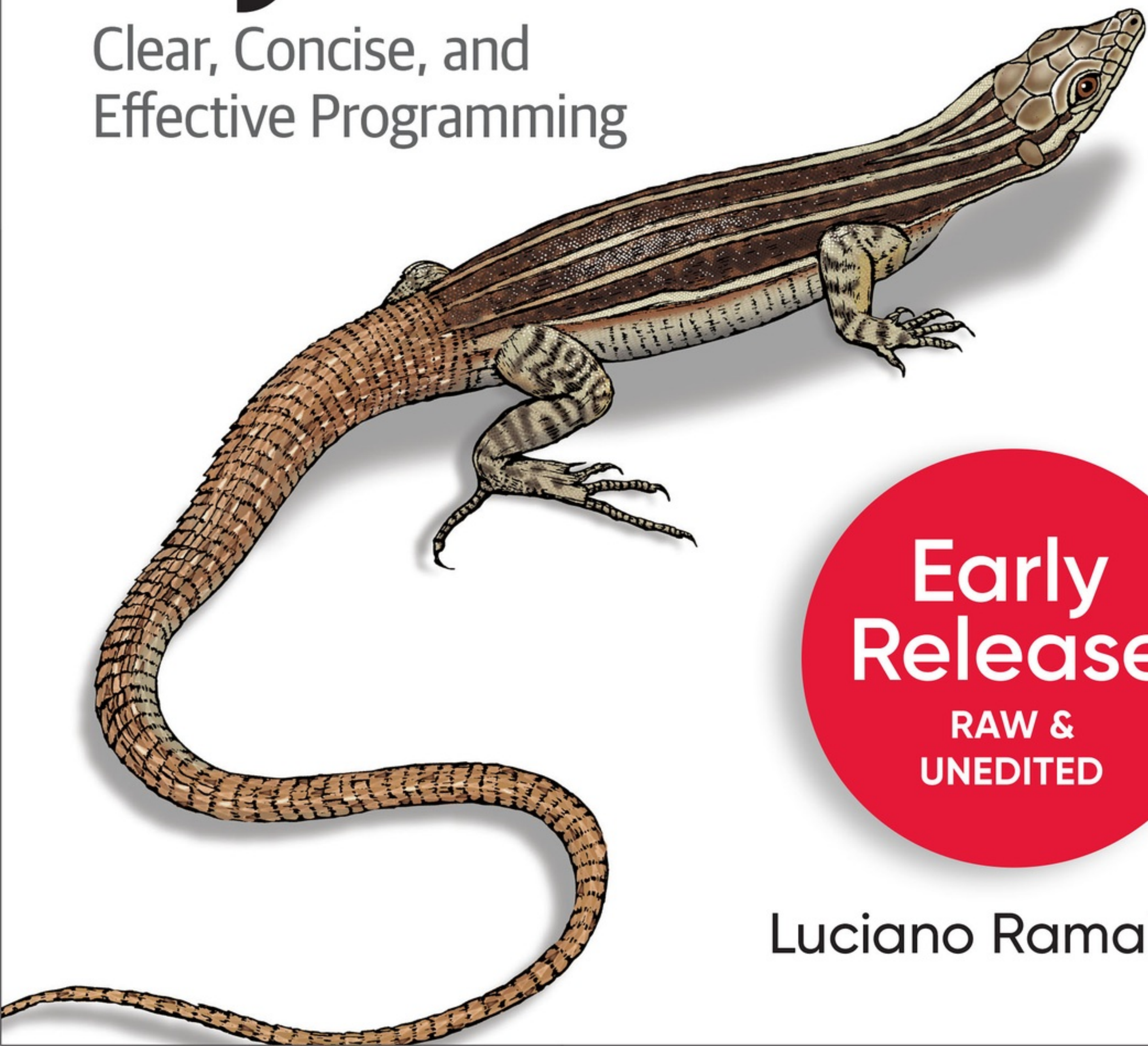

Early Release
RAW & UNEDITED

Luciano Ramalho

Fluent Python

SECOND EDITION

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Luciano Ramalho

Fluent Python

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[LSI]

Dedication

Para Marta, com todo o meu amor.

Preface

> **WARNING**
>
> The Preface has not been updated from the *First Edition*. This will be the last part of the book to be updated for the *Second Edition*.

Here's the plan: when someone uses a feature you don't understand, simply shoot them. This is easier than learning something new, and before too long the only living coders will be writing in an easily understood, tiny subset of Python 0.9.6 <wink>.[1]

—Tim Peters, Legendary core developer and author of The Zen of Python

"Python is an easy to learn, powerful programming language." Those are the first words of the official Python Tutorial. That is true, but there is a catch: because the language is easy to learn and put to use, many practicing Python programmers leverage only a fraction of its powerful features.

An experienced programmer may start writing useful Python code in a matter of hours. As the first productive hours become weeks and months, a lot of developers go on writing Python code with a very strong accent carried from languages learned before. Even if Python is your first language, often in academia and in introductory books it is presented while carefully avoiding language-specific features.

As a teacher introducing Python to programmers experienced in other languages, I see another problem that this book tries to address: we only miss stuff we know about. Coming from another language, anyone may guess that Python supports regular expressions, and look that up in the docs. But if you've never seen tuple unpacking or descriptors before, you will probably not search for them, and may end up not using those features just because they are specific to Python.

This book is not an A-to-Z exhaustive reference of Python. Its emphasis is on the language features that are either unique to Python or not found in many other popular languages. This is also mostly a book about the core language and some of its libraries. I will rarely talk about packages that are not in the standard library, even though the Python package index now lists more than 60,000 libraries and many of them are incredibly useful.

Who This Book Is For

This book was written for practicing Python programmers who want to become proficient in Python 3. If you know Python 2 but are willing to migrate to Python 3.4 or later, you should be fine. At the time of this writing, the majority of professional Python programmers are using Python 2, so I took special care to highlight Python 3 features that may be new to that audience.

However, *Fluent Python* is about making the most of Python 3.4, and I do not spell out the fixes needed to make the code work in earlier versions. Most examples should run in Python 2.7 with little or no changes, but in some cases, backporting would require significant rewriting.

Having said that, I believe this book may be useful even if you must stick with Python 2.7, because the core concepts are still the same. Python 3 is not a new language, and most differences can be learned in an afternoon. What's New in Python 3.0 is a good starting point. Of course, there have been changes since Python 3.0 was released in 2009, but none as important as those in 3.0.

If you are not sure whether you know enough Python to follow along, review the topics of the official Python Tutorial. Topics covered in the tutorial will not be explained here, except for some features that are new in Python 3.

Who This Book Is Not For

If you are just learning Python, this book is going to be hard to follow. Not only that, if you read it too early in your Python journey, it may give you the impression that every Python script should leverage special methods and metaprogramming tricks. Premature abstraction is as bad as premature optimization.

How This Book Is Organized

The core audience for this book should not have trouble jumping directly to any chapter in this book. However, each of the six parts forms a book within the book. I conceived the chapters within each part to be read in sequence.

I tried to emphasize using what is available before discussing how to build your own. For example, in Part II, Chapter 2 covers sequence types that are ready to use, including some that don't get a lot of attention, like `collections.deque`. Building user-defined sequences is only addressed in Part IV, where we also see how to leverage the abstract base classes (ABCs) from `collections.abc`. Creating your own ABCs is discussed even later in Part IV, because I believe it's important to be comfortable using an ABC before writing your own.

This approach has a few advantages. First, knowing what is ready to use can save you from reinventing the wheel. We use existing collection classes more often than we implement our own, and we can give more attention to the advanced usage of available tools by deferring the discussion on how to create new ones. We are also more likely to inherit from existing ABCs than to create a new ABC from scratch. And finally, I believe it is easier to understand the abstractions after you've seen them in action.

The downside of this strategy are the forward references scattered throughout the chapters. I hope these will be easier to tolerate now that you know why I chose this path.

Here are the main topics in each part of the book:

Part I, Prologue

A single chapter about the Python Data Model explaining how the special methods (e.g., `__repr__`) are the key to the consistent behavior of objects of all types—in a language that is admired for its consistency. Understanding various facets of the data model is the subject of most of the rest of the book, but Chapter 1 provides a high-level overview.

Part II, Data Structures

The chapters in this part cover the use of collection types: sequences, mappings, and sets, as well as the `str` versus `bytes` split—the cause of much celebration among Python 3 users and much pain for Python 2 users who have not yet migrated their codebases. The main goals are to recall what is already available and to explain some behavior that is sometimes surprising, like the reordering of `dict` keys when we are not looking, or the caveats of locale-dependent Unicode string sorting. To achieve these goals, the coverage is sometimes high level and wide (e.g., when many variations of sequences and mappings are presented) and sometimes deep (e.g., when we dive into the hash tables underneath the `dict` and `set` types).

Part III, Functions as Objects

Here we talk about functions as first-class objects in the language: what that means, how it affects some popular design patterns, and how to implement function decorators by leveraging closures. Also covered here is the general concept of callables in Python, function attributes, introspection, parameter annotations, and the new `nonlocal` declaration in Python 3.

Part IV, Classes and Protocols

Now the focus is on building classes. In Part II, the `class` declaration appears in few examples; Part IV presents many classes. Like any object-oriented (OO) language, Python has its particular set of features that may or may not be present in the language in which you and I learned class-based programming. The chapters explain how references work, what mutability really means, the lifecycle of instances, how to build your own collections and ABCs, how to cope with multiple inheritance, and how to implement operator overloading—when that makes sense.

[Link to Come]

Covered in this part are the language constructs and libraries that go beyond sequential control flow with conditionals, loops, and subroutines. We start with generators, then visit context managers and coroutines, including the challenging but powerful new `yield from` syntax. [Link to Come] closes with a high-level introduction to modern concurrency in Python with `collections.futures` (using threads and processes under the covers with the help of futures) and doing event-oriented I/O with `asyncio` (leveraging futures on top of coroutines and `yield from`).

[Link to Come]

This part starts with a review of techniques for building classes with attributes created dynamically to handle semi-structured data such as JSON datasets. Next, we cover the familiar properties mechanism, before diving into how object attribute access works at a lower level in Python using descriptors. The relationship between functions, methods, and descriptors is explained. Throughout [Link to Come], the step-by-step implementation of a field validation library uncovers subtle issues that lead to the use of the advanced tools of the final chapter: class decorators and metaclasses.

Hands-On Approach

Often we'll use the interactive Python console to explore the language and libraries. I feel it is important to emphasize the power of this learning tool, particularly for those readers who've had more experience with static, compiled languages that don't provide a read-eval-print loop (REPL).

One of the standard Python testing packages, `doctest`, works by simulating console sessions and verifying that the expressions evaluate to the responses shown. I used `doctest` to check most of the code in this book, including the console listings. You don't need to use or even know about `doctest` to follow along: the key feature of doctests is that they look like transcripts of interactive Python console sessions, so you can easily try out the demonstrations yourself.

Sometimes I will explain what we want to accomplish by showing a doctest before the code that makes it pass. Firmly establishing what is to be done before thinking about how to do it helps focus our coding effort. Writing tests first is the basis of test driven development (TDD) and I've also found it helpful when teaching. If you are unfamiliar with `doctest`, take a look at its documentation and this book's source code repository. You'll find that you can verify the correctness of most of the code in the book by typing `python3 -m doctest example_script.py` in the command shell of your OS.

Hardware Used for Timings

The book has some simple benchmarks and timings. Those tests were performed on one or the other laptop I used to write the book: a 2011 MacBook Pro 13″ with a 2.7 GHz Intel Core i7 CPU, 8GB of RAM, and a spinning hard disk, and a 2014 MacBook Air 13″ with a 1.4 GHz Intel Core i5 CPU, 4GB of RAM, and a solid-state disk. The MacBook Air has a slower CPU and less RAM, but its RAM is faster (1600 versus 1333 MHz) and the SSD is much faster than the HD. In daily usage, I can't tell which machine is faster.

Soapbox: My Personal Perspective

I have been using, teaching, and debating Python since 1998, and I enjoy studying and comparing programming languages, their design, and the theory behind them. At the end of some chapters, I have added "Soapbox" sidebars with my own perspective about Python and other languages. Feel free to skip these if you are not into such discussions. Their content is completely optional.

Python Jargon

I wanted this to be a book not only about Python but also about the culture around it. Over more than 20 years of communications, the Python community has developed its own particular lingo and acronyms. Here you'll see that some words—like "decorator", "descriptor", and "protocol"—have special meaning among Pythonistas. You'll also get fluent with Python slang like "dunder", "listcomp", and "genexp".

Python Version Covered

I tested all the code in the book using Python 3.4—that is, CPython 3.4, the most popular Python implementation written in C. There is only one exception: "Using @ as an infix operator" shows the `@` operator, which is only supported by Python 3.5.

Almost all code in the book should work with any Python 3.x–compatible interpreter, including PyPy3 2.4.0, which is compatible with Python 3.2.5. The notable exceptions are the examples using `yield from` and `asyncio`, which are only available in Python 3.3 or later.

Most code should also work with Python 2.7 with minor changes, except the Unicode-related examples in Chapter 4, and the exceptions already noted for Python 3 versions earlier than 3.3.

Conventions Used in This Book

The following typographical conventions are used in this book:

Italic

Indicates new terms, URLs, email addresses, filenames, and file extensions.

`Constant width`

Used for program listings, as well as within paragraphs to refer to program elements such as variable or function names, databases, data types, environment variables, statements, and keywords.

Note that when a line break falls within a `constant_width` term, a hyphen is not added—it could be misunderstood as part of the term.

`Constant width bold`

Shows commands or other text that should be typed literally by the user.

`Constant width italic`

Shows text that should be replaced with user-supplied values or by values determined by context.

> **TIP**
>
> This element signifies a tip or suggestion.

> **NOTE**
>
> This element signifies a general note.

> **WARNING**
>
> This element indicates a warning or caution.

Using Code Examples

Every script and most code snippets that appear in the book are available in the Fluent Python code repository on GitHub.

We appreciate, but do not require, attribution. An attribution usually includes the title, author, publisher, and ISBN. For example: "*Fluent Python* by Luciano Ramalho (O'Reilly). Copyright 2015 Luciano Ramalho, 978-1-491-94600-8."

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We have a web page for this book, where we list errata, examples, and any additional information. You can access this page at *http://bit.ly/fluent-python*.

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Acknowledgments

The Bauhaus chess set by Josef Hartwig is an example of excellent design: beautiful, simple, and clear. Guido van Rossum, son of an architect and brother of a master font designer, created a masterpiece of language design. I love teaching Python because it is beautiful, simple, and clear.

Alex Martelli and Anna Ravenscroft were the first people to see the outline of this book and encouraged me to submit it to O'Reilly for publication. Their books taught me idiomatic Python and are models of clarity, accuracy, and depth in technical writing. Alex's 5,000+ Stack Overflow posts are a fountain of insights about the language and its proper use.

Martelli and Ravenscroft were also technical reviewers of this book, along with Lennart Regebro and Leonardo Rochael. Everyone in this outstanding technical review team has at least 15 years of Python experience, with many contributions to high-impact Python projects in close contact with other developers in the community. Together they sent me hundreds of corrections, suggestions, questions, and opinions, adding tremendous value to the book. Victor Stinner kindly reviewed Chapter 22, bringing his expertise as an `asyncio` maintainer to the technical review team. It was a great privilege and a pleasure to collaborate with them over these past several months.

Editor Meghan Blanchette was an outstanding mentor, helping me improve the organization and flow of the book, letting me know when it was boring, and keeping me from delaying even more. Brian MacDonald edited chapters in Part III while Meghan was away. I enjoyed working with them, and with everyone I've contacted at O'Reilly, including the Atlas development and support team (Atlas is the O'Reilly book publishing platform, which I was fortunate to use to write this book).

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The wonderful Brazilian Python community is knowledgeable, generous, and fun. The Python Brasil group has thousands of people and our national conferences bring together hundreds, but the most influential in my journey as a Pythonista were Leonardo Rochael, Adriano Petrich, Daniel Vainsencher, Rodrigo RBP Pimentel, Bruno Gola, Leonardo Santagada, Jean Ferri, Rodrigo Senra, J. S. Bueno, David Kwast, Luiz Irber, Osvaldo Santana, Fernando Masanori, Henrique Bastos, Gustavo Niemayer, Pedro Werneck, Gustavo Barbieri, Lalo Martins, Danilo Bellini, and Pedro Kroger.

Dorneles Tremea was a great friend (incredibly generous with his time and knowledge), an amazing hacker, and the most inspiring leader of the Brazilian Python Association. He left us too early.

My students over the years taught me a lot through their questions, insights, feedback, and creative solutions to problems. Érico Andrei and Simples Consultoria made it possible for me to focus on being a Python teacher for the first time.

Martijn Faassen was my Grok mentor and shared invaluable insights with me about Python and Neanderthals. His work and that of Paul Everitt, Chris McDonough, Tres Seaver, Jim Fulton, Shane Hathaway, Lennart Regebro, Alan Runyan, Alexander Limi, Martijn Pieters, Godefroid Chapelle, and others from the Zope, Plone, and Pyramid planets have been decisive in my career. Thanks to Zope and surfing the first web wave, I was able to start making a living with Python in 1998. José Octavio Castro Neves was my partner in the first Python-centric software house in Brazil.

I have too many gurus in the wider Python community to list them all, but besides those already mentioned, I am indebted to Steve Holden, Raymond

Hettinger, A.M. Kuchling, David Beazley, Fredrik Lundh, Doug Hellmann, Nick Coghlan, Mark Pilgrim, Martijn Pieters, Bruce Eckel, Michele Simionato, Wesley Chun, Brandon Craig Rhodes, Philip Guo, Daniel Greenfeld, Audrey Roy, and Brett Slatkin for teaching me new and better ways to teach Python.

Most of these pages were written in my home office and in two labs: CoffeeLab and Garoa Hacker Clube. CoffeeLab is the caffeine-geek headquarters in Vila Madalena, São Paulo, Brazil. Garoa Hacker Clube is a hackerspace open to all: a community lab where anyone can freely try out new ideas.

The Garoa community provided inspiration, infrastructure, and slack. I think Aleph would enjoy this book.

My mother, Maria Lucia, and my father, Jairo, always supported me in every way. I wish he was here to see the book; I am glad I can share it with her.

My wife, Marta Mello, endured 15 months of a husband who was always working, but remained supportive and coached me through some critical moments in the project when I feared I might drop out of the marathon.

Thank you all, for everything.

---

1 Message to the comp.lang.python Usenet group, Dec. 23, 2002: "Acrimony in c.l.p."

Part I. Prologue

Chapter 1. The Python Data Model

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 1st chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Guido's sense of the aesthetics of language design is amazing. I've met many fine language designers who could build theoretically beautiful languages that no one would ever use, but Guido is one of those rare people who can build a language that is just slightly less theoretically beautiful but thereby is a joy to write programs in.*[1]
>
> —Jim Hugunin, Creator of Jython, cocreator of AspectJ, architect of the .Net DLR

One of the best qualities of Python is its consistency. After working with Python for a while, you are able to start making informed, correct guesses about features that are new to you.

However, if you learned another object-oriented language before Python, you may find it strange to use `len(collection)` instead of `collection.len()`. This apparent oddity is the tip of an iceberg that, when properly understood, is the key to everything we call *Pythonic*. The iceberg is called the Python Data Model, and it is the API that we use to make our own objects play well with the most idiomatic language features.

You can think of the data model as a description of Python as a framework. It formalizes the interfaces of the building blocks of the language itself, such as sequences, functions, iterators, coroutines, classes, context managers, and so on.

When using a framework, we spend a lot of time coding methods that are called by the framework. The same happens when we leverage the Python Data Model to build new classes. The Python interpreter invokes special methods to perform basic object operations, often triggered by special syntax. The special method names are always written with leading and trailing double underscores. For example, the syntax `obj[key]` is supported by the `__getitem__` special method. In order to evaluate `my_collection[key]`, the interpreter calls `my_collection.__getitem__(key)`.

We implement special methods when we want our objects to support and interact with fundamental language constructs such as:

- Collections;
- Attribute access;
- Iteration (including asynchronous iteration using `async for`);
- Operator overloading;
- Function and method invocation;
- String representation and formatting;
- Asynchronous programing using `await`;
- Object creation and destruction;
- Managed contexts using the `with` or `async with` statements.

> **MAGIC AND DUNDER**
>
> The term *magic method* is slang for special method, but how do we talk about a specific method like `__getitem__`? I learned to say "dunder-getitem" from author and teacher Steve Holden. "Dunder" is a shortcut for "double underscore before and after". That's why the special methods are also known as *dunder methods*. The *Lexical Analysis* chapter of *The Python Language Reference* warns that "*Any* use of `__*__` names, in any context, that does not follow explicitly documented use, is subject to breakage without warning."

What's new in this chapter

This chapter had few changes from the first edition because it is an introduction to the Python Data Model, which is quite stable. The most significant changes are:

- Special methods supporting asynchronous programming and other new features, added to the tables in "Overview of Special Methods".
- Figure 1-2 showing the use of special methods in "Collection API", including the `collections.abc.Collection` abstract base class introduced in Python 3.6.

Also, here and throughout this *Second Edition* I adopted the *f-string* syntax introduced in Python 3.6, which is more readable and often more convenient than the older string formatting notations: the `str.format()` method and the `%` operator.

> **TIP**
>
> One reason to still use `my_fmt.format()` is when the definition of `my_fmt` must be in a different place in the code than where the formatting operation needs to happen. For instance, when `my_fmt` has multiple lines and is better defined in a constant, or when it must come from a configuration file, or from the database. Those are real needs, but don't happen very often.

A Pythonic Card Deck

Example 1-1 is simple, but it demonstrates the power of implementing just two special methods, `__getitem__` and `__len__`.

Example 1-1. A deck as a sequence of playing cards

```
import collections

Card = collections.namedtuple('Card', ['rank', 'suit'])

class FrenchDeck:
    ranks = [str(n) for n in range(2, 11)] + list('JQKA')
    suits = 'spades diamonds clubs hearts'.split()

    def __init__(self):
        self._cards = [Card(rank, suit) for suit in self.suits
                                        for rank in self.ranks]

    def __len__(self):
        return len(self._cards)

    def __getitem__(self, position):
        return self._cards[position]
```

The first thing to note is the use of `collections.namedtuple` to construct a simple class to represent individual cards. We use `namedtuple` to build classes of objects that are just bundles of attributes with no custom methods, like a database record. In the example, we use it to provide a nice representation for the cards in the deck, as shown in the console session:

```
>>> beer_card = Card('7', 'diamonds')
>>> beer_card
Card(rank='7', suit='diamonds')
```

But the point of this example is the `FrenchDeck` class. It's short, but it packs a punch. First, like any standard Python collection, a deck responds to the `len()` function by returning the number of cards in it:

```
>>> deck = FrenchDeck()
>>> len(deck)
```

Reading specific cards from the deck—say, the first or the last—is easy, thanks to the `__getitem__` method:

```
>>> deck[0]
Card(rank='2', suit='spades')
>>> deck[-1]
Card(rank='A', suit='hearts')
```

Should we create a method to pick a random card? No need. Python already has a function to get a random item from a sequence: `random.choice`. We can use it on a deck instance:

```
>>> from random import choice
>>> choice(deck)
Card(rank='3', suit='hearts')
>>> choice(deck)
Card(rank='K', suit='spades')
>>> choice(deck)
Card(rank='2', suit='clubs')
```

We've just seen two advantages of using special methods to leverage the Python Data Model:

- Users of your classes don't have to memorize arbitrary method names for standard operations ("How to get the number of items? Is it `.size()`, `.length()`, or what?").
- It's easier to benefit from the rich Python standard library and avoid reinventing the wheel, like the `random.choice` function.

But it gets better.

Because our `__getitem__` delegates to the `[]` operator of `self._cards`, our deck automatically supports slicing. Here's how we look at the top three cards from a brand-new deck, and then pick just the Aces by starting at index 12 and skipping 13 cards at a time:

```
>>> deck[:3]
[Card(rank='2', suit='spades'), Card(rank='3', suit='spades'),
Card(rank='4', suit='spades')]
>>> deck[12::13]
[Card(rank='A', suit='spades'), Card(rank='A', suit='diamonds'),
Card(rank='A', suit='clubs'), Card(rank='A', suit='hearts')]
```

Just by implementing the `__getitem__` special method, our deck is also iterable:

```
>>> for card in deck:  # doctest: +ELLIPSIS
...   print(card)
Card(rank='2', suit='spades')
Card(rank='3', suit='spades')
Card(rank='4', suit='spades')
...
```

We can also iterate over the deck in reverse:

```
>>> for card in reversed(deck):  # doctest: +ELLIPSIS
...   print(card)
Card(rank='A', suit='hearts')
Card(rank='K', suit='hearts')
Card(rank='Q', suit='hearts')
...
```

ELLIPSIS IN DOCTESTS

Whenever possible, I extracted the Python console listings in this book from doctests to ensure accuracy. When the output was too long, the elided part is marked by an ellipsis (`...`) like in the last line in the preceding code. In such cases, I used the `# doctest: +ELLIPSIS` directive to make the doctest pass. If you are trying these examples in the interactive console, you may omit the doctest comments altogether.

Iteration is often implicit. If a collection has no `__contains__` method, the `in` operator does a sequential scan. Case in point: `in` works with our `FrenchDeck` class because it is iterable. Check it out:

```
>>> Card('Q', 'hearts') in deck
True
```

```
>>> Card('7', 'beasts') in deck
False
```

How about sorting? A common system of ranking cards is by rank (with aces being highest), then by suit in the order of spades (highest), hearts, diamonds, and clubs (lowest). Here is a function that ranks cards by that rule, returning `0` for the 2 of clubs and `51` for the ace of spades:

```
suit_values = dict(spades=3, hearts=2, diamonds=1, clubs=0)

def spades_high(card):
    rank_value = FrenchDeck.ranks.index(card.rank)
    return rank_value * len(suit_values) + suit_values[card.suit]
```

Given `spades_high`, we can now list our deck in order of increasing rank:

```
>>> for card in sorted(deck, key=spades_high):  # doctest:
+ELLIPSIS
...      print(card)
Card(rank='2', suit='clubs')
Card(rank='2', suit='diamonds')
Card(rank='2', suit='hearts')
... (46 cards omitted)
Card(rank='A', suit='diamonds')
Card(rank='A', suit='hearts')
Card(rank='A', suit='spades')
```

Although `FrenchDeck` implicitly inherits from the `object` class, most of its functionality is not inherited, but comes from leveraging the data model and composition. By implementing the special methods `__len__` and `__getitem__`, our `FrenchDeck` behaves like a standard Python sequence, allowing it to benefit from core language features (e.g., iteration and slicing) and from the standard library, as shown by the examples using `random.choice`, `reversed`, and `sorted`. Thanks to composition, the `__len__` and `__getitem__` implementations can delegate all the work to a `list` object, `self._cards`.

HOW ABOUT SHUFFLING?

As implemented so far, a `FrenchDeck` cannot be shuffled, because it is *immutable*: the cards, and their positions cannot be changed, except by violating encapsulation and handling the `_cards` attribute directly. In Chapter 13, we will fix that by adding a one-line `__setitem__` method.

How Special Methods Are Used

The first thing to know about special methods is that they are meant to be called by the Python interpreter, and not by you. You don't write `my_object.__len__()`. You write `len(my_object)` and, if `my_object` is an instance of a user-defined class, then Python calls the `__len__` method you implemented.

But the interpreter takes a shortcut when dealing for built-in types like `list`, `str`, `bytearray`, or extensions like the NumPy arrays. Python variable-sized collections written in C include a struct[2] called `PyVarObject`, which has an `ob_size` field holding the number of items in the collection. So, if `my_object` is an instance of one of those built-ins, then `len(my_object)` retrieves the value of the `ob_size` field, and this is much faster than calling a method.

More often than not, the special method call is implicit. For example, the statement `for i in x:` actually causes the invocation of `iter(x)`, which in turn may call `x.__iter__()` if that is available, or use `x.__getitem__()`—as in the `FrenchDeck` example.

Normally, your code should not have many direct calls to special methods. Unless you are doing a lot of metaprogramming, you should be implementing special methods more often than invoking them explicitly. The only special method that is frequently called by user code directly is `__init__`, to invoke the initializer of the superclass in your own `__init__` implementation.

If you need to invoke a special method, it is usually better to call the related built-in function (e.g., `len`, `iter`, `str`, etc). These built-ins call the corresponding special method, but often provide other services and—for built-in types—are faster than method calls. See, for example, "A Closer Look at the iter Function" in Chapter 17.

In the next sections, we'll see some of the most important uses of special methods:

- Emulating numeric types;
- String representation of objects;
- Boolean value of an object;
- Implementing collections.

Emulating Numeric Types

Several special methods allow user objects to respond to operators such as `+`. We will cover that in more detail in Chapter 16, but here our goal is to further illustrate the use of special methods through another simple example.

We will implement a class to represent two-dimensional vectors—that is Euclidean vectors like those used in math and physics (see Figure 1-1).

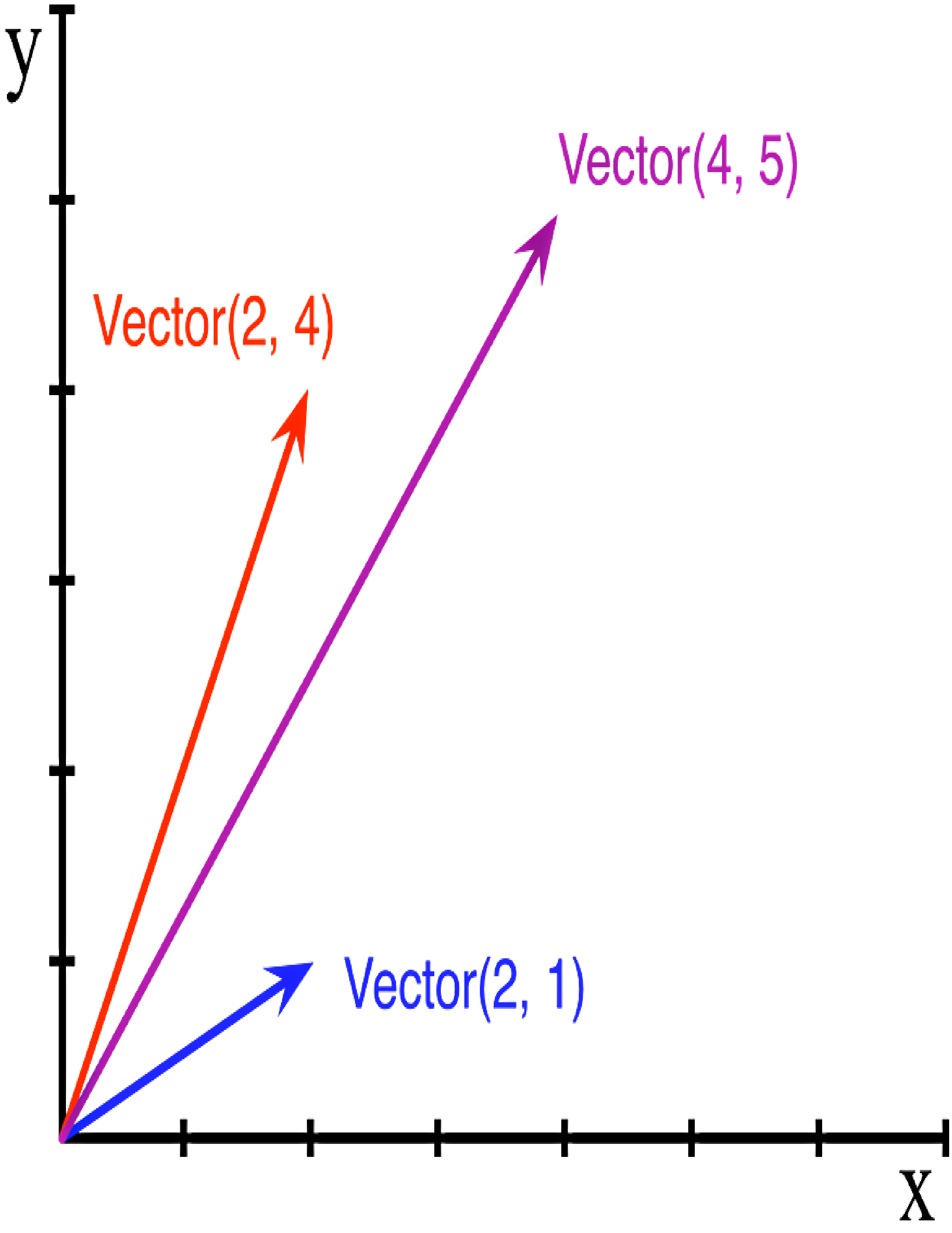


Figure 1-1. Example of two-dimensional vector addition; Vector(2, 4) + Vector(2, 1) results in Vector(4, 5).

TIP

The built-in `complex` type can be used to represent two-dimensional vectors, but our class can be extended to represent *n*-dimensional vectors. We will do that in Chapter 17.

We will start by designing the API for such a class by writing a simulated console session that we can use later as a doctest. The following snippet tests the vector addition pictured in Figure 1-1:

```
>>> v1 = Vector(2, 4)
>>> v2 = Vector(2, 1)
>>> v1 + v2
Vector(4, 5)
```

Note how the `+` operator results in a new `Vector`, displayed in a friendly format at the console.

The `abs` built-in function returns the absolute value of integers and floats, and the magnitude of `complex` numbers, so to be consistent, our API also uses `abs` to calculate the magnitude of a vector:

```
>>> v = Vector(3, 4)
>>> abs(v)
5.0
```

We can also implement the `*` operator to perform scalar multiplication (i.e., multiplying a vector by a number to make a new vector with the same direction and a multiplied magnitude):

```
>>> v * 3
Vector(9, 12)
>>> abs(v * 3)
15.0
```

Example 1-2 is a `Vector` class implementing the operations just described, through the use of the special methods `__repr__`, `__abs__`, `__add__` and `__mul__`.

Example 1-2. A simple two-dimensional vector class

```python
"""
vector2d.py: a simplistic class demonstrating some special methods

It is simplistic for didactic reasons. It lacks proper error
handling,
especially in the ``__add__`` and ``__mul__`` methods.

This example is greatly expanded later in the book.

Addition::

    >>> v1 = Vector(2, 4)
    >>> v2 = Vector(2, 1)
    >>> v1 + v2
    Vector(4, 5)

Absolute value::

    >>> v = Vector(3, 4)
    >>> abs(v)
    5.0

Scalar multiplication::

    >>> v * 3
    Vector(9, 12)
    >>> abs(v * 3)
    15.0

"""


import math

class Vector:

    def __init__(self, x=0, y=0):
        self.x = x
        self.y = y

    def __repr__(self):
        return f'Vector({self.x!r}, {self.y!r})'

    def __abs__(self):
        return math.hypot(self.x, self.y)
```

```python
    def __bool__(self):
        return bool(abs(self))

    def __add__(self, other):
        x = self.x + other.x
        y = self.y + other.y
        return Vector(x, y)

    def __mul__(self, scalar):
        return Vector(self.x * scalar, self.y * scalar)
```

We implemented five special methods in addition to the familiar `__init__`. Note that none of them is directly called within the class or in the typical usage of the class illustrated by the doctests. As mentioned before, the Python interpreter is the only frequent caller of most special methods.

Example 1-2 implements two operators: `+` and `*`, to show basic usage of `__add__` and `__mul__`. In both cases, the methods create and return a new instance of `Vector`, and do not modify either operand—`self` or `other` are merely read. This is the expected behavior of infix operators: to create new objects and not touch their operands. I will have a lot more to say about that in Chapter 16.

> **WARNING**
>
> As implemented, Example 1-2 allows multiplying a `Vector` by a number, but not a number by a `Vector`, which violates the commutative property of scalar multiplication. We will fix that with the special method `__rmul__` in Chapter 16.

In the following sections, we discuss the code for the other special methods in `Vector`.

String Representation

The `__repr__` special method is called by the `repr` built-in to get the string representation of the object for inspection. Without a custom `__repr__`, Python's console would display a `Vector` instance `<Vector object at 0x10e100070>`.

The interactive console and debugger call `repr` on the results of the expressions evaluated, as does the `%r` placeholder in classic formatting with the `%` operator, and the `!r` conversion field in the new Format String Syntax used in *f-strings* the `str.format` method.

Note that the *f-string* in our `__repr__`, uses `!r` to get the standard representation of the attributes to be displayed. This is good practice, because it shows the crucial difference between `Vector(1, 2)` and `Vector('1', '2')`—the latter would not work in the context of this example, because the constructor's arguments should be numbers, not `str`.

The string returned by `__repr__` should be unambiguous and, if possible, match the source code necessary to re-create the represented object. That is why our `Vector` representation looks like calling the constructor of the class (e.g., `Vector(3, 4)`).

In contrast, `__str__` is called by the `str()` built-in and implicitly used by the `print` function. It should return a string suitable for display to end users.

Sometimes same string returned by `__repr__` is user-friendly, and you don't need to code `__str__` because the implementation inherited from the `object` class calls `__repr__` as a fallback. Example 5-2 is one of several examples in this book with a custom `__str__`.

> **TIP**
>
> Programmers with prior experience in languages with a `toString` method tend to implement `__str__` and not `__repr__`. If you only implement one of these special methods in Python, choose `__repr__`.
>
> "Difference between `__str__` and `__repr__` in Python" is a Stack Overflow question with excellent contributions from Pythonistas Alex Martelli and Martijn Pieters.

Boolean Value of a Custom Type

Although Python has a `bool` type, it accepts any object in a boolean context, such as the expression controlling an `if` or `while` statement, or as operands to `and`, `or`, and `not`. To determine whether a value `x` is *truthy* or *falsy*, Python applies `bool(x)`, which returns either `True` or `False`.

By default, instances of user-defined classes are considered truthy, unless either `__bool__` or `__len__` is implemented. Basically, `bool(x)` calls `x.__bool__()` and uses the result. If `__bool__` is not implemented, Python tries to invoke `x.__len__()`, and if that returns zero, `bool` returns `False`. Otherwise `bool` returns `True`.

Our implementation of `__bool__` is conceptually simple: it returns `False` if the magnitude of the vector is zero, `True` otherwise. We convert the magnitude to a Boolean using `bool(abs(self))` because `__bool__` is expected to return a boolean. Outside of `__bool__` methods, it is rarely necessary to call `bool()` explicitly, because any object can be used in a boolean context.

Note how the special method `__bool__` allows your objects to follow the truth value testing rules defined in the "Built-in Types" chapter of *The Python Standard Library* documentation.

NOTE

A faster implementation of `Vector.__bool__` is this:

```
    def __bool__(self):
        return bool(self.x or self.y)
```

This is harder to read, but avoids the trip through `abs`, `__abs__`, the squares, and square root. The explicit conversion to `bool` is needed because `__bool__` must return a boolean and `or` returns either operand as is: `x or y` evaluates to `x` if that is *truthy*, otherwise the result is `y`, whatever that is.

Collection API

Figure 1-2 documents the interfaces of the essential collection types in the language. All the classes in the diagram are ABCs—*abstract base classes*. ABCs and the `collections.abc` module are covered in Chapter 13. The goal of this brief section is to give a panoramic view of Python's most important collection interfaces, showing how they are built from special methods.

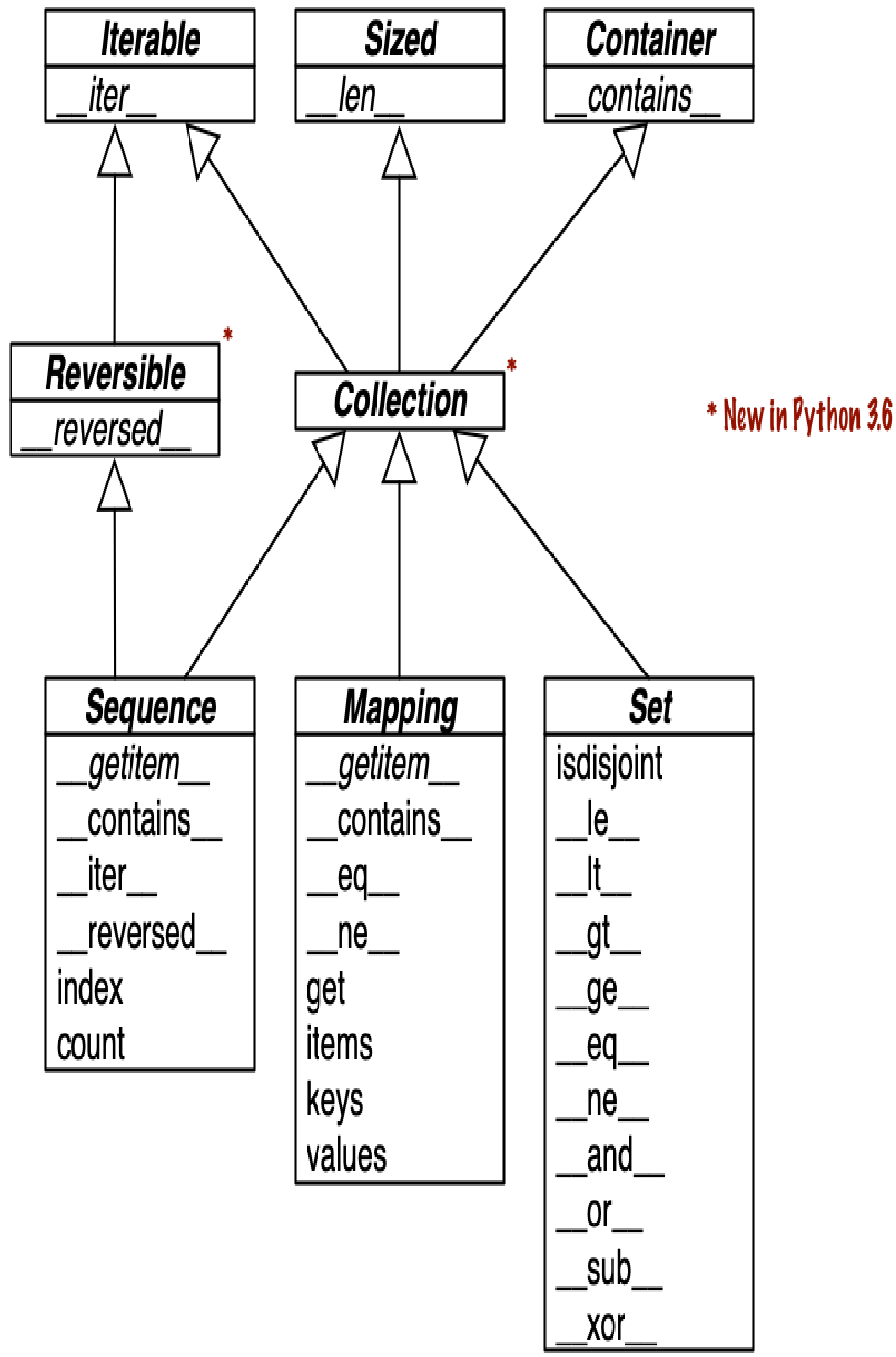


Figure 1-2. UML class diagram with fundamental collection types. Method names in italic are abstract, so they must be implemented by concrete subclasses such as `list` and `dict`. The remaining methods have concrete implementations, therefore subclasses can inherit them.

Each of the top ABCs has a single special method. The `Collection` ABC (new in Python 3.6) unifies the three essential interfaces that every collection should implement:

- `Iterable` to support `for`, unpacking, and other forms of iteration;
- `Sized` to support the `len` built-in function;
- `Contains` to support the `in` operator.

Python does not require concrete classes to actually inherit from any of these ABCs. Any class that implements `__len__` satisfies the `Sized` interface.

Three very important specializations of `Collection` are:

- `Sequence`, formalizing the interface of built-ins like `list` and `str`;
- `Mapping`, implemented by `dict`, `collections.defaultdict`, etc.;
- `Set`: the interface of the `set` and `frozenset` built-in types.

Only `Sequence` is `Reversible`, because sequences support arbitrary ordering of their contents, while mappings and sets do not.

> **NOTE**
>
> Since Python 3.7, the `dict` type is officially "ordered", but that only means that the key insertion order is preserved. You cannot rearrange the keys in a `dict` however you like.

All the special methods in the `Set` ABC implement infix operators. For example, `a & b` computes the intersection of sets `a` and `b`, and is implemented in the `__and__` special method.

The next two chapters will cover standard library sequences, mappings, and sets in detail.

Now let's consider the major categories of special methods defined in the Python Data Model.

Overview of Special Methods

The “Data Model” chapter of *The Python Language Reference* lists more than 80 special method names. More than half of them implement arithmetic, bitwise, and comparison operators. As an overview of what is available, see following tables.

Table 1-1 shows special method names excluding those used to implement infix operators or core math functions like `abs`. Most of these methods will be covered throughout the book, including the most recent additions: asynchronous special methods such as `__anext__` (added in Python 3.5), and the class customization hook, `__init_subclass__` (from Python 3.6).

Table 1-1. Special method names (ope

rators excluded)

Category	Method names
String/bytes representation	`__repr__` `__str__` `__format__` `__bytes__` `__fspath__`
Conversion to number	`__bool__` `__complex__` `__int__` `__float__` `__hash__` `__index__`
Emulating collections	`__len__` `__getitem__` `__setitem__` `__delitem__` `__contains__`
Iteration	`__iter__` `__aiter__` `__next__`, `__anext__` `__reversed__`
Callable or coroutine execution	`__call__` `__await__`
Context management	`__enter__` `__exit__` `__aexit__` `__aenter__`
Instance creation and destruction	`__new__` `__init__` `__del__`

Attribute management	`__getattr__` `__getattribute__` `__setattr__` `__delattr__` `__dir__`
Attribute descriptors	`__get__` `__set__` `__delete__` `__set_name__`
Abstract base classes	`__instancecheck__` `__subclasscheck__`
Class metaprogramming	`__prepare__` `__init_subclass__` `__class_getitem__` `__mro_entries__`

Infix and numerical operators are supported by the special methods in 1-2. Here the most recent names are `__matmul__`, `__rmatmul__`, and `__imatmul__`, added in Python 3.5 to support the use of `@` as an infix operator for matrix multiplication, as we'll see in Chapter 16.

Table 1-2. Special method names and symb *olsforoperators*

Operator category	Symbols	Method names
Unary numeric	`-` `+` `abs()`	`__neg__` `__pos__` `__abs__`
Rich comparison	`<` `\<=` `==` `!=` `>` `>=`	`__lt__` `__le__` `__eq__` `__ne__` `__gt__` `__ge__`
Arithmetic	`+` `-` `*` `/` `//` `%` `@` `divmod()` `round()` `**` `pow()`	`__add__` `__sub__` `__mul__` `__truediv__` `__floordiv__` `__mod__` `__matmul__` `__divmod__` `__round__` `__pow__`
Reversed arithmetic	(arithmetic operators with swapped operands)	`__radd__` `__rsub__` `__rmul__` `__rtruediv__` `__rfloordiv__` `__rmod__` `__rmatmul__` `__rdivmod__` `__rpow__`
Augmented assignment arithmetic	`+=` `-=` `*=` `/=` `//=` `%=` `@=` `**=`	`__iadd__` `__isub__` `__imul__` `__itruediv__` `__ifloordiv__` `__imod__` `__imatmul__` `__ipow__`
Bitwise	`&` `|` `^` `<<` `>>` `~`	`__and__` `__or__` `__xor__` `__lshift__` `__rshift__` `__invert__`

Reversed bitwise	(bitwise operators with swapped operands)	`__rand__` `__ror__` `__rxor__` `__rlshift__` `__rrshift__`
Augmented assignment bitwise	`&=` `|=` `^=` `<<=` `>>=`	`__iand__` `__ior__` `__ixor__` `__ilshift__` `__irshift__`

> **NOTE**
>
> Python calls a reversed operator special method on the second operand when the corresponding special method on the first operand cannot be used. Augmented assignments are shortcuts combining an infix operator with variable assignment, e.g. `a += b`.
>
> Chapter 16 explains reversed operators and augmented assignment in detail.

Why len Is Not a Method

I asked this question to core developer Raymond Hettinger in 2013 and the key to his answer was a quote from The Zen of Python: "practicality beats purity." In "How Special Methods Are Used", I described how `len(x)` runs very fast when `x` is an instance of a built-in type. No method is called for the built-in objects of CPython: the length is simply read from a field in a C struct. Getting the number of items in a collection is a common operation and must work efficiently for such basic and diverse types as `str`, `list`, `memoryview`, and so on.

In other words, `len` is not called as a method because it gets special treatment as part of the Python Data Model, just like `abs`. But thanks to the special method `__len__`, you can also make `len` work with your own custom objects. This is a fair compromise between the need for efficient built-in objects and the consistency of the language. Also from The Zen of Python: "Special cases aren't special enough to break the rules."

NOTE

If you think of `abs` and `len` as unary operators, you may be more inclined to forgive their functional look-and-feel, as opposed to the method call syntax one might expect in an OO language. In fact, the ABC language—a direct ancestor of Python that pioneered many of its features—had an # operator that was the equivalent of `len` (you'd write `#s`). When used as an infix operator, written `x#s`, it counted the occurrences of `x` in `s`, which in Python you get as `s.count(x)`, for any sequence `s`.

Chapter Summary

By implementing special methods, your objects can behave like the built-in types, enabling the expressive coding style the community considers Pythonic.

A basic requirement for a Python object is to provide usable string representations of itself, one used for debugging and logging, another for presentation to end users. That is why the special methods `__repr__` and `__str__` exist in the data model.

Emulating sequences, as shown with the `FrenchDeck` example, is one of the most common uses of the special methods. For example, database libraries often return query results wrapped in sequence-like collections. Making the most of existing sequence types is the subject of Chapter 2. Implementing your own sequences will be covered in Chapter 12, when we create a multidimensional extension of the `Vector` class.

Thanks to operator overloading, Python offers a rich selection of numeric types, from the built-ins to `decimal.Decimal` and `fractions.Fraction`, all supporting infix arithmetic operators. The *NumPy* data science libraries support infix operators with matrices and tensors. Implementing operators—including reversed operators and augmented assignment—will be shown in Chapter 16 via enhancements of the `Vector` example.

The use and implementation of the majority of the remaining special methods of the Python Data Model are covered throughout this book.

Further Reading

The "Data Model" chapter of *The Python Language Reference* is the canonical source for the subject of this chapter and much of this book.

Python in a Nutshell, 3rd Edition (O'Reilly) by Alex Martelli, Anna Ravenscroft, and Steve Holden has excellent coverage of the data model. Their description of the mechanics of attribute access is the most authoritative I've seen apart from the actual C source code of CPython. Martelli is also a prolific contributor to Stack Overflow, with more than 6,200 answers posted. See his user profile at Stack Overflow.

David Beazley has two books covering the data model in detail in the context of Python 3: *Python Essential Reference, 4th Edition* (Addison-Wesley Professional), and *Python Cookbook, 3rd Edition* (O'Reilly), coauthored with Brian K. Jones.

The Art of the Metaobject Protocol (AMOP, MIT Press) by Gregor Kiczales, Jim des Rivieres, and Daniel G. Bobrow explains the concept of a metaobject protocol, of which the Python Data Model is one example.

SOAPBOX

Data Model or Object Model?

What the Python documentation calls the "Python Data Model," most authors would say is the "Python object model." Martelli, Ravenscroft & Holden's *Python in a Nutshell 3E*, and David Beazley's *Python Essential Reference 4E* are the best books covering the "Python Data Model," but they refer to it as the "object model." On Wikipedia, the first definition of object model is "The properties of objects in general in a specific computer programming language." This is what the "Python Data Model" is about. In this book, I will use "data model" because the documentation favors that term when referring to the Python object model, and because it is the title of the chapter of *The Python Language Reference* most relevant to our discussions.

Muggle Methods

The *The Original Hacker's Dictionary* defines *magic* as "as yet unexplained, or too complicated to explain" or "a feature not generally publicized which allows something otherwise impossible."

The Ruby community calls their equivalent of the special methods *magic methods*. Many in the Python community adopt that term as well. I believe the special methods are the opposite of magic. Python and Ruby empower their users with a rich metaobject protocol that is fully documented, enabling muggles like you and I to emulate many of the features available to core developers who write the interpreters for those languages.

In contrast, consider Go. Some objects in that language have features that are magic, in the sense that we cannot emulate them in our own user-defined types. For example, Go arrays, strings, and maps support the use brackets for item access, as in `a[i]`. But there's no way to make the `[]` notation work with a new collection type that you define. Even worse, Go has no user-level concept of an iterable interface or an iterator object, therefore its `for/range` syntax is limited to supporting five “magic” built-in types, including arrays, strings and maps.

Maybe in the future, the designers of Go will enhance its metaobject protocol. But currently, it is much more limited than what we have in Python or Ruby.

Metaobjects

The Art of the Metaobject Protocol (AMOP) is my favorite computer book title. But I mention it because the term *metaobject protocol* is useful to think about the Python Data Model and similar features in other languages. The *metaobject* part refers to the objects that are the building blocks of the language itself. In this context, *protocol* is a synonym of *interface*. So a *metaobject protocol* is a fancy synonym for object model: an API for core language constructs.

A rich metaobject protocol enables extending a language to support new programming paradigms. Gregor Kiczales, the first author of the *AMOP* book, later became a pioneer in aspect-oriented programming and the initial author of AspectJ, an extension of Java implementing that paradigm. Aspect-oriented programming is much easier to implement in a dynamic language like Python, and some frameworks do it. The most important example is *zope.interface*, part of the framework on which the Plone content management system is build.

---

1 Story of Jython, written as a Foreword to *Jython Essentials* (O’Reilly, 2002), by Samuele Pedroni and Noel Rappin.

2 A C struct is a record type with named fields.

Part II. Data Structures

Chapter 2. An Array of Sequences

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 2nd chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

As you may have noticed, several of the operations mentioned work equally for texts, lists and tables. Texts, lists and tables together are called trains. […] The `FOR` command also works generically on trains.[1]

—Geurts, Meertens, and Pemberton, ABC Programmer's Handbook

Before creating Python, Guido was a contributor to the ABC language—a 10-year research project to design a programming environment for beginners. ABC introduced many ideas we now consider "Pythonic": generic operations on different types of sequences, built-in tuple and mapping types, structure by indentation, strong typing without variable declarations, and more. It's no accident that Python is so user-friendly.

Python inherited from ABC the uniform handling of sequences. Strings, lists, byte sequences, arrays, XML elements, and database results share a rich set of common operations including iteration, slicing, sorting, and concatenation.

Understanding the variety of sequences available in Python saves us from reinventing the wheel, and their common interface inspires us to create APIs that properly support and leverage existing and future sequence types.

Most of the discussion in this chapter applies to sequences in general, from the familiar `list` to the `str` and `bytes` types added in Python 3. Specific topics on lists, tuples, arrays, and queues are also covered here, but the specifics of Unicode strings and byte sequences appear in Chapter 4. Also, the idea here is to cover sequence types that are ready to use. Creating your own sequence types is the subject of Chapter 12.

These are the main topics this chapter will cover:

- List comprehensions and the basics of generator expressions;
- Using tuples as records, versus using tuples as immutable lists;
- Sequence unpacking and sequence patterns;
- Reading from slices and writing to slices;
- Specialized sequence types, like arrays and queues.

What's new in this chapter

The most important update in this chapter is "Pattern Matching with Sequences". That's the first time the new pattern matching feature of Python 3.10 appears in this *Second Edition*.

Other changes are not updates but improvements over the *First Edition*:

- New diagram and description of the internals of sequences, contrasting containers and flat sequences.
- Brief comparison of the performance and storage characteristics of `list` versus `tuple`.

- Caveats of tuples with mutable elements, and how to detect them if needed.

I moved coverage of named tuples to “Classic Named Tuples” in Chapter 5, where they are compared to `typing.NamedTuple` and `@dataclass`.

> **NOTE**
>
> To make room for new content and keep the page count within reason, the section *Managing Ordered Sequences with Bisect* from the *First Edition* is now a post in the *fluentpython.com* companion Web site.

Overview of Built-In Sequences

The standard library offers a rich selection of sequence types implemented in C:

Container sequences

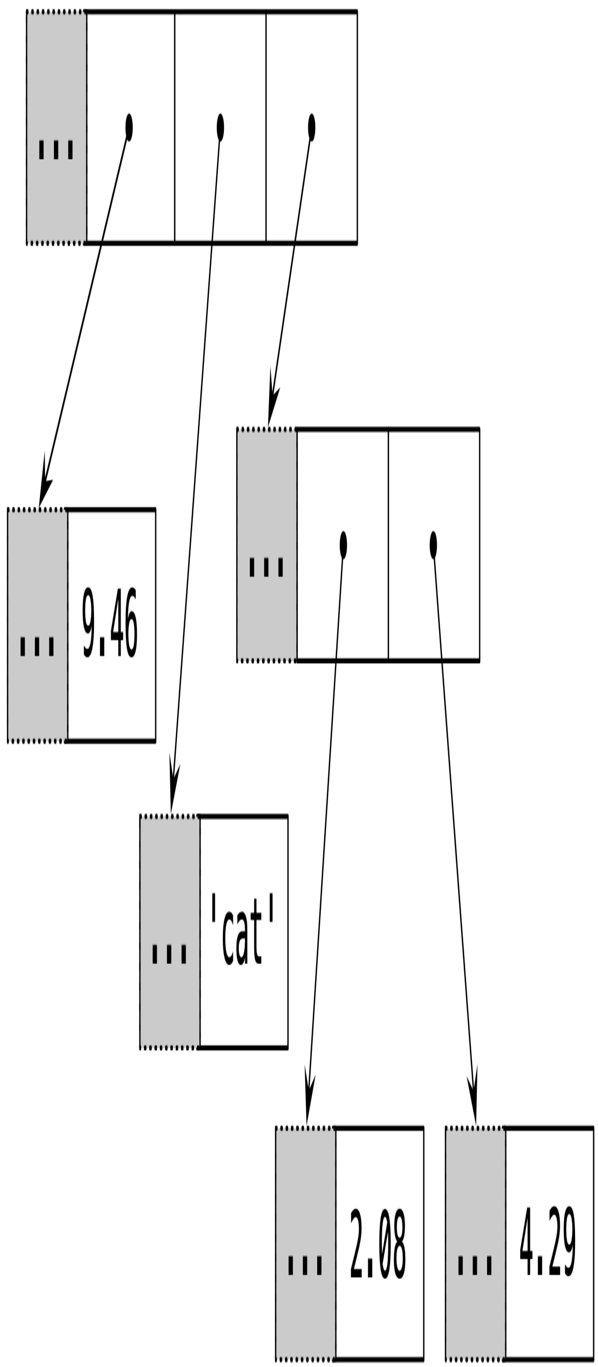
Can hold items of different types, including nested containers. Some examples: `list`, `tuple`, and `collections.deque`.

Flat sequences

Hold items of one simple type. Some examples: `str`, `bytes`, and `array.array`.

A *container sequence* holds references to the objects it contains, which may be of any type, while a *flat sequence* stores the value of its contents in its own memory space, and not as distinct Python objects. See Figure 2-1.

(9.46, 'cat', [2.08, 4.29])



array('d', [9.46, 2.08, 4.29])

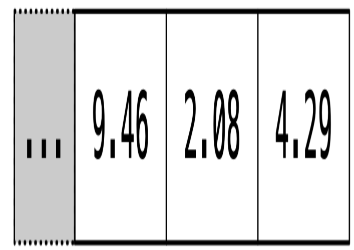


Figure 2-1. Simplified memory diagrams for a `tuple` and an `array`, each with 3 items. Gray cells represent the in-memory header of each Python object—not drawn to proportion. The `tuple` has an array of references to its items. Each item is a separate Python object, possibly holding references to other Python objects, like that 2-item list. In contrast, the Python `array` is a single object, holding a C language array of 3 doubles.

Thus, flat sequences are more compact, but they are limited to holding primitive machine values like bytes, integers, and floats.

> **NOTE**
>
> Every Python object in memory has a header with metadata. The simplest Python object, a `float`, has a value field and two metadata fields:
>
> - `ob_refcnt`: the object's reference count;
> - `ob_type`: a pointer to the object's type;
> - `ob_fval`: a C `double` holding the value of the `float`.
>
> On a 64-bit Python build, each of those fields takes 8 bytes. That's why an array of floats is much more compact than a tuple of floats: the array is a single object holding the raw values of the floats, while the tuple consists of several objects—the tuple itself and each `float` object contained in it.

Another way of grouping sequence types is by mutability:

Mutable sequences

E.g. `list`, `bytearray`, `array.array`, and `collections.deque`.

Immutable sequences

E.g. `tuple`, `str`, and `bytes`.

Figure 2-2 helps visualize how mutable sequences inherit all methods from immutable sequences, and implement several additional methods. The built-in concrete sequence types do not actually subclass the `Sequence` and `MutableSequence` abstract base classes (ABCs), but they are *virtual* *subclasses* registered with those ABCs—as we'll see in Chapter 13. Being virtual subclasses, `tuple` and `list` pass these tests:

```
>>> from collections import abc
>>> issubclass(tuple, abc.Sequence)
True
>>> issubclass(list, abc.MutableSequence)
True
```

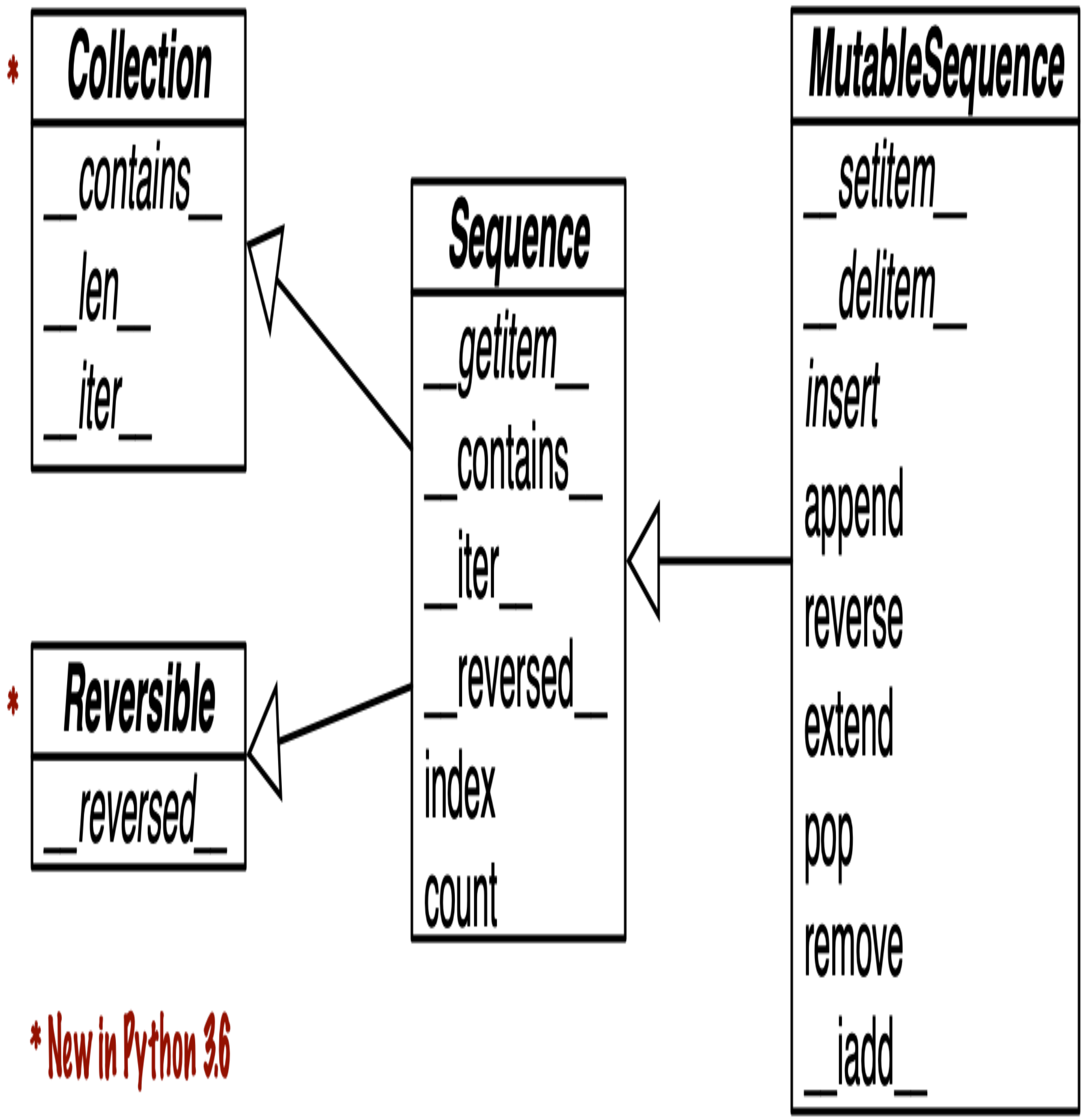


Figure 2-2. Simplified UML class diagram for some classes from collections.abc (superclasses are on the left; inheritance arrows point from subclasses to superclasses; names in italic are abstract classes and abstract methods)

Keep in mind these common traits: mutable versus immutable; container versus flat. They are helpful to extrapolate what you know about one sequence type to others.

The most fundamental sequence type is the `list`: a mutable container. I expect you are very familiar with lists, so we’ll jump right into list comprehensions, a powerful way of building lists that is sometimes underused because the syntax may look unusual at first. Mastering list comprehensions opens the door to generator expressions, which—among other uses—can produce elements to fill up sequences of any type. Both are the subject of the next section.

List Comprehensions and Generator Expressions

A quick way to build a sequence is using a list comprehension (if the target is a `list`) or a generator expression (for other kinds of sequences). If you are not using these syntactic forms on a daily basis, I bet you are missing opportunities to write code that is more readable and often faster at the same time.

If you doubt my claim that these constructs are “more readable,” read on. I’ll try to convince you.

> **TIP**
>
> For brevity, many Python programmers refer to list comprehensions as *listcomps*, and generator expressions as *genexps*. I will use these words as well.

List Comprehensions and Readability

Here is a test: which do you find easier to read, Example 2-1 or Example 2-2?

Example 2-1. Build a list of Unicode codepoints from a string

```
>>> symbols = '$¢£¥€¤'
>>> codes = []
>>> for symbol in symbols:
...     codes.append(ord(symbol))
...
>>> codes
[36, 162, 163, 165, 8364, 164]
```

Example 2-2. Build a list of Unicode codepoints from a string, using a listcomp

```
>>> symbols = '$¢£¥€¤'
>>> codes = [ord(symbol) for symbol in symbols]
>>> codes
[36, 162, 163, 165, 8364, 164]
```

Anybody who knows a little bit of Python can read Example 2-1. However, after learning about listcomps, I find Example 2-2 more readable because its intent is explicit.

A `for` loop may be used to do lots of different things: scanning a sequence to count or pick items, computing aggregates (sums, averages), or any number of other tasks. The code in Example 2-1 is building up a list. In contrast, a listcomp is more explicit. Its goal is always to build a new list.

Of course, it is possible to abuse list comprehensions to write truly incomprehensible code. I've seen Python code with listcomps used just to repeat a block of code for its side effects. If you are not doing something with the produced list, you should not use that syntax. Also, try to keep it short. If the list comprehension spans more than two lines, it is probably best to break it apart or rewrite as a plain old `for` loop. Use your best judgment: for Python as for English, there are no hard-and-fast rules for clear writing.

SYNTAX TIP

In Python code, line breaks are ignored inside pairs of `[]`, `{}`, or `()`. So you can build multiline lists, listcomps, tuples, dictionaries etc. without using the `\` line continuation escape which doesn't work if you accidentally type a space after it. Also, when those delimiter pairs are used to define a literal with a comma-separated series of items, a trailing comma will be ignored. So, for example, when coding a multi-line list literal, it is thoughtful to put a comma after the last item, making it a little easier for the next coder do add one more item to that list, and reducing noise when reading diffs.

LOCAL SCOPE WITHIN COMPREHENSIONS AND GENERATOR EXPRESSIONS

In Python 3, list comprehensions, generator expressions, and their siblings `set` and `dict` comprehensions have a local scope to hold the variables assigned in the `for` clause.

However, variables assigned with the “Walrus operator” `:=` remain accessible after those comprehensions or expressions return—unlike local variables in a function. *PEP 572—Assignment Expressions* defines the scope of the target of `:=` as the enclosing function, unless there is a `global` or `nonlocal` declaration for that target.[2]

```
>>> x = 'ABC'
>>> codes = [ord(x) for x in x]
>>> x  ❶
'ABC'
>>> codes
[65, 66, 67]
>>> codes = [last := ord(c) for c in x]
>>> last ❷
67
>>> c ❸
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
NameError: name 'c' is not defined
```

❶ `x` was not clobbered: it’s still bound to `'ABC'`;

❷ `last` remains;

❸ `c` existed only inside the listcomp.

List comprehensions build lists from sequences or any other iterable type by filtering and transforming items. The `filter` and `map` built-ins can be composed to do the same, but readability suffers, as we will see next.

Listcomps Versus map and filter

Listcomps do everything the `map` and `filter` functions do, without the contortions of the functionally challenged Python `lambda`. Consider Example 2-3.

Example 2-3. The same list built by a listcomp and a map/filter composition

```
>>> symbols = '$¢£¥€¤'
>>> beyond_ascii = [ord(s) for s in symbols if ord(s) > 127]
>>> beyond_ascii
[162, 163, 165, 8364, 164]
>>> beyond_ascii = list(filter(lambda c: c > 127, map(ord,
symbols)))
>>> beyond_ascii
[162, 163, 165, 8364, 164]
```

I used to believe that `map` and `filter` were faster than the equivalent listcomps, but Alex Martelli pointed out that's not the case—at least not in the preceding examples. The *02-array-seq/listcomp_speed.py* script in the *Fluent Python* code repository is a simple speed test comparing listcomp with `filter/map`.

I'll have more to say about `map` and `filter` in Chapter 7. Now we turn to the use of listcomps to compute Cartesian products: a list containing tuples built from all items from two or more lists.

Cartesian Products

Listcomps can build lists from the Cartesian product of two or more iterables. The items that make up the Cartesian product are tuples made from items from every input iterable. The resulting list has a length equal to the lengths of the input iterables multiplied. See Figure 2-3.

For example, imagine you need to produce a list of T-shirts available in two colors and three sizes. Example 2-4 shows how to produce that list using a listcomp. The result has six items.

Example 2-4. Cartesian product using a list comprehension

```
>>> colors = ['black', 'white']
>>> sizes = ['S', 'M', 'L']
```

```
>>> tshirts = [(color, size) for color in colors for size in sizes]
❶
>>> tshirts
[('black', 'S'), ('black', 'M'), ('black', 'L'), ('white', 'S'),
 ('white', 'M'), ('white', 'L')]
>>> for color in colors:  ❷
...     for size in sizes:
...         print((color, size))
...
('black', 'S')
('black', 'M')
('black', 'L')
('white', 'S')
('white', 'M')
('white', 'L')
>>> tshirts = [(color, size) for size in sizes      ❸
...                          for color in colors]
>>> tshirts
[('black', 'S'), ('white', 'S'), ('black', 'M'), ('white', 'M'),
 ('black', 'L'), ('white', 'L')]
```

❶ This generates a list of tuples arranged by color, then size.

❷ Note how the resulting list is arranged as if the `for` loops were nested in the same order as they appear in the listcomp.

❸ To get items arranged by size, then color, just rearrange the `for` clauses; adding a line break to the listcomp makes it easier to see how the result will be ordered.

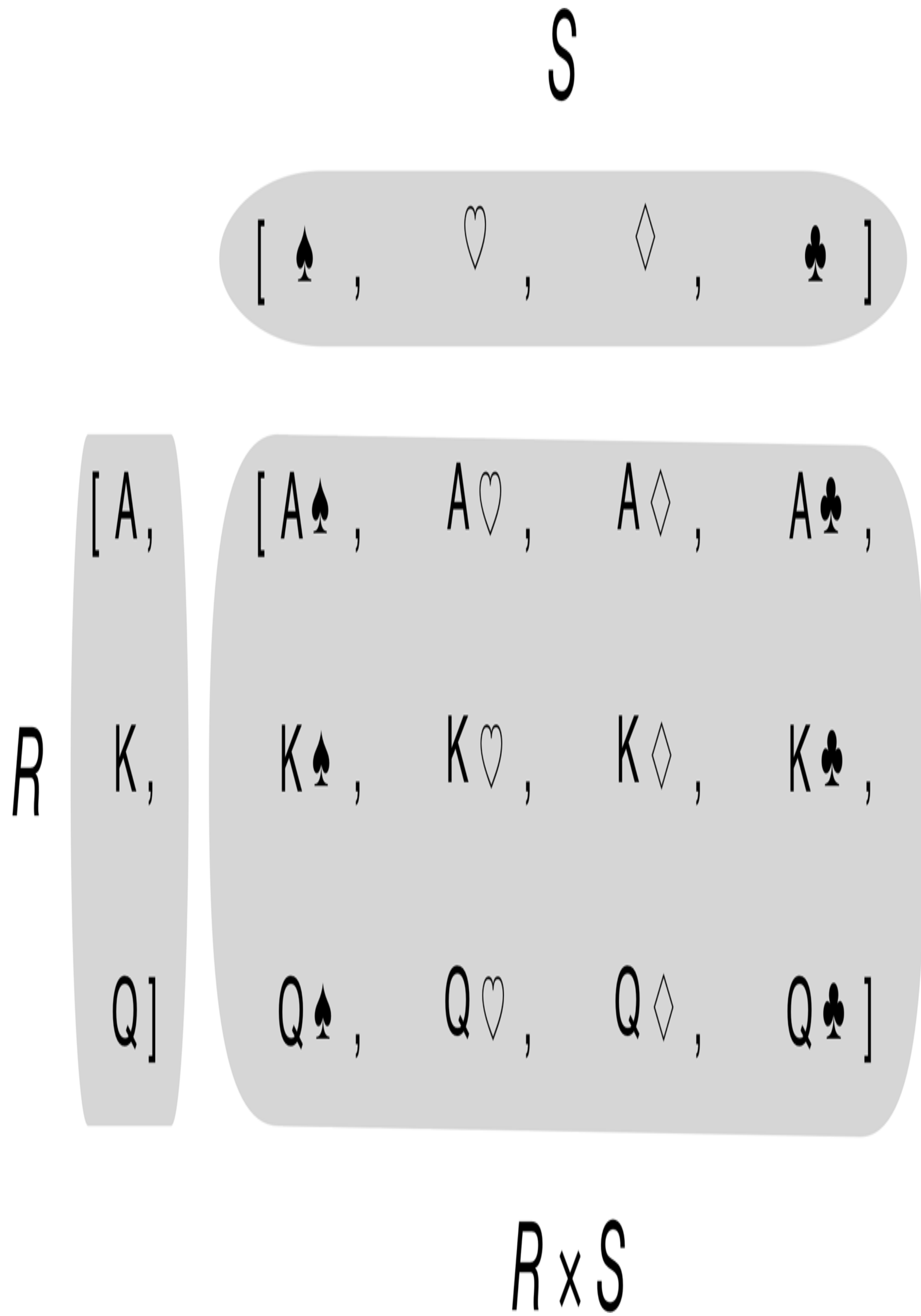


Figure 2-3. The Cartesian product of three card ranks and four suits is a sequence of twelve pairings

In Example 1-1 (Chapter 1), I used the following expression to initialize a card deck with a list made of 52 cards from all 13 ranks of each of the 4 suits, sorted by suit then rank:

```
        self._cards = [Card(rank, suit) for suit in self.suits
                                        for rank in self.ranks]
```

Listcomps are a one-trick pony: they build lists. To generate data for other sequence types, a genexp is the way to go. The next section is a brief look at genexps in the context of building sequences that are not lists.

Generator Expressions

To initialize tuples, arrays, and other types of sequences, you could also start from a listcomp, but a genexp saves memory because it yields items one by one using the iterator protocol instead of building a whole list just to feed another constructor.

Genexps use the same syntax as listcomps, but are enclosed in parentheses rather than brackets.

Example 2-5 shows basic usage of genexps to build a tuple and an array.

Example 2-5. Initializing a tuple and an array from a generator expression

```
>>> symbols = '$¢£¥€¤'
>>> tuple(ord(symbol) for symbol in symbols)  ❶
(36, 162, 163, 165, 8364, 164)
>>> import array
>>> array.array('I', (ord(symbol) for symbol in symbols))  ❷
array('I', [36, 162, 163, 165, 8364, 164])
```

❶ If the generator expression is the single argument in a function call, there is no need to duplicate the enclosing parentheses.

❷ The `array` constructor takes two arguments, so the parentheses around the generator expression are mandatory. The first argument of the `array` constructor defines the storage type used for the numbers in the array, as we'll see in "Arrays".

Example 2-6 uses a genexp with a Cartesian product to print out a roster of T-shirts of two colors in three sizes. In contrast with Example 2-4, here the six-item list of T-shirts is never built in memory: the generator expression feeds the `for` loop producing one item at a time. If the two lists used in the Cartesian product had 1,000 items each, using a generator expression would save the cost of building a list with a million items just to feed the `for` loop.

Example 2-6. Cartesian product in a generator expression

```
>>> colors = ['black', 'white']
>>> sizes = ['S', 'M', 'L']
>>> for tshirt in (f'{c} {s}' for c in colors for s in sizes):  ❶
...     print(tshirt)
...
black S
black M
black L
white S
white M
white L
```

❶ The generator expression yields items one by one; a list with all six T-shirt variations is never produced in this example.

> **NOTE**
>
> Chapter 17 is explains how generators work in detail. Here the idea was just to show the use of generator expressions to initialize sequences other than lists, or to produce output that you don't need to keep in memory.

Now we move on to the other fundamental sequence type in Python: the tuple.

Tuples Are Not Just Immutable Lists

Some introductory texts about Python present tuples as "immutable lists," but that is short selling them. Tuples do double duty: they can be used as immutable lists and also as records with no field names. This use is sometimes overlooked, so we will start with that.

Tuples as Records

Tuples hold records: each item in the tuple holds the data for one field and the position of the item gives its meaning.

If you think of a tuple just as an immutable list, the quantity and the order of the items may or may not be important, depending on the context. But when using a tuple as a collection of fields, the number of items is usually fixed and their order is always important.

Example 2-7 shows tuples used as records. Note that in every expression, sorting the tuple would destroy the information because the meaning of each field is given by its position in the tuple.

Example 2-7. Tuples used as records

```
>>> lax_coordinates = (33.9425, -118.408056)  ❶
>>> city, year, pop, chg, area = ('Tokyo', 2003, 32_450, 0.66,
8014)  ❷
>>> traveler_ids = [('USA', '31195855'), ('BRA', 'CE342567'),  ❸
...     ('ESP', 'XDA205856')]
>>> for passport in sorted(traveler_ids):  ❹
...     print('%s/%s' % passport)  ❺
...
BRA/CE342567
ESP/XDA205856
USA/31195855
>>> for country, _ in traveler_ids:  ❻
...     print(country)
...
USA
BRA
ESP
```

❶ Latitude and longitude of the Los Angeles International Airport.

❷ Data about Tokyo: name, year, population (thousands), population change (%), area (km²).

❸ A list of tuples of the form `(country_code, passport_number)`.

❹ As we iterate over the list, `passport` is bound to each tuple.

❺ The `%` formatting operator understands tuples and treats each item as a separate field.

❻ The `for` loop knows how to retrieve the items of a tuple separately—this is called "unpacking." Here we are not interested in the second item, so we assign it to _, a dummy variable.

> **TIP**
>
> In general, using _ as a dummy variable is just a convention. It's just a strange but valid variable name. However, there are two contexts where _ is special:
>
> 1. In the Python console, the result of executing a line is assigned to _—unless the result is `None`.
> 2. In a `match/case` statement, _ is a wildcard that matches any value but is never assigned a value. See "Pattern Matching with Sequences".

We often think of records as data structures with named fields. Chapter 5 presents two ways of creating tuples with named fields.

But often, there's no need to go through the trouble of creating a class just to name the fields, especially if you leverage unpacking and avoid using indexes to access the fields. In Example 2-7, we assigned `('Tokyo', 2003, 32_450, 0.66, 8014)` to `city, year, pop, chg, area` in a single statement. Then, the `%` operator assigned each item in the `passport` tuple to the corresponding slot in the format string in the `print` argument. Those are two examples of *tuple unpacking*.

NOTE

The term *tuple unpacking* is widely used by Pythonistas, but *iterable unpacking* is gaining traction, as in the title of PEP 3132 — Extended Iterable Unpacking.

"Unpacking sequences and iterables" presents a lot more about unpacking not only tuples, but sequences and iterables in general.

Now let's consider the `tuple` class as an immutable variant of the `list` class.

Tuples as Immutable Lists

The Python interpreter and standard library make extensive use of tuples as immutable lists, and so should you. This brings two key benefits:

1. Clarity: when you see a `tuple` in code, you know its length will never change.
2. Performance: a `tuple` uses less memory than a `list` of the same length, and they allow Python to do some optimizations.

However, be aware that the immutability of a `tuple` only applies to the references contained in it. References in a tuple cannot be deleted or replaced. But if one of those references points to a mutable object, and that object is changed, then the value of the `tuple` changes. The next snippet illustrate this point by creating two tuples—`a` and `b`—which are initially equal. Figure 2-4 represents the initial layout of the `b` tuple in memory.

When the last item in `b` is changed, `b` and `a` become different:

```
>>> a = (10, 'alpha', [1, 2])
>>> b = (10, 'alpha', [1, 2])
>>> a == b
True
>>> b[-1].append(99)
>>> a == b
False
```

```
>>> b
(10, 'alpha', [1, 2, 99])
```

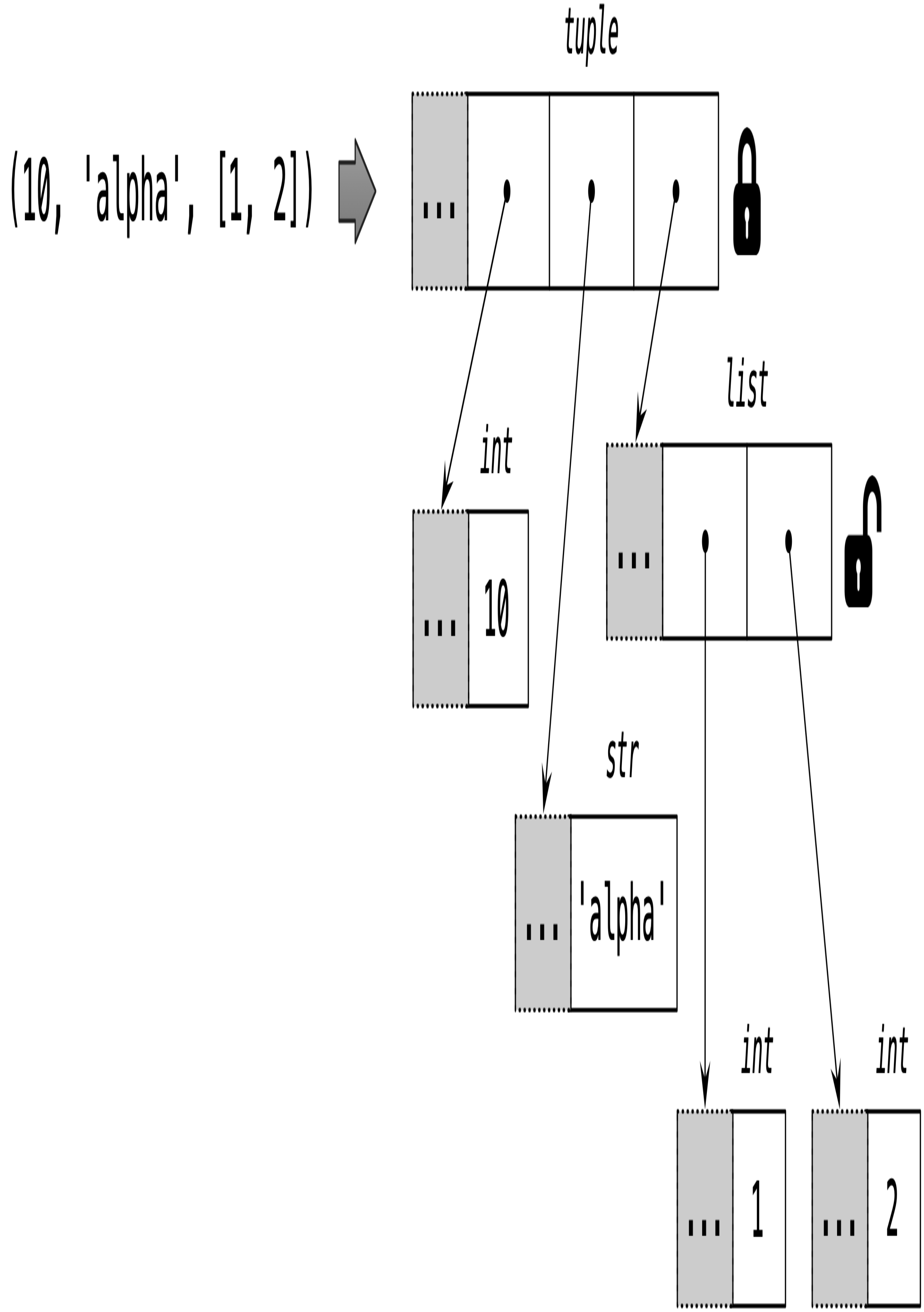

(10, 'alpha', [1, 2])
tuple
...
list
...
int
...
10
str
...
'alpha'
int
...
1
int
...
2

Figure 2-4. The content of the tuple itself is immutable, but that only means the references held by the tuple will always point to the same objects. However, if one of the referenced objects is mutable—like a list—its content may change.

Tuples with mutable items can be a source of bugs. As we'll see in "What is Hashable", an object is only hashable if its value cannot ever change. An unhashable tuple cannot be inserted as a `dict` key, or a `set` element.

If you want to determine explicitly if a tuple (or any object) has a fixed value, you can use the `hash` built-in to create a `fixed` function like this:

```
>>> def fixed(o):
...     try:
...         hash(o)
...     except TypeError:
...         return False
...     return True
...
>>> tf = (10, 'alpha', (1, 2))
>>> tm = (10, 'alpha', [1, 2])
>>> fixed(tf)
True
>>> fixed(tm)
False
```

We explore this issue further in "The Relative Immutability of Tuples".

Despite this caveat, tuples are widely used as immutable lists. They offer some performance advantages explained by Python core developer Raymond Hettinger in a StackOverflow answer to the question Are tuples more efficient than lists in Python? To summarize, Hettinger wrote:

- To evaluate a tuple literal, the Python compiler generates bytecode for a tuple constant in one operation, but for a list literal, the generated bytecode pushes each element as a separate constant to the data stack, and then builds the list.
- Given a tuple `t`, `tuple(t)` simply returns a reference to the same `t`. There's no need to copy. In contrast, given a list `l`, the `list(l)` constructor must create a new copy of `l`.

- Because of its fixed length, a `tuple` instance is allocated the exact memory space in needs. Instances of `list`, on the other hand, are allocated with room to spare, to amortize the cost of future appends.

- The references to the items in a tuple are stored in an array in the tuple struct, while a list holds a pointer to an array of references stored elsewhere. The indirection is necessary because when a list grows beyond the space currently allocated, Python needs to realocate the array of references to make room. The extra indirection makes CPU caches less effective.

Comparing Tuple and List Methods

When using a tuple as an immutable variation of list, it is good to know how similar their APIs are. As you can see in Table 2-1, `tuple` supports all `list` methods that do not involve adding or removing items, with one exception—tuple lacks the `__reversed__` method. However, that is just for optimization; `reversed(my_tuple)` works without it.

Table 2-1. Methods and attributes found *inlistortuple(methodsimplementedbyob*

jectareomittedforbrevity)

	list	tuple	
`s.__add__(s2)`	●	●	`s + s2`—concatenation
`s.__iadd__(s2)`	●		`s += s2`—in-place concatenation
`s.append(e)`	●		Append one element after last
`s.clear()`	●		Delete all items

`s.__contains__(e)`	●	●	`e in s`
`s.copy()`	●		Shallow copy of the list
`s.count(e)`	●	●	Count occurrences of an element
`s.__delitem__(p)`	●		Remove item at position `p`
`s.extend(it)`	●		Append items from iterable `it`
`s.__getitem__(p)`	●	●	`s[p]`—get item at position
`s.__getnewargs__()`		●	Support for optimized serialization with `pickle`
`s.index(e)`	●	●	Find position of first occurrence of `e`
`s.insert(p, e)`	●		Insert element `e` before the item at position `p`
`s.__iter__()`	●	●	Get iterator
`s.__len__()`	●	●	`len(s)`—number of items
`s.__mul__(n)`	●	●	`s * n`—repeated concatenation
`s.__imul__(n)`	●		`s *= n`—in-place repeated concatenation
`s.__rmul__(n)`	●	●	`n * s`—reversed repeated concatenation[a]
`s.pop([p])`	●		Remove and return last item or item at optional position `p`
`s.remove(e)`	●		Remove first occurrence of element `e` by value

`s.reverse()`	●		Reverse the order of the items in place
`s.__reversed__()`	●		Get iterator to scan items from last to first
`s.__setitem__(p, e)`	●		`s[p] = e`—put `e` in position `p`, overwriting existing item[b]
`s.sort([key], [reverse])`	●		Sort items in place with optional keyword arguments `key` and `reverse`

a Reversed operators are explained in Chapter 16.

b Also used to overwrite a subsequence. See "Assigning to Slices".

Now let's switch to an important subject for idiomatic Python programming: tuple, list and iterable unpacking.

Unpacking sequences and iterables

Unpacking is important because it avoids unnecessary and error-prone use of indexes to extract elements from sequences. Also, unpacking works with any iterable object as the data source—including iterators which don't support index notation `[]`. The only requirement is that the iterable yields exactly one item per variable in the receiving end, unless you use a star (`*`) to capture excess items as explained in "Using * to grab excess items".

The most visible form of unpacking is *parallel assignment*; that is, assigning items from an iterable to a tuple of variables, as you can see in this example:

```
>>> lax_coordinates = (33.9425, -118.408056)
>>> latitude, longitude = lax_coordinates  # unpacking
>>> latitude
33.9425
>>> longitude
-118.408056
```

An elegant application of unpacking is swapping the values of variables without using a temporary variable:

```
>>> b, a = a, b
```

Another example of unpacking is prefixing an argument with `*` when calling a function:

```
>>> divmod(20, 8)
(2, 4)
>>> t = (20, 8)
>>> divmod(*t)
(2, 4)
>>> quotient, remainder = divmod(*t)
>>> quotient, remainder
(2, 4)
```

The preceding code shows another use of unpacking: allowing functions to return multiple values in a way that is convenient to the caller. As another example, the `os.path.split()` function builds a tuple `(path, last_part)` from a filesystem path:

```
>>> import os
>>> _, filename = os.path.split('/home/luciano/.ssh/id_rsa.pub')
>>> filename
'id_rsa.pub'
```

Another way of using just some of the items when unpacking is to use the `*` syntax, as we'll see right away.

Using * to grab excess items

Defining function parameters with `*args` to grab arbitrary excess arguments is a classic Python feature.

In Python 3, this idea was extended to apply to parallel assignment as well:

```
>>> a, b, *rest = range(5)
>>> a, b, rest
```

```
(0, 1, [2, 3, 4])
>>> a, b, *rest = range(3)
>>> a, b, rest
(0, 1, [2])
>>> a, b, *rest = range(2)
>>> a, b, rest
(0, 1, [])
```

In the context of parallel assignment, the `*` prefix can be applied to exactly one variable, but it can appear in any position:

```
>>> a, *body, c, d = range(5)
>>> a, body, c, d
(0, [1, 2], 3, 4)
>>> *head, b, c, d = range(5)
>>> head, b, c, d
([0, 1], 2, 3, 4)
```

Unpacking with * in function calls and sequence literals

PEP 448—Additional Unpacking Generalizations introduced more flexible syntax for iterable unpacking, best summarized in What's New In Python 3.5.

In function calls, we can use `*` multiple times:

```
>>> def fun(a, b, c, d, *rest):
...     return a, b, c, d, rest
...
>>> fun(*[1, 2], 3, *range(4, 7))
(1, 2, 3, 4, (5, 6))
```

The `*` can also be used when defining `list`, `tuple`, or `set` literals, as shown these examples from What's New In Python 3.5:

```
>>> *range(4), 4
(0, 1, 2, 3, 4)
>>> [*range(4), 4]
[0, 1, 2, 3, 4]
>>> {*range(4), 4, *(5, 6, 7)}
{0, 1, 2, 3, 4, 5, 6, 7}
```

PEP 448 introduced similar new syntax for `**`, which we'll see in "Unpacking Mappings".

Finally, a powerful feature of tuple unpacking is that it works with nested structures.

Nested Unpacking

The target of an unpacking can use nesting, e.g. `(a, b, (c, d))`. Python will do the right thing if the value has the same nesting structure. Example 2-8 shows nested unpacking in action.

Example 2-8. Unpacking nested tuples to access the longitude

```
metro_areas = [
    ('Tokyo', 'JP', 36.933, (35.689722, 139.691667)),  ❶
    ('Delhi NCR', 'IN', 21.935, (28.613889, 77.208889)),
    ('Mexico City', 'MX', 20.142, (19.433333, -99.133333)),
    ('New York-Newark', 'US', 20.104, (40.808611, -74.020386)),
    ('São Paulo', 'BR', 19.649, (-23.547778, -46.635833)),
]

def main():
    print(f'{"":15} | {"latitude":>9} | {"longitude":>9}')
    for name, _, _, (lat, lon) in metro_areas:  ❷
        if lon <= 0:  ❸
            print(f'{name:15} | {lat:9.4f} | {lon:9.4f}')

if __name__ == '__main__':
    main()
```

❶ Each tuple holds a record with four fields, the last of which is a coordinate pair.

❷ By assigning the last field to a nested tuple, we unpack the coordinates.

❸ The `lon <= 0:` test selects only cities in the Western hemisphere.

The output of Example 2-8 is:

```
                |   lat.    |   lon.
Mexico City     |   19.4333 |  -99.1333
```

```
New York-Newark |   40.8086 |   -74.0204
São Paulo       |  -23.5478 |   -46.6358
```

The target of an unpacking assignment can also be a list, but good use cases are rare. Here is the only one I know: if you have a database query that returns a single record (e.g. the SQL code has a `LIMIT 1` clause), then you can unpack and at the same time make sure there's only one result with this code:

```
>>> [record] = query_returning_single_row()
```

If the record has only one field, you can get it directly like this:

```
>>> [[field]] = query_returning_single_row_with_single_field()
```

Both of these could be written with tuples, but don't forget the syntax quirk that single-item tuples must be written with a trailing comma. So the first target would be `(record,)` and the second `((field,),)`. In both cases you get a silent bug if you forget a comma.[3]

Now let's study pattern matching, which supports even more powerful ways to unpack sequences.

Pattern Matching with Sequences

The most visible new feature in Python 3.10 is pattern matching with the `match/case` statement proposed in *PEP 634—Structural Pattern Matching: Specification*.

> **NOTE**
>
> Python core developer Carol Willing wrote an excellent quick introducion to pattern matching in the *Structural Pattern Matching* section of *What's New In Python 3.10*. I will assume you've read Willing's intro, and give a brief overview focusing on `match/case` with sequence subjects and patterns.

On the surface, `match/case` may look like a the `switch/case` statement from the C language—but that's only half the story.[4] One key improvement of `match` over `switch` is *destructuring*—a more advanced form of unpacking. Destructuring is a new word in the Python vocabulary, but it is commonly used in the documentation of languages that support pattern matching—like Scala and Elixir.

As a first example of destructuring, Example 2-9 shows part of Example 2-8 rewritten with `match/case`.

Example 2-9. Destructuring nested tuples—requires Python ≥ 3.10.

```
metro_areas = [
    ('Tokyo', 'JP', 36.933, (35.689722, 139.691667)),
    ('Delhi NCR', 'IN', 21.935, (28.613889, 77.208889)),
    ('Mexico City', 'MX', 20.142, (19.433333, -99.133333)),
    ('New York-Newark', 'US', 20.104, (40.808611, -74.020386)),
    ('São Paulo', 'BR', 19.649, (-23.547778, -46.635833)),
]

def main():
    print(f'{"":15} | {"latitude":>9} | {"longitude":>9}')
    for record in metro_areas:
        match record:  ❶
            case [name, _, _, (lat, lon)] if lon <= 0:  ❷
                print(f'{name:15} | {lat:9.4f} | {lon:9.4f}')
```

❶ The subject of this `match` is `record`— i.e. each of the tuples in `metro_areas`.

❷ A `case` clause has two parts: a pattern and an optional guard with the `if` keyword.

In general, a sequence pattern matches the subject if:

1. the subject is a sequence *and*;
2. the subject and the pattern have the same number of items *and*;
3. each corresponding item matches, including nested items.

For example, the pattern `[name, _, _, (lat, lon)]` in Example 2-9 matches a sequence with 4 items, and the last item must be a two-item sequence.

Sequence patterns may be written as tuples or lists or any combination of nested tuples and lists, but it makes no difference which syntax you use: in a pattern, tuples and lists match any sequence. I wrote the pattern as a list with a nested 2-tuple just to avoid repeating brackets or parentheses in Example 2-9.

A sequence pattern can match instances of any actual or virtual subclass of `` collections.abc.Sequence`footnote:[A virtual `Sequence `` subclass is any class registered by calling the `Sequence.register()` class method, as detailed in "A Virtual Subclass of an ABC". Types implemented via Python/C API are eligible if they set a specific marker bit. See Py_TPFLAGS_SEQUENCE.] except for `str`, `bytes`, `bytearray` which are excluded for practical reasons. In the standard library, these types are compatible with sequence patterns:

```
list      memoryview    array.array
tuple     range         collections.deque
```

Unlike unpacking, patterns don't destructure iterables that are not sequences.

The _ symbol is special in patterns: it matches any single item in that position, but it is never bound to the value of the matched item. Also, the _ is the only variable that can appear more than once in pattern—unless the pattern is a combination of patterns joined by the `|` operator (which also has special meaning in a `case` clause).

A sequence pattern can be more strict using type information. For example, the following pattern matches the same nested sequence structure as the one in Example 2-9, but the first item must be an instance of `str`, and both items in the 2-tuple must be instances of `float`.

```
        case [str(name), _, _, (float(lat), float(lon))]:
```

On the other hand, if we want to match any subject sequence starting with a `str`, and ending with a nested sequence of two floats, we can write:

```
        case [str(name), *_, (float(lat), float(lon))]:
```

The `*_` matches any number of items, without binding them to a variable. Using `*extra` instead of `*_` would bind the items to `extra` as a `list` with 0 or more items.

The optional guard clause starting with `if` is evaluated only if the pattern matches, and can reference variables bound in the pattern, as in Example 2-9:

```
        match record:
            case [name, _, _, (lat, lon)] if lon <= 0:
                print(f'{name:15} | {lat:9.4f} | {lon:9.4f}')
```

The nested block with the `print` statement runs only if the pattern matches and the guard expression is *truthy*.

> **TIP**
>
> Desctructuring with patterns is so expressive that sometimes a `match` with a single `case` can make code simpler. Guido van Rossum has a collection of `case/match` examples, including one that he titled *A very deep iterable and type match with extraction*.

Example 2-9 is not an improvement over Example 2-8. It's just an example to contrast two ways of doing the same thing. The next example shows how pattern matching can make some code safer, shorter, and easier to read.

Pattern Matching Sequences in an Interpreter

Peter Norvig of Stanford University wrote *lis.py*: an interpreter for a subset of the Scheme dialect of Lisp in 132 lines of beautiful and readable Python code. I took Norvig's MIT-licensed code and updated it to Python 3.10 to showcase pattern matching. In this section, I contrast parts of Norvig's code, using `if/elif` and unpacking, with a rewrite using `match/case`.

The two main functions of *lis.py* are `parse` and `evaluate`.[5] The parser takes Scheme parenthesized expressions and returns Python lists. For example:

```
>>> parse('(gcd 18 44)')
['gcd', 18, 44]
>>> parse('(define double (lambda (n) (* n 2)))')
['define', 'double', ['lambda', ['n'], ['*', 'n', 2]]]
```

The evaluator takes lists like those and executes them.

Our focus here is destructuring, so I will not explain the evaluator actions. See "Pattern Matching: a Case Study" to learn more about how *lis.py* works.

Here is Norvig's evaluator with minor changes, abbreviated to show only the sequence patterns:

Example 2-10. Matching patterns without `match/case`.

```
def evaluate(x, env):
    "Evaluate an expression in an environment."
    if ...:  # several lines omitted
        ...
    elif x[0] == 'quote':          # (quote exp)
        (_, exp) = x
        return exp
    elif x[0] == 'if':             # (if test conseq alt)
        (_, test, conseq, alt) = x
        exp = (conseq if evaluate(test, env) else alt)
        return evaluate(exp, env)
    elif x[0] == 'define':         # (define var exp)
        (_, var, exp) = x
        env[var] = evaluate(exp, env)
    elif x[0] == 'lambda':         # (lambda (var...) body...)
        (_, parms, *body) = x
        return Procedure(parms, body, env)
    # more lines omitted
```

Note how the `elif` blocks check the first item of the list, and then unpack the list, ignoring the first item. The extensive use of unpacking suggests that

that Norvig is a fan of pattern matching, but he wrote that code originally for Python 2 (though it now works with any Python 3).

Using Python 3.10, we can refactor `evaluate` like this:

Example 2-11. Pattern matching with `match/case`—requires Python ≥ 3.10.

```
def evaluate(exp, env):
    "Evaluate an expression in an environment."
    match exp:
        case ...:  # several lines omitted
            ...
        case ['quote', exp]:  ❶
            return exp
        case ['if', test, conseq, alt]:  ❷
            exp = (conseq if evaluate(test, env) else alt)
            return evaluate(exp, env)
        case ['define', Symbol(var), exp]:  ❸
            env[var] = evaluate(exp, env)
        case ['lambda', parms, *body] if len(body) >= 1:  ❹
            return Procedure(parms, body, env)
        # more lines omitted
        case _:
            raise SyntaxError(repr(exp))  ❺
```

❶ Match if subject is a 2-item sequence starting with `'quote'`.

❷ Match if subject is a 4-item sequence starting with `'if'`.

❸ Match if subject is a 3-item sequence starting with `'define'`, followed by an instance of `Symbol`.

❹ Match if subject is a sequence of 3 or more items starting with `'lambda'`. The guard ensures that `*body` captures at least one item.

❺ When there are multiple `case` clauses, it is good practice to have a catch-all `case`. In this example, if the `exp` doesn't match any of the patterns, the expression is malformed, and I raise `SyntaxError`.

Without a catch-all, the whole `match` statement does nothing when a subject doesnt’t match any case—and this can be a silent failure.

Norvig deliberately avoided error checking in *lis.py*, to keep the code easy to understand. With pattern matching, we can add more checks and still keep it readable. For example: in the `'define'` pattern, the original code does not ensure that `var` is an instance of `Symbol`—that would require an `if` block, an `isinstance` call, and more code. Example 2-11 is shorter and safer than Example 2-10.

We can make the `'lambda'` pattern safer using a nested sequence pattern. This is the syntax of `lambda` in Scheme:

```
(lambda (parms...) body1 body2...)
```

The nested list after the `lambda` keyword is where the names of the formal parameters for the function are declared, and it must be a list, even if it has only one element. It may also be an empty list, if the function has no parameters—like Python’s `random.random()`.

However, as written in Example 2-11, the `case` for `'lambda'` matches any value in the `parms` position, including the first `'x'` in this invalid subject:

```
['lambda', 'x', ['*', 'x', 2]]
```

To enforce the rule that `parms` must be a nested list, we can rewrite that `case` like this:

```
        case ['lambda', [*parms], *body] if len(body) >= 1:
            return Procedure(parms, body, env)
```

In a sequence pattern, `*` can appear only once per sequence. Here we have two sequences: the outer and the inner.

We only added the characters `[*]` to the `case`, made it look more like the Scheme syntax it handles, and implemented a new structural safety check.

Pattern matching supports declarative programming: the code describes “what” you want to match, instead of “how” to match it. The shape of the code follows the shape of the data.

Table 2-2. Some Scheme syntactic forms a *nd the patterns to handle them.*

Scheme syntax	Pattern
(quote exp)	['quote', exp]
(if test conseq alt)	['if', test, conseq, alt]
(define var exp)	['define', Symbol(var), exp]
(lambda (parms…) body1 bod	['lambda', [*parms], *body] if len(bod

`y2…)`	`y) >= 1`

I hope this refactoring of Norvig's `evaluate` with pattern matching convinced you that `match/case` can make some code more readable and safer. Recall that this was a quick overview focusing on sequence patterns. We'll cover other pattern forms in later chapters. Carol Willing's introduction to pattern matching offers more motivation, explanations and examples.

> **NOTE**
>
> If you are intrigued and want to learn more about Norvig's *lis.py*, read his wonderful post (How to Write a (Lisp) Interpreter (in Python)). For more on refactoring *lis.py* with pattern matching, see "Pattern Matching: a Case Study".

This concludes our brief tour of unpacking, destructuring, and pattern matching with sequences.

Every Python programmer knows that sequences can be sliced using the `s[a:b]` syntax. We now turn to some less well-known facts about slicing.

Slicing

A common feature of `list`, `tuple`, `str`, and all sequence types in Python is the support of slicing operations, which are more powerful than most people realize.

In this section, we describe the *use* of these advanced forms of slicing. Their implementation in a user-defined class will be covered in Chapter 12, in keeping with our philosophy of covering ready-to-use classes in this part of the book, and creating new classes in Part IV.

Why Slices and Range Exclude the Last Item

The Pythonic convention of excluding the last item in slices and ranges works well with the zero-based indexing used in Python, C, and many other languages. Some convenient features of the convention are:

- It's easy to see the length of a slice or range when only the stop position is given: `range(3)` and `my_list[:3]` both produce three items.
- It's easy to compute the length of a slice or range when start and stop are given: just subtract `stop - start`.
- It's easy to split a sequence in two parts at any index `x`, without overlapping: simply get `my_list[:x]` and `my_list[x:]`. For example:

```
>>> l = [10, 20, 30, 40, 50, 60]
>>> l[:2]  # split at 2
[10, 20]
>>> l[2:]
[30, 40, 50, 60]
>>> l[:3]  # split at 3
[10, 20, 30]
>>> l[3:]
[40, 50, 60]
```

The best arguments for this convention were written by the Dutch computer scientist Edsger W. Dijkstra (see the last reference in "Further Reading").

Now let's take a close look at how Python interprets slice notation.

Slice Objects

This is no secret, but worth repeating just in case: `s[a:b:c]` can be used to specify a stride or step `c`, causing the resulting slice to skip items. The stride can also be negative, returning items in reverse. Three examples make this clear:

```
>>> s = 'bicycle'
>>> s[::3]
```

```
'bye'
>>> s[::-1]
'elcycib'
>>> s[::-2]
'eccb'
```

Another example was shown in Chapter 1 when we used `deck[12::13]` to get all the aces in the unshuffled deck:

```
>>> deck[12::13]
[Card(rank='A', suit='spades'), Card(rank='A', suit='diamonds'),
Card(rank='A', suit='clubs'), Card(rank='A', suit='hearts')]
```

The notation `a:b:c` is only valid within `[]` when used as the indexing or subscript operator, and it produces a slice object: `slice(a, b, c)`. As we will see in "How Slicing Works", to evaluate the expression `seq[start:stop:step]`, Python calls `seq.__getitem__(slice(start, stop, step))`. Even if you are not implementing your own sequence types, knowing about slice objects is useful because it lets you assign names to slices, just like spreadsheets allow naming of cell ranges.

Suppose you need to parse flat-file data like the invoice shown in Example 2-12. Instead of filling your code with hardcoded slices, you can name them. See how readable this makes the `for` loop at the end of the example.

Example 2-12. Line items from a flat-file invoice

```
>>> invoice = """
...
0.....6................................40........52...55........
... 1909  Pimoroni PiBrella                     $17.50    3
$52.50
... 1489  6mm Tactile Switch x20                 $4.95    2
$9.90
... 1510  Panavise Jr. - PV-201                 $28.00    1
$28.00
... 1601  PiTFT Mini Kit 320x240                $34.95    1
$34.95
... """
>>> SKU = slice(0, 6)
```

```
>>> DESCRIPTION = slice(6, 40)
>>> UNIT_PRICE = slice(40, 52)
>>> QUANTITY =  slice(52, 55)
>>> ITEM_TOTAL = slice(55, None)
>>> line_items = invoice.split('\n')[2:]
>>> for item in line_items:
...     print(item[UNIT_PRICE], item[DESCRIPTION])
...
    $17.50   Pimoroni PiBrella
     $4.95   6mm Tactile Switch x20
    $28.00   Panavise Jr. - PV-201
    $34.95   PiTFT Mini Kit 320x240
```

We'll come back to `slice` objects when we discuss creating your own collections in "Vector Take #2: A Sliceable Sequence". Meanwhile, from a user perspective, slicing includes additional features such as multidimensional slices and ellipsis (`...`) notation. Read on.

Multidimensional Slicing and Ellipsis

The `[]` operator can also take multiple indexes or slices separated by commas. The `__getitem__` and `__setitem__` special methods that handle the `[]` operator simply receive the indices in `a[i, j]` as a tuple. In other words, to evaluate `a[i, j]`, Python calls `a.__getitem__((i, j))`.

This is used, for instance, in the external NumPy package, where items of a two-dimensional `numpy.ndarray` can be fetched using the syntax `a[i, j]` and a two-dimensional slice obtained with an expression like `a[m:n, k:l]`. Example 2-21 later in this chapter shows the use of this notation.

Except for `memoryview`, the built-in sequence types in Python are one-dimensional, so they support only one index or slice, and not a tuple of them.[6]

The ellipsis—written with three full stops (`...`) and not … (Unicode U+2026)—is recognized as a token by the Python parser. It is an alias to the `Ellipsis` object, the single instance of the `ellipsis` class.[7] As such, it can be passed as an argument to functions and as part of a slice specification, as in `f(a, ..., z)` or `a[i:...]`. NumPy uses `...` as a shortcut when slicing arrays of many dimensions; for example, if `x` is a four-dimensional array, `x[i, ...]` is a shortcut for `x[i, :, :, :,]`. See the Tentative NumPy Tutorial to learn more about this.

At the time of this writing, I am unaware of uses of `Ellipsis` or multidimensional indexes and slices in the Python standard library. If you spot one, let me know. These syntactic features exist to support user-defined types and extensions such as NumPy.

Slices are not just useful to extract information from sequences; they can also be used to change mutable sequences in place—that is, without rebuilding them from scratch.

Assigning to Slices

Mutable sequences can be grafted, excised, and otherwise modified in place using slice notation on the left-hand side of an assignment statement or as the target of a `del` statement. The next few examples give an idea of the power of this notation:

```
>>> l = list(range(10))
>>> l
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
>>> l[2:5] = [20, 30]
>>> l
[0, 1, 20, 30, 5, 6, 7, 8, 9]
>>> del l[5:7]
>>> l
[0, 1, 20, 30, 5, 8, 9]
>>> l[3::2] = [11, 22]
>>> l
[0, 1, 20, 11, 5, 22, 9]
>>> l[2:5] = 100  ❶
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: can only assign an iterable
>>> l[2:5] = [100]
>>> l
[0, 1, 100, 22, 9]
```

❶ When the target of the assignment is a slice, the right-hand side must be an iterable object, even if it has just one item.

Every coder knows that concatenation is a common operation with sequences. Introductory Python tutorials explain the use of + and * for that purpose, but there are some subtle details on how they work, which we cover next.

Using + and * with Sequences

Python programmers expect that sequences support + and *. Usually both operands of + must be of the same sequence type, and neither of them is modified but a new sequence of that same type is created as result of the concatenation.

To concatenate multiple copies of the same sequence, multiply it by an integer. Again, a new sequence is created:

```
>>> l = [1, 2, 3]
>>> l * 5
[1, 2, 3, 1, 2, 3, 1, 2, 3, 1, 2, 3, 1, 2, 3]
>>> 5 * 'abcd'
'abcdabcdabcdabcdabcd'
```

Both + and * always create a new object, and never change their operands.

> **WARNING**
>
> Beware of expressions like `a * n` when `a` is a sequence containing mutable items because the result may surprise you. For example, trying to initialize a list of lists as `my_list = [[]] * 3` will result in a list with three references to the same inner list, which is probably not what you want.

The next section covers the pitfalls of trying to use * to initialize a list of lists.

Building Lists of Lists

Sometimes we need to initialize a list with a certain number of nested lists—for example, to distribute students in a list of teams or to represent squares on a game board. The best way of doing so is with a list comprehension, as in Example 2-13.

Example 2-13. A list with three lists of length 3 can represent a tic-tac-toe board

```
>>> board = [['_'] * 3 for i in range(3)]  ❶
>>> board
[['_', '_', '_'], ['_', '_', '_'], ['_', '_', '_']]
>>> board[1][2] = 'X'  ❷
>>> board
[['_', '_', '_'], ['_', '_', 'X'], ['_', '_', '_']]
```

❶ Create a list of three lists of three items each. Inspect the structure.

❷ Place a mark in row 1, column 2, and check the result.

A tempting but wrong shortcut is doing it like Example 2-14.

Example 2-14. A list with three references to the same list is useless

```
>>> weird_board = [['_'] * 3] * 3  ❶
>>> weird_board
[['_', '_', '_'], ['_', '_', '_'], ['_', '_', '_']]
>>> weird_board[1][2] = 'O' ❷
>>> weird_board
[['_', '_', 'O'], ['_', '_', 'O'], ['_', '_', 'O']]
```

❶ The outer list is made of three references to the same inner list. While it is unchanged, all seems right.

❷ Placing a mark in row 1, column 2, reveals that all rows are aliases referring to the same object.

The problem with Example 2-14 is that, in essence, it behaves like this code:

```
row = ['_'] * 3
board = []
for i in range(3):
    board.append(row)  ❶
```

❶ The same `row` is appended three times to `board`.

On the other hand, the list comprehension from Example 2-13 is equivalent to this code:

```
>>> board = []
>>> for i in range(3):
...     row = ['_'] * 3  ❶
...     board.append(row)
...
>>> board
[['_', '_', '_'], ['_', '_', '_'], ['_', '_', '_']]
>>> board[2][0] = 'X'
>>> board  ❷
[['_', '_', '_'], ['_', '_', '_'], ['X', '_', '_']]
```

❶ Each iteration builds a new `row` and appends it to `board`.

❷ Only row 2 is changed, as expected.

> **TIP**
>
> If either the problem or the solution in this section are not clear to you, relax. Chapter 6 was written to clarify the mechanics and pitfalls of references and mutable objects.

So far we have discussed the use of the plain `+` and `*` operators with sequences, but there are also the `+=` and `*=` operators, which produce very different results depending on the mutability of the target sequence. The following section explains how that works.

Augmented Assignment with Sequences

The augmented assignment operators `+=` and `*=` behave quite differently depending on the first operand. To simplify the discussion, we will focus on augmented addition first (`+=`), but the concepts also apply to `*=` and to other augmented assignment operators.

The special method that makes `+=` work is `__iadd__` (for "in-place addition"). However, if `__iadd__` is not implemented, Python falls back to calling `__add__`. Consider this simple expression:

```
>>> a += b
```

If `a` implements `__iadd__`, that will be called. In the case of mutable sequences (e.g., `list`, `bytearray`, `array.array`), `a` will be changed in place (i.e., the effect will be similar to `a.extend(b)`). However, when `a` does not implement `__iadd__`, the expression `a += b` has the same effect as `a = a + b`: the expression `a + b` is evaluated first, producing a new object, which is then bound to `a`. In other words, the identity of the object bound to `a` may or may not change, depending on the availability of `__iadd__`.

In general, for mutable sequences, it is a good bet that `__iadd__` is implemented and that `+=` happens in place. For immutable sequences, clearly there is no way for that to happen.

What I just wrote about `+=` also applies to `*=`, which is implemented via `__imul__`. The `__iadd__` and `__imul__` special methods are discussed in Chapter 16.

Here is a demonstration of `*=` with a mutable sequence and then an immutable one:

```
>>> l = [1, 2, 3]
>>> id(l)
4311953800  ❶
>>> l *= 2
>>> l
[1, 2, 3, 1, 2, 3]
>>> id(l)
```

```
4311953800  ❷
>>> t = (1, 2, 3)
>>> id(t)
4312681568  ❸
>>> t *= 2
>>> id(t)
4301348296  ❹
```

❶ ID of the initial list

❷ After multiplication, the list is the same object, with new items appended

❸ ID of the initial tuple

❹ After multiplication, a new tuple was created

Repeated concatenation of immutable sequences is inefficient, because instead of just appending new items, the interpreter has to copy the whole target sequence to create a new one with the new items concatenated.[8]

We've seen common use cases for `+=`. The next section shows an intriguing corner case that highlights what "immutable" really means in the context of tuples.

A += Assignment Puzzler

Try to answer without using the console: what is the result of evaluating the two expressions in Example 2-15?[9]

Example 2-15. A riddle

```
>>> t = (1, 2, [30, 40])
>>> t[2] += [50, 60]
```

What happens next? Choose the best answer:

1. `t` becomes `(1, 2, [30, 40, 50, 60])`.

2. `TypeError` is raised with the message `'tuple' object does not support item assignment`.

3. Neither.

4. Both A and B.

When I saw this, I was pretty sure the answer was B, but it's actually D, "Both A and B"! Example 2-16 is the actual output from a Python 3.9 console.[10]

Example 2-16. The unexpected result: item t2 is changed and an exception is raised

```
>>> t = (1, 2, [30, 40])
>>> t[2] += [50, 60]
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: 'tuple' object does not support item assignment
>>> t
(1, 2, [30, 40, 50, 60])
```

Online Python Tutor is an awesome online tool to visualize how Python works in detail. Figure 2-5 is a composite of two screenshots showing the initial and final states of the tuple `t` from Example 2-16.

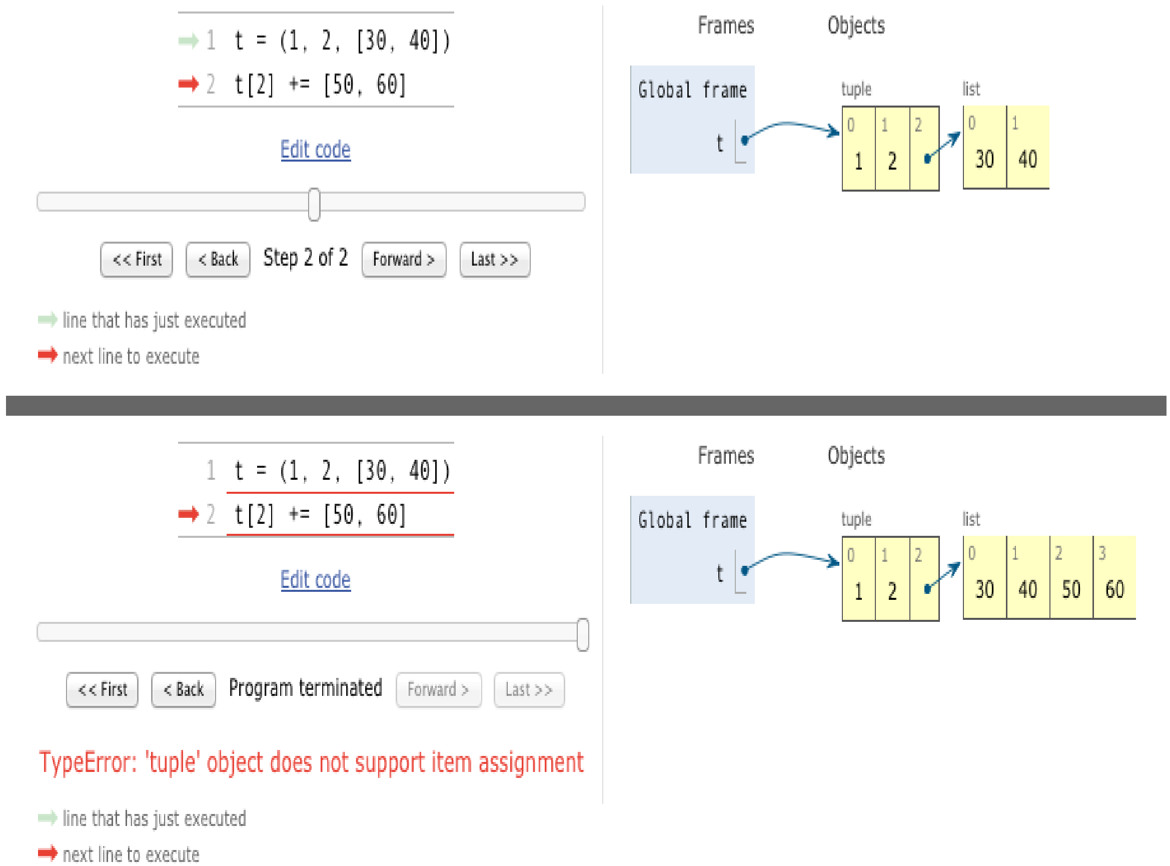


Figure 2-5. Initial and final state of the tuple assignment puzzler (diagram generated by Online Python Tutor)

If you look at the bytecode Python generates for the expression `s[a] += b` (Example 2-17), it becomes clear how that happens.

Example 2-17. Bytecode for the expression s[a] += b

```
>>> dis.dis('s[a] += b')
  1           0 LOAD_NAME                0 (s)
              3 LOAD_NAME                1 (a)
              6 DUP_TOP_TWO
              7 BINARY_SUBSCR                      ❶
              8 LOAD_NAME                2 (b)
             11 INPLACE_ADD                        ❷
             12 ROT_THREE
             13 STORE_SUBSCR                       ❸
             14 LOAD_CONST               0 (None)
             17 RETURN_VALUE
```

❶ Put the value of `s[a]` on `TOS` (Top Of Stack).

2. Perform `TOS += b`. This succeeds if `TOS` refers to a mutable object (it's a list, in Example 2-16).

3. Assign `s[a] = TOS`. This fails if `s` is immutable (the `t` tuple in Example 2-16).

This example is quite a corner case—in 20 years using Python, I have never seen this strange behavior actually bite somebody.

I take three lessons from this:

- Avoid putting mutable items in tuples.
- Augmented assignment is not an atomic operation—we just saw it throwing an exception after doing part of its job.
- Inspecting Python bytecode is not too difficult, and can be helpful to see what is going on under the hood.

After witnessing the subtleties of using `+` and `*` for concatenation, we can change the subject to another essential operation with sequences: sorting.

list.sort versus the sorted Built-In

The `list.sort` method sorts a list in-place—that is, without making a copy. It returns `None` to remind us that it changes the receiver[11] and does not create a new list. This is an important Python API convention: functions or methods that change an object in-place should return `None` to make it clear to the caller that the receiver was changed, and no new object was created. Similar behavior can be seen, for example, in the `random.shuffle(s)` function, which shuffles the mutable sequence `s` in-place, and returns `None`.

> **NOTE**
>
> The convention of returning `None` to signal in-place changes has a drawback: we cannot cascade calls to those methods. In contrast, methods that return new objects (e.g., all `str` methods) can be cascaded in the fluent interface style. See Wikipedia's "Fluent interface" entry for further description of this topic.

In contrast, the built-in function `sorted` creates a new list and returns it. It accepts any iterable object as an argument, including immutable sequences and generators (see Chapter 17). Regardless of the type of iterable given to `sorted`, it always returns a newly created list.

Both `list.sort` and `sorted` take two optional, keyword-only arguments:

`reverse`

: If `True`, the items are returned in descending order (i.e., by reversing the comparison of the items). The default is `False`.

`key`

: A one-argument function that will be applied to each item to produce its sorting key. For example, when sorting a list of strings, `key=str.lower` can be used to perform a case-insensitive sort, and `key=len` will sort the strings by character length. The default is the identity function (i.e., the items themselves are compared).

> **TIP**
>
> You can also use the optional keyword parameter `key` with the `min()` and `max()` built-ins and with other functions from the standard library (e.g., `itertools.groupby()` and `heapq.nlargest()`).

Here are a few examples to clarify the use of these functions and keyword arguments. The examples also demonstrate that Python's sorting algorithm is stable (i.e., it preserves the relative ordering of items that compare equal):[12]

```
>>> fruits = ['grape', 'raspberry', 'apple', 'banana']
>>> sorted(fruits)
['apple', 'banana', 'grape', 'raspberry']  ❶
>>> fruits
['grape', 'raspberry', 'apple', 'banana']  ❷
>>> sorted(fruits, reverse=True)
['raspberry', 'grape', 'banana', 'apple']  ❸
>>> sorted(fruits, key=len)
['grape', 'apple', 'banana', 'raspberry']  ❹
>>> sorted(fruits, key=len, reverse=True)
['raspberry', 'banana', 'grape', 'apple']  ❺
>>> fruits
['grape', 'raspberry', 'apple', 'banana']  ❻
>>> fruits.sort()                          ❼
>>> fruits
['apple', 'banana', 'grape', 'raspberry']  ❽
```

❶ This produces a new list of strings sorted alphabetically.[13]

❷ Inspecting the original list, we see it is unchanged.

❸ This is the previous "alphabetical" ordering, reversed.

❹ A new list of strings, now sorted by length. Because the sorting algorithm is stable, "grape" and "apple," both of length 5, are in the original order.

❺ These are the strings sorted by length in descending order. It is not the reverse of the previous result because the sorting is stable, so again "grape" appears before "apple."

❻ So far, the ordering of the original `fruits` list has not changed.

❼ This sorts the list in place, and returns `None` (which the console omits).

❽ Now `fruits` is sorted.

WARNING

By default, Python sorts strings lexicographically by character code. That means ASCII uppercase letters will come before lowercase letters, and non-ASCII characters are unlikely to be sorted in a sensible way. "Sorting Unicode Text" covers proper ways of sorting text as humans would expect.

Once your sequences are sorted, they can be very efficiently searched. A binary search algorithm is already provided in the `bisect` module of the Python standard library. That module also includes the `bisect.insort` function, which you can use to make sure that your sorted sequences stay sorted. You'll find an illustrated introduction to the `bisect` module in *Managing Ordered Sequences with Bisect* post in the *fluentpython.com* companion Web site.

Much of what we have seen so far in this chapter applies to sequences in general, not just lists or tuples. Python programmers sometimes overuse the `list` type because it is so handy—I know I've done it. For example, if you are processing large lists of numbers, you should consider using arrays instead. The remainder of the chapter is devoted to alternatives to lists and tuples.

When a List Is Not the Answer

The `list` type is flexible and easy to use, but depending on specific requirements, there are better options. For example, an `array` saves a lot of memory when you need to handle millions of floating-point values. On the other hand, if you are constantly adding and removing items from opposite ends of a list, it's good to know that a `deque` (double-ended queue) is a more efficient FIFO[14] data structure.

> **TIP**
>
> If your code frequently checks whether an item is present in a collection (e.g., `item in my_collection`), consider using a `set` for `my_collection`, especially if it holds a large number of items. Sets are optimized for fast membership checking. They are also iterable, but they are not sequences because the ordering of set items is unspecified.. We cover them in Chapter 3.

For the remainder of this chapter, we discuss mutable sequence types that can replace lists in many cases, starting with arrays.

Arrays

If a list only contains numbers, an `array.array` is a more efficient replacement. Arrays support all mutable sequence operations (including `.pop`, `.insert`, and `.extend`), as well as additional methods for fast loading and saving such as `.frombytes` and `.tofile`.

A Python array is as lean as a C array. As shown in Figure 2-1, an `array` of `float` values does not hold full-fledged `float` instances, but only the packed bytes representing their machine values—similar to an array of `double` in the C language. When creating an `array`, you provide a typecode, a letter to determine the underlying C type used to store each item in the array. For example, `b` is the typecode for what C calls a `signed char`, an integer ranging from –128 to 127. If you create an `array('b')`, then each item will be stored in a single byte and interpreted as an integer. For large sequences of numbers, this saves a lot of memory. And Python will not let you put any number that does not match the type for the array.

Example 2-18 shows creating, saving, and loading an array of 10 million floating-point random numbers.

Example 2-18. Creating, saving, and loading a large array of floats

```
>>> from array import array  ❶
>>> from random import random
>>> floats = array('d', (random() for i in range(10**7)))  ❷
```

```
>>> floats[-1]  ❸
0.07802343889111107
>>> fp = open('floats.bin', 'wb')
>>> floats.tofile(fp)  ❹
>>> fp.close()
>>> floats2 = array('d')  ❺
>>> fp = open('floats.bin', 'rb')
>>> floats2.fromfile(fp, 10**7)  ❻
>>> fp.close()
>>> floats2[-1]  ❼
0.07802343889111107
>>> floats2 == floats  ❽
True
```

❶ Import the `array` type.

❷ Create an array of double-precision floats (typecode `'d'`) from any iterable object—in this case, a generator expression.

❸ Inspect the last number in the array.

❹ Save the array to a binary file.

❺ Create an empty array of doubles.

❻ Read 10 million numbers from the binary file.

❼ Inspect the last number in the array.

❽ Verify that the contents of the arrays match.

As you can see, `array.tofile` and `array.fromfile` are easy to use. If you try the example, you'll notice they are also very fast. A quick experiment shows that it takes about 0.1s for `array.fromfile` to load 10 million double-precision floats from a binary file created with `array.tofile`. That is nearly 60 times faster than reading the numbers from a text file, which also involves parsing each line with the `float` built-in. Saving with `array.tofile` is about 7 times faster than writing one float per line in a text file. In addition, the size of the binary file with 10 million doubles is 80,000,000 bytes (8 bytes per double, zero overhead), while the text file has 181,515,739 bytes, for the same data.

For the specific case of numeric arrays representing binary data, such as raster images, Python has the `bytes` and `bytearray` types discussed in Chapter 4.

We wrap up this section on arrays with Table 2-3, comparing the features of `list` and `array.array`.

Table 2-3. Methods and attributes found *inlistorarray(deprecatedarraymethods*

andthosealsoimplementedbyobjectwereo

mitted for brevity)

	list	array	
`s.__add__(s2)`	●	●	`s + s2`—concatenation
`s.__iadd__(s2)`	●	●	`s += s2`—in-place concatenation
`s.append(e)`	●	●	Append one element after last
`s.byteswap()`		●	Swap bytes of all items in array for endianness conversion
`s.clear()`	●		Delete all items
`s.__contains__(e)`	●	●	`e in s`
`s.copy()`	●		Shallow copy of the list
`s.__copy__()`		●	Support for `copy.copy`

`s.count(e)`	●	●	Count occurrences of an element
`s.__deepcopy__()`		●	Optimized support for `copy.deepcopy`
`s.__delitem__(p)`	●	●	Remove item at position `p`
`s.extend(it)`	●	●	Append items from iterable `it`
`s.frombytes(b)`		●	Append items from byte sequence interpreted as packed machine values
`s.fromfile(f, n)`		●	Append `n` items from binary file `f` interpreted as packed machine values
`s.fromlist(l)`		●	Append items from list; if one causes `TypeError`, none are appended
`s.__getitem__(p)`	●	●	`s[p]`—get item or slice at position
`s.index(e)`	●	●	Find position of first occurrence of `e`
`s.insert(p, e)`	●	●	Insert element `e` before the item at position `p`
`s.itemsize`		●	Length in bytes of each array item
`s.__iter__()`	●	●	Get iterator
`s.__len__()`	●	●	`len(s)`—number of items
`s.__mul__(n)`	●	●	`s * n`—repeated concatenation
`s.__imul__(n)`	●	●	`s *= n`—in-place repeated concatenation

`s.__rmul__(n)`	●	●	`n * s`—reversed repeated concatenation[a]
`s.pop([p])`	●	●	Remove and return item at position `p` (default: last)
`s.remove(e)`	●	●	Remove first occurrence of element `e` by value
`s.reverse()`	●	●	Reverse the order of the items in place
`s.__reversed__()`	●		Get iterator to scan items from last to first
`s.__setitem__(p, e)`	●	●	`s[p] = e`—put `e` in position `p`, overwriting existing item or slice.
`s.sort([key], [reverse])`	●		Sort items in place with optional keyword arguments `key` and `reverse`
`s.tobytes()`		●	Return items as packed machine values in a `bytes` object
`s.tofile(f)`		●	Save items as packed machine values to binary file `f`
`s.tolist()`		●	Return items as numeric objects in a `list`
`s.typecode`		●	One-character string identifying the C type of the items

a Reversed operators are explained in Chapter 16.

TIP

As of Python 3.10, the `array` type does not have an in-place `sort` method like `list.sort()`. If you need to sort an array, use the built-in `sorted` function to rebuild the array:

```
a = array.array(a.typecode, sorted(a))
```

To keep a sorted array sorted while adding items to it, use the `bisect.insort` function.

If you do a lot of work with arrays and don't know about `memoryview`, you're missing out. See the next topic.

Memory Views

The built-in `memoryview` class is a shared-memory sequence type that lets you handle slices of arrays without copying bytes. It was inspired by the NumPy library (which we'll discuss shortly in "NumPy"). Travis Oliphant, lead author of NumPy, answers When should a memoryview be used? like this:

> *A memoryview is essentially a generalized NumPy array structure in Python itself (without the math). It allows you to share memory between data-structures (things like PIL images, SQLite databases, NumPy arrays, etc.) without first copying. This is very important for large data sets.*

Using notation similar to the `array` module, the `memoryview.cast` method lets you change the way multiple bytes are read or written as units without moving bits around. `memoryview.cast` returns yet another `memoryview` object, always sharing the same memory.

Example 2-19 shows how to create alternate views on the same array of 6 bytes, to operate on it as 2×3 matrix or a 3×2 matrix:

Example 2-19. Handling 6 bytes memory of as 1×6, 2×3, and 3×2 views

```
>>> from array import array
>>> octets = array('B', range(6))  ❶
>>> m1 = memoryview(octets)  ❷
>>> m1.tolist()
[0, 1, 2, 3, 4, 5]
>>> m2 = m1.cast('B', [2, 3])  ❸
>>> m2.tolist()
[[0, 1, 2], [3, 4, 5]]
>>> m3 = m1.cast('B', [3, 2])  ❹
>>> m3.tolist()
[[0, 1], [2, 3], [4, 5]]
>>> m2[1,1] = 22  ❺
>>> m3[1,1] = 33  ❻
>>> octets  ❼
array('B', [0, 1, 2, 33, 22, 5])
```

❶ Build array of 6 bytes (typecode `'B'`).

❷ Build `memoryview` from that array, then export it as list.

❸ Build new `memoryview` from that previous one, but with 2 rows and 3 columns.

❹ Yet another `memoryview`, now with 3 rows and 2 columns.

❺ Overwrite byte in `m2` at row 1, column 1 with 22.

❻ Overwrite byte in `m3` at row 1, column 1 with 33.

❼ Display original array, proving that the memory was shared among `octets`, `m1`, `m2`, and `m3`.

The awesome power of `memoryview` can also be used to corrupt. Example 2-20 shows how to change a single byte of an item in an array of 16-bit integers.

Example 2-20. Changing the value of an 16-bit integer array item by poking one of its bytes

```
>>> numbers = array.array('h', [-2, -1, 0, 1, 2])
>>> memv = memoryview(numbers)  ❶
```

```
>>> len(memv)
5
>>> memv[0]  ❷
-2
>>> memv_oct = memv.cast('B')  ❸
>>> memv_oct.tolist()  ❹
[254, 255, 255, 255, 0, 0, 1, 0, 2, 0]
>>> memv_oct[5] = 4  ❺
>>> numbers
array('h', [-2, -1, 1024, 1, 2])  ❻
```

❶ Build `memoryview` from array of 5 16-bit signed integers (typecode `'h'`).

❷ `memv` sees the same 5 items in the array.

❸ Create `memv_oct` by casting the elements of `memv` to bytes (typecode `'B'`).

❹ Export elements of `memv_oct` as a list of 10 bytes, for inspection.

❺ Assign value 4 to byte offset 5.

❻ Note the change to `numbers`: a 4 in the most significant byte of a 2-byte unsigned integer is 1024.

> **NOTE**
>
> You'll find an example of inspecting `memoryview` with the `struct` package at *fluentpython.com*: Parsing binary records with struct.

Meanwhile, if you are doing advanced numeric processing in arrays, you should be using the NumPy libraries. We'll take a brief look at them right away.

NumPy

Throughout this book, I make a point of highlighting what is already in the Python standard library so you can make the most of it. But NumPy is so awesome that a detour is warranted.

For advanced array and matrix operations, NumPy is the reason why Python became mainstream in scientific computing applications. NumPy implements multi-dimensional, homogeneous arrays and matrix types that hold not only numbers but also user-defined records, and provides efficient elementwise operations.

SciPy is a library, written on top of NumPy, offering many scientific computing algorithms from linear algebra, numerical calculus, and statistics. SciPy is fast and reliable because it leverages the widely used C and Fortran codebase from the Netlib Repository. In other words, SciPy gives scientists the best of both worlds: an interactive prompt and high-level Python APIs, together with industrial-strength number-crunching functions optimized in C and Fortran.

As a very brief NumPy demo, Example 2-21 shows some basic operations with two-dimensional arrays.

Example 2-21. Basic operations with rows and columns in a numpy.ndarray

```
>>> import numpy as np ❶
>>> a = np.arange(12)  ❷
>>> a
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
>>> type(a)
<class 'numpy.ndarray'>
>>> a.shape  ❸
(12,)
>>> a.shape = 3, 4  ❹
>>> a
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
>>> a[2]  ❺
array([ 8,  9, 10, 11])
>>> a[2, 1]  ❻
9
>>> a[:, 1]  ❼
array([1, 5, 9])
>>> a.transpose()  ❽
```

```
array([[ 0,  4,  8],
       [ 1,  5,  9],
       [ 2,  6, 10],
       [ 3,  7, 11]])
```

❶ Import NumPy, after installing (it's not in the Python standard library). Conventionally, `numpy` is imported as `np`.

❷ Build and inspect a `numpy.ndarray` with integers 0 to 11.

❸ Inspect the dimensions of the array: this is a one-dimensional, 12-element array.

❹ Change the shape of the array, adding one dimension, then inspecting the result.

❺ Get row at index `2`.

❻ Get element at index `2, 1`.

❼ Get column at index `1`.

❽ Create a new array by transposing (swapping columns with rows).

NumPy also supports high-level operations for loading, saving, and operating on all elements of a `numpy.ndarray`:

```
>>> import numpy
>>> floats = numpy.loadtxt('floats-10M-lines.txt')  ❶
>>> floats[-3:]  ❷
array([ 3016362.69195522,   535281.10514262,  4566560.44373946])
>>> floats *= .5  ❸
>>> floats[-3:]
array([ 1508181.34597761,   267640.55257131,  2283280.22186973])
>>> from time import perf_counter as pc ❹
>>> t0 = pc(); floats /= 3; pc() - t0 ❺
0.03690556302899495
>>> numpy.save('floats-10M', floats)  ❻
>>> floats2 = numpy.load('floats-10M.npy', 'r+')  ❼
>>> floats2 *= 6
```

```
>>> floats2[-3:]  ❽
memmap([ 3016362.69195522,   535281.10514262,  4566560.44373946])
```

❶ Load 10 million floating-point numbers from a text file.

❷ Use sequence slicing notation to inspect the last three numbers.

❸ Multiply every element in the `floats` array by .5 and inspect the last three elements again.

❹ Import the high-resolution performance measurement timer (available since Python 3.3).

❺ Divide every element by 3; the elapsed time for 10 million floats is less than 40 milliseconds.

❻ Save the array in a *.npy* binary file.

❼ Load the data as a memory-mapped file into another array; this allows efficient processing of slices of the array even if it does not fit entirely in memory.

❽ Inspect the last three elements after multiplying every element by 6.

This was just an appetizer.

NumPy and SciPy are formidable libraries, and are the foundation of other awesome tools such as the Pandas—which implements efficient array types that can hold nonnumeric data and provides import/export functions for many different formats like *.csv*, *.xls*, SQL dumps, HDF5, etc.—and Scikit-learn—currently the most widely used Machine Learning toolset. Most NumPy and SciPy functions are implemented in C or C++, and can leverage all CPU cores because they release Python’s GIL (Global Interpreter Lock). The Dask project supports parallelizing NumPy, Pandas, and Scikit-Learn processing across clusters of machines. These packages deserve entire books about them. This is not one of those books. But no overview of Python sequences would be complete without at least a quick look at NumPy arrays.

Having looked at flat sequences—standard arrays and NumPy arrays—we now turn to a completely different set of replacements for the plain old `list`: queues.

Deques and Other Queues

The `.append` and `.pop` methods make a `list` usable as a stack or a queue (if you use `.append` and `.pop(0)`, you get FIFO behavior). But inserting and removing from the head of a list (the 0-index end) is costly because the entire list must be shifted in memory.

The class `collections.deque` is a thread-safe double-ended queue designed for fast inserting and removing from both ends. It is also the way to go if you need to keep a list of "last seen items" or something of that nature, because a `deque` can be bounded—i.e., created with a fixed maximum length. If a bounded `deque` is full, when you add a new item it discards an item from the opposite end. Example 2-22 shows some typical operations performed on a `deque`.

Example 2-22. Working with a deque

```
>>> from collections import deque
>>> dq = deque(range(10), maxlen=10)  ❶
>>> dq
deque([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], maxlen=10)
>>> dq.rotate(3)  ❷
>>> dq
deque([7, 8, 9, 0, 1, 2, 3, 4, 5, 6], maxlen=10)
>>> dq.rotate(-4)
>>> dq
deque([1, 2, 3, 4, 5, 6, 7, 8, 9, 0], maxlen=10)
>>> dq.appendleft(-1)  ❸
>>> dq
deque([-1, 1, 2, 3, 4, 5, 6, 7, 8, 9], maxlen=10)
>>> dq.extend([11, 22, 33])  ❹
>>> dq
deque([3, 4, 5, 6, 7, 8, 9, 11, 22, 33], maxlen=10)
>>> dq.extendleft([10, 20, 30, 40])  ❺
```

```
>>> dq
deque([40, 30, 20, 10, 3, 4, 5, 6, 7, 8], maxlen=10)
```

❶ The optional `maxlen` argument sets the maximum number of items allowed in this instance of `deque`; this sets a read-only `maxlen` instance attribute.

❷ Rotating with `n > 0` takes items from the right end and prepends them to the left; when `n < 0` items are taken from left and appended to the right.

❸ Appending to a `deque` that is full (`len(d) == d.maxlen`) discards items from the other end; note in the next line that the `0` is dropped.

❹ Adding three items to the right pushes out the leftmost `-1`, `1`, and `2`.

❺ Note that `extendleft(iter)` works by appending each successive item of the `iter` argument to the left of the deque, therefore the final position of the items is reversed.

Table 2-4 compares the methods that are specific to `list` and `deque` (removing those that also appear in `object`).

Note that `deque` implements most of the `list` methods, and adds a few that are specific to its design, like `popleft` and `rotate`. But there is a hidden cost: removing items from the middle of a `deque` is not as fast. It is really optimized for appending and popping from the ends.

The `append` and `popleft` operations are atomic, so `deque` is safe to use as a FIFO queue in multithreaded applications without the need for locks.

Table 2-4. Methods implemented in li

stordeque (those that are also implem

ented by object were omitted for brevi

t
y
)

	list	deque	
s.__add__(s2)	●		s + s2—concatenation
s.__iadd__(s2)	●	●	s += s2—in-place concatenation
s.append(e)	●	●	Append one element to the right (after last)
s.appendleft(e)		●	Append one element to the left (before first)
s.clear()	●	●	Delete all items
s.__contains__(e)	●		e in s
s.copy()	●		Shallow copy of the list
s.__copy__()		●	Support for copy.copy (shallow copy)
s.count(e)	●	●	Count occurrences of an element
s.__delitem__(p)	●	●	Remove item at position p
s.extend(i)	●	●	Append items from iterable i to the right
s.extendleft(i)		●	Append items from iterable i to the left
s.__getitem__(p)	●	●	s[p]—get item or slice at position

`s.index(e)`	●		Find position of first occurrence of `e`
`s.insert(p, e)`	●		Insert element `e` before the item at position `p`
`s.__iter__()`	●	●	Get iterator
`s.__len__()`	●	●	`len(s)`—number of items
`s.__mul__(n)`	●		`s * n`—repeated concatenation
`s.__imul__(n)`	●		`s *= n`—in-place repeated concatenation
`s.__rmul__(n)`	●		`n * s`—reversed repeated concatenation[a]
`s.pop()`	●	●	Remove and return last item[b]
`s.popleft()`		●	Remove and return first item
`s.remove(e)`	●	●	Remove first occurrence of element `e` by value
`s.reverse()`	●	●	Reverse the order of the items in place
`s.__reversed__()`	●	●	Get iterator to scan items from last to first
`s.rotate(n)`		●	Move `n` items from one end to the other
`s.__setitem__(p, e)`	●	●	`s[p] = e`—put `e` in position `p`, overwriting existing item or slice.
`s.sort([key], [reverse])`	●		Sort items in place with optional keyword arguments `key` and `reverse`

[a] Reversed operators are explained in Chapter 16.

[b] `a_list.pop(p)` allows removing from position `p` but `deque` does not support that option.

Besides `deque`, other Python standard library packages implement queues:

`queue`

This provides the synchronized (i.e., thread-safe) classes `SimpleQueue`, `Queue`, `LifoQueue`, and `PriorityQueue`. These can be used for safe communication between threads. All except `SimpleQueue` can be bounded by providing a `maxsize` argument greater than 0 to the constructor. However, they don't discard items to make room as `deque` does. Instead, when the queue is full the insertion of a new item blocks—i.e., it waits until some other thread makes room by taking an item from the queue, which is useful to throttle the number of live threads.

`multiprocessing`

Implements its own unbounded `SimpleQueue` and bounded `Queue`, very similar to those in the `queue` package, but designed for interprocess communication. A specialized `multiprocessing.JoinableQueue` is provided for task management.

`asyncio`

Provides `Queue`, `LifoQueue`, `PriorityQueue`, and `JoinableQueue` with APIs inspired by the classes in the `queue` and `multiprocessing` modules, but adapted for managing tasks in asynchronous programming.

`heapq`

In contrast to the previous three modules, `heapq` does not implement a queue class, but provides functions like `heappush` and `heappop` that let you use a mutable sequence as a heap queue or priority queue.

This ends our overview of alternatives to the `list` type, and also our exploration of sequence types in general—except for the particulars of `str` and binary sequences, which have their own chapter (Chapter 4).

Chapter Summary

Mastering the standard library sequence types is a prerequisite for writing concise, effective, and idiomatic Python code.

Python sequences are often categorized as mutable or immutable, but it is also useful to consider a different axis: flat sequences and container sequences. The former are more compact, faster, and easier to use, but are limited to storing atomic data such as numbers, characters, and bytes. Container sequences are more flexible, but may surprise you when they hold mutable objects, so you need to be careful to use them correctly with nested data structures.

Unfortunately, Python has no foolproof immutable container sequence type: even “immutable” tuples can have their values changed, when they contain mutable items like lists or user-defined objects.

List comprehensions and generator expressions are powerful notations to build and initialize sequences. If you are not yet comfortable with them, take the time to master their basic usage. It is not hard, and soon you will be hooked.

Tuples in Python play two roles: as records with unnamed fields and as immutable lists. When using a tuple as an immutable list, remember that a tuple value is only guaranteed to be fixed if all the items in it are also immutable. Calling `hash(t)` on a tuple is a quick way to assert that its value is fixed. A `TypeError` will be raised if `t` contains mutable items.

When a tuple is used as a record, tuple unpacking is the safest, most readable way of extracting the the fields of the tuple. Beyond tuples, `*` works with lists and iterables in many contexts, and some of its use cases appeared in Python 3.5 with PEP 448—Additional Unpacking Generalizations. Python 3.10 introduced pattern matching with `match/case`, supporting more powerful unpacking, known as destructuring.

Sequence slicing is a favorite Python syntax feature, and it is even more powerful than many realize. Multidimensional slicing and ellipsis (`...`)

notation, as used in NumPy, may also be supported by user-defined sequences. Assigning to slices is a very expressive way of editing mutable sequences.

Repeated concatenation as in `seq * n` is convenient and, with care, can be used to initialize lists of lists containing immutable items. Augmented assignment with `+=` and `*=` behaves differently for mutable and immutable sequences. In the latter case, these operators necessarily build new sequences. But if the target sequence is mutable, it is usually changed in place—but not always, depending on how the sequence is implemented.

The `sort` method and the `sorted` built-in function are easy to use and flexible, thanks to the optional `key` argument: a function to calculate the ordering criterion. By the way, `key` can also be used with the `min` and `max` built-in functions.

Beyond lists and tuples, the Python standard library provides `array.array`. Although NumPy and SciPy are not part of the standard library, if you do any kind of numerical processing on large sets of data, studying even a small part of these libraries can take you a long way.

We closed by visiting the versatile and thread-safe `collections.deque`, comparing its API with that of `list` in Table 2-4 and mentioning other queue implementations in the standard library.

Further Reading

Chapter 1, "Data Structures" of *Python Cookbook, 3rd Edition* (O'Reilly) by David Beazley and Brian K. Jones has many recipes focusing on sequences, including "Recipe 1.11. Naming a Slice," from which I learned the trick of assigning slices to variables to improve readability, illustrated in our Example 2-12.

The second edition of *Python Cookbook* was written for Python 2.4, but much of its code works with Python 3, and a lot of the recipes in Chapters 5 and 6 deal with sequences. The book was edited by Alex Martelli, Anna

Martelli Ravenscroft, and David Ascher, and it includes contributions by dozens of Pythonistas. The third edition was rewritten from scratch, and focuses more on the semantics of the language—particularly what has changed in Python 3—while the older volume emphasizes pragmatics (i.e., how to apply the language to real-world problems). Even though some of the second edition solutions are no longer the best approach, I honestly think it is worthwhile to have both editions of *Python Cookbook* on hand.

The official Python Sorting HOW TO has several examples of advanced tricks for using `sorted` and `list.sort`.

PEP 3132 — Extended Iterable Unpacking is the canonical source to read about the new use of `*extra` syntax on the left hand of parallel assignments. If you'd like a glimpse of Python evolving, Missing *-unpacking generalizations is a bug tracker issue proposing enhancements to the iterable unpacking notation. PEP 448 — Additional Unpacking Generalizations resulted from the discussions in that issue.

As I mentioned in "Pattern Matching with Sequences", Carol Willing's *Structural Pattern Matching* section of *What's New In Python 3.10* is a great introduction to this major new feature in about 1400 words (that's less than 5 pages when Firefox makes a PDF from the HTML). *PEP 636—Structural Pattern Matching: Tutorial* is also good, but longer. The same PEP 636 includes Appendix A—Quick Intro. It is shorter than Willing's intro because it omits high level considerations about why pattern matching is good for you. If you need more arguments to convince yourself or others that pattern matching is good for Python, read the 22-page PEP 635—Structural Pattern Matching: Motivation and Rationale.

Eli Bendersky's blog post "Less Copies in Python with the Buffer Protocol and memoryviews" includes a short tutorial on `memoryview`.

There are numerous books covering NumPy in the market, and many don't mention "NumPy" in the title. Two examples are the open access Python Data Science Handbook by Jake VanderPlas, and Wes McKinney's *Python for Data Analysis, 2e*.

“NumPy is all about vectorization”. That is the opening sentence of Nicolas P. Rougier’s open access book From Python to NumPy. Vectorized operations apply mathematical functions to all elements of an array without an explicit loop written in Python. They can operate in parallel, using special vector instructions in modern CPUs, leveraging multiple cores or delegating to the GPU, depending on the library. The first example in Rougier’s book shows a speedup of 500 times after refactoring a nice Pythonic class using a generator method, into a lean and mean function calling a couple of NumPy vector functions.

To learn how to use `deque` (and other collections) see the examples and practical recipes in 8.3. collections — Container datatypes in the Python documentation.

The best defense of the Python convention of excluding the last item in ranges and slices was written by Edsger W. Dijkstra himself, in a short memo titled “Why Numbering Should Start at Zero”. The subject of the memo is mathematical notation, but it’s relevant to Python because Dijkstra explains with rigor and humor why a sequence like 2, 3, …, 12 should always be expressed as $2 \leq i < 13$. All other reasonable conventions are refuted, as is the idea of letting each user choose a convention. The title refers to zero-based indexing, but the memo is really about why it is desirable that `'ABCDE'[1:3]` means `'BC'` and not `'BCD'` and why it makes perfect sense to write `range(2, 13)` to produce 2, 3, 4, …, 12. By the way, the memo is a handwritten note, but it’s beautiful and totally readable. Dijkstra’s handwriting is so clear that someone created a font out of his notes.

SOAPBOX

The Nature of Tuples

In 2012, I presented a poster about the ABC language at PyCon US. Before creating Python, Guido van Rossum had worked on the ABC interpreter, so he came to see my poster. Among other things, we talked about the ABC *compounds*, which are clearly the predecessors of Python tuples. Compounds also support parallel assignment and are used as composite keys in dictionaries (or *tables*, in ABC parlance). However, compounds are not sequences. They are not iterable and you cannot retrieve a field by index, much less slice them. You either handle the compound as whole or extract the individual fields using parallel assignment, that's all.

I told Guido that these limitations make the main purpose of compounds very clear: they are just records without field names. His response: "Making tuples behave as sequences was a hack."

This illustrates the pragmatic approach that made Python more practical and more successful than ABC. From a language implementer perspective, making tuples behave as sequences costs little. As a result, the main use case for tuples as records is not so obvious, but we gained immutable lists—even if their type is not as clearly named as `frozenlist`.

Flat Versus Container Sequences

To highlight the different memory models of the sequence types, I used the terms *container sequence* and *flat sequence*. The "container" word is from the Data Model documentation:

> *Some objects contain references to other objects; these are called containers.*

I used the term "container sequence" to be specific, because there are containers in Python that are not sequences, like `dict` and `set`.

Container sequences can be nested because they may contain objects of any type, including their own type.

On the other hand, *flat sequences* are sequence types that cannot be nested because they only hold simple atomic types like integers, floats, or characters.

I adopted the term *flat sequence* because I needed something to contrast with “container sequence.”

Update: despite the previous use of the word “containers” in the official documentation, there is an abstract class in `collections.abc` called `Container`. That ABC has just one method, `__contains__`—the special method behind the `in` operator. This means that strings and arrays, which are not containers in the traditional sense, are virtual subclasses of `Container` because they implement `__contains__`. This is just one more example of humans using a word to mean different things. In this book I’ll write “container” with lowercase letters to mean “an object that contains references to other objects” and `Container` with capitalized initial in a single-spaced font to refer to `collections.abc.Container`.

Mixed Bag Lists

Introductory Python texts emphasize that lists can contain objects of mixed types, but in practice that feature is not very useful: we put items in a list to process them later, which implies that all items should support at least some operation in common (i.e., they should all “quack” whether or not they are genetically 100% ducks). For example, you can’t sort a list in Python 3 unless the items in it are comparable:

```
>>> l = [28, 14, '28', 5, '9', '1', 0, 6, '23', 19]
>>> sorted(l)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unorderable types: str() < int()
```

Unlike lists, tuples often hold items of different types. That's natural: if each item in a tuple is a field, then each field may have a different type.

Key Is Brilliant

The optional `key` argument of `list.sort`, `sorted`, `max`, and `min` is a great idea. Other languages force you to provide a two-argument comparison function like the deprecated `cmp(a, b)` function in Python 2. Using `key` is both simpler and more efficient. It's simpler because you just define a one-argument function that retrieves or calculates whatever criterion you want to use to sort your objects; this is easier than writing a two-argument function to return –1, 0, 1. It is also more efficient because the key function is invoked only once per item, while the two-argument comparison is called every time the sorting algorithm needs to compare two items. Of course, Python also has to compare the keys while sorting, but that comparison is done in optimized C code and not in a Python function that you wrote.

By the way, using `key` we can sort a mixed bag of numbers and number-like strings. We just need to decide whether we want to treat all items as integers or strings:

```
>>> l = [28, 14, '28', 5, '9', '1', 0, 6, '23', 19]
>>> sorted(l, key=int)
[0, '1', 5, 6, '9', 14, 19, '23', 28, '28']
>>> sorted(l, key=str)
[0, '1', 14, 19, '23', 28, '28', 5, 6, '9']
```

Oracle, Google, and the Timbot Conspiracy

The sorting algorithm used in `sorted` and `list.sort` is Timsort, an adaptive algorithm that switches from insertion sort to merge sort strategies, depending on how ordered the data is. This is efficient because real-world data tends to have runs of sorted items. There is a Wikipedia article about it.

Timsort was first deployed in CPython, in 2002. Since 2009, Timsort is also used to sort arrays in both standard Java and Android, a fact that became widely known when Oracle used some of the code related to Timsort as evidence of Google infringement of Sun's intellectual property. See Oracle v. Google - Day 14 Filings.

Timsort was invented by Tim Peters, a Python core developer so prolific that he is believed to be an AI, the Timbot. You can read about that conspiracy theory in Python Humor. Tim also wrote The Zen of Python: `import this`.

---

1 Leo Geurts, Lambert Meertens, and Steven Pemberton, *ABC Programmer's Handbook*, p. 8.

2 Thanks to reader Tina Lapine for pointing this out.

3 Thanks to tech reviewer Leonardo Rochael for this example.

4 In my view, a sequence of `if/elif/elif/.../else` blocks is a fine replacement for `switch/case`. It doesn't suffer from the fallthrough and dangling else problems that some language designers irrationally copied from C—decades after they were widely known as the cause of countless bugs.

5 The latter is named `eval` in Norvig's code; I renamed it to avoid confusion with Python's `eval` built-in.

6 In "Memory Views" we show that especially constructed memory views can have more than one dimension.

7 No, I did not get this backwards: the `ellipsis` class name is really all lowercase and the instance is a built-in named `Ellipsis`, just like `bool` is lowercase but its instances are `True` and `False`.

8 `str` is an exception to this description. Because string building with `+=` in loops is so common in real codebases, CPython is optimized for this use case. Instances `str` are allocated in memory with extra room, so that concatenation does not require copying the whole string every time.

9 Thanks to Leonardo Rochael and Cesar Kawakami for sharing this riddle at the 2013 PythonBrasil Conference.

10 Readers suggested that the operation in the example can be done with `t[2].extend([50,60])`, without errors. I am aware of that, but my intent is to show the strange behavior of the `+=` operator in this case.

11 Receiver is the target of a method call, the object bound to `self` in the method body.

12 Python's main sorting algorithm is named Timsort after its creator, Tim Peters. For a bit of Timsort trivia, see the "Soapbox".

13 The words in this example are sorted alphabetically because they are 100% made of lowercase ASCII characters. See warning after the example.

14 First in, first out—the default behavior of queues.

Chapter 3. Dictionaries and Sets

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 3rd chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Python is basically dicts wrapped in loads of syntactic sugar.*
>
> —Lalo Martins, early digital nomad and Pythonista.

We use dictionaties in all our Python programs. If not directly in our code, then indirectly because the `dict` type is a fundamental part of Python's implementation. Class and instance attributes, module namespaces, and function keyword arguments are some of the core Python constructs represented by dictionaries in memory. The `__builtins__.__dict__` stores all built-in types, objects, and functions.

Because of their crucial role, Python dicts are highly optimized—and continue to get improvements. *Hash tables* are the engines behind Python's high-performance dicts.

Other built-in types based on hash tables are `set` and `frozenset`. These offer richer APIs and operators than the sets you may have encountered in other popular languages. In particular, Python sets implement all the fundamental operations from set theory, like union, intersection, subset tests etc. With them, we can express algorithms in a more declarative way, avoiding lots of nested loops and conditionals.

Here is a brief outline of this chapter:

- Modern syntax to build and handle `dicts` and mappings, including enhanced unpacking and pattern matching.
- Common methods of mapping types.
- Special handling for missing keys.
- Variations of `dict` in the standard library.
- The `set` and `frozenset` types.
- Implications of hash tables in the behavior of sets and dictionaries.

What's new in this chapter

Most changes in this *Second Edition* cover new features related to mapping types:

- "Modern `dict` Syntax" covers enhanced unpacking syntax and different ways of merging mappings—including the `|` and `|=` operators supported by dicts since Python 3.9.
- "Pattern Matching with Mappings" illustrates handling mappings with `match/case`, since Python 3.10.
- Section "`collections.OrderedDict`" now focuses on the small but still relevant differences between `dict` and `OrderedDict`—considering that `dict` keeps the key insertion order since Python 3.6.
- New sections on the view objects returned by `dict.keys`, `dict.items`, and `dict.values`: "Dictionary views" and "Set operations on `dict` views".

The underlying implementation of `dict` and `set` still relies on hash tables, but the `dict` code has two important optimizations which save memory and preserve the insertion order of the keys in `dict`. The "Practical Consequences of How dict Works" and "Practical Consequences of How Sets Work" summarize what you need to know to use them well.

NOTE

After adding more than 200 pages in this *Second Edition*, I moved the optional section *Internals of sets and dicts* to the *fluentpython.com* companion Web site. The updated and expanded 18-page post includes explanations and diagrams about:

- The hash table algorithm and data structures, starting with its use in `set`, which is simpler to understand.
- The memory optimization that preserves key insertion order in `dict` instances (since Python 3.6).
- The key-sharing layout for dictionaries holding instance attributes—the `__dict__` of user-defined objects (optimization implemented in Python 3.3).

Modern `dict` Syntax

The next sections decribes advanced syntax features to build, unpack, and process mappings. Some of these features are not new in the language, but but may be new to you. Others require Python 3.9 (like the `|` operator) or Python 3.10 (like `match/case`). Let's start with one of the best and oldest of these features.

dict Comprehensions

Since Python 2.7, the syntax of listcomps and genexps was adapted to `dict` comprehensions (and `set` comprehensions as well, which we'll soon visit). A *dictcomp* builds a `dict` instance by taking `key:value` pairs from any iterable. Example 3-1 shows the use of `dict` comprehensions to build two dictionaries from the same list of tuples.

Example 3-1. Examples of dict comprehensions

```
>>> dial_codes = [                                                  ❶
...     (880, 'Bangladesh'),
...     (55,  'Brazil'),
...     (86,  'China'),
...     (91,  'India'),
...     (62,  'Indonesia'),
...     (81,  'Japan'),
...     (234, 'Nigeria'),
...     (92,  'Pakistan'),
```

```
...     (7,    'Russia'),
...     (1,    'United States'),
... ]
>>> country_dial = {country: code for code, country in dial_codes}  ❷
>>> country_dial
{'Bangladesh': 880, 'Brazil': 55, 'China': 86, 'India': 91,
'Indonesia': 62,
'Japan': 81, 'Nigeria': 234, 'Pakistan': 92, 'Russia': 7, 'United
States': 1}
>>> {code: country.upper()                                          ❸
...     for country, code in sorted(country_dial.items())
...     if code < 70}
{55: 'BRAZIL', 62: 'INDONESIA', 7: 'RUSSIA', 1: 'UNITED STATES'}
```

❶ An iterable of key-value pairs like `dial_codes` can be passed directly to the `dict` constructor, but…

❷ …here we swap the pairs: `country` is the key, and `code` is the value.

❸ Sorting `country_dial` by name, reversing the pairs again, uppercasing values, and filtering items with `code < 70`.

If you're used to listcomps, dictcomps are a natural next step. If you aren't, the spread of the comprehension syntax means it's now more profitable than ever to become fluent in it.

Unpacking Mappings

PEP 448—Additional Unpacking Generalizations enhanced the support of mapping unpackings in two ways, since Python 3.5.

First, we can apply `**` to more than one argument in a function call. This works when keys are all strings and unique accross all arguments (because duplicate keyword arguments are forbidden).

```
>>> def dump(**kwargs):
...     return kwargs
...
>>> dump(**{'x': 1}, y=2, **{'z': 3})
{'x': 1, 'y': 2, 'z': 3}
```

Second, `**` can be used inside a `dict` literal—also multiple times.

```
>>> {'a': 0, **{'x': 1}, 'y': 2, **{'z': 3, 'x': 4}}
{'a': 0, 'x': 4, 'y': 2, 'z': 3}
```

In this case, duplicate keys are allowed. Later occurrences overwrite previous ones—see the value mapped to `x` in the example.

This syntax can also be used to merge mappings, but there are other ways. Please read on.

Merging Mappings with |

Python 3.9 supports using `|` and `|=` to merge mappings. This makes sense, since these are also the set union operators.

The `|` operator creates a new mapping:

```
>>> d1 = {'a': 1, 'b': 3}
>>> d2 = {'a': 2, 'b': 4, 'c': 6}
>>> d1 | d2
{'a': 2, 'b': 4, 'c': 6}
```

Usually the type of the new mapping will be the same as the type of the left operand—`d1` in the example—but it can be the type of the second operand if user-defined types are involved, according the operator overloading rules we explore in Chapter 16.

To update an existing mapping in-place, use `|=`. Continuing from the previous example, `d1` was not changed, but now it is:

```
>>> d1
{'a': 1, 'b': 3}
>>> d1 |= d2
>>> d1
{'a': 2, 'b': 4, 'c': 6}
```

> **TIP**
>
> If you need to maintain code to run on Python 3.8 or earlier, the *Motivation* section of *PEP 584—Add Union Operators To dict* provides a good summary of other ways to merge mappings.

Now let’s see how pattern matching applies to mappings.

Pattern Matching with Mappings

The `match/case` statement supports subjects that are mapping objects. Patterns for mappings look like `dict` literals, but they can match instances of any actual or virtual subclass of `collections.abc.Mapping`.[1]

In Chapter 2 we focused on sequence patterns only, but different types of patterns can be combined and nested. Thanks to destructuring, pattern matching is a powerful tool to process records structured like nested mappings and sequences, which we often need to read from JSON APIs and databases with semi-structured schemas, like MongoDB, EdgeDB, or PostgreSQL. Example 3-2 demonstrates that. The simple type hints in `get_creators` make it clear that it takes a `dict` and returns a `list`.

Example 3-2. creator.py: get_creators() extracts names of creators from media records.

```
def get_creators(record: dict) -> list:
    match record:
        case {'type': 'book', 'api': 2, 'authors': [*names]}:  ❶
            return names
        case {'type': 'book', 'api': 1, 'author': name}:  ❷
            return [name]
        case {'type': 'book'}:  ❸
            raise ValueError(f"Invalid 'book' record: {record!r}")
        case {'type': 'movie', 'director': name}:  ❹
            return [name]
        case _:  ❺
            raise ValueError(f'Invalid record: {record!r}')
```

❶ Match any mapping with `'type': 'book', 'api' :2` and an `'authors'` key mapped to a sequence. Return the items in the sequence, as a new `list`.

❷ Match any mapping with `'type': 'book', 'api' :1` and an `'author'` key mapped to any object. Return the object inside a `list`.

❸ Any other mapping with `'type': 'book'` is invalid, raise `ValueError`.

❹ Match any mapping with `'type': 'movie'` and a `'director'` key mapped to a single object. Return the object inside a `list`.

❺ Any other subject is invalid, raise `ValueError`.

Example 3-2 shows some useful practices for handling semi-structured data such as JSON records:

- include a field describing the kind of record (e.g. `'type': 'movie'`);
- include a field identifying the schema version (e.g. `'api': 2'`) to allow for future evolution of public APIs;
- have `case` clauses to handle invalid records of a specific type (e.g. `'book'`), as well as a catch-all.

Now let's see how `get_creators` handles some concrete doctests:

```
>>> b1 = dict(api=1, author='Douglas Hofstadter',
...         type='book', title='Gödel, Escher, Bach')
>>> get_creators(b1)
['Douglas Hofstadter']
>>> from collections import OrderedDict
>>> b2 = OrderedDict(api=2, type='book',
...         title='Python in a Nutshell',
...         authors='Martelli Ravenscroft Holden'.split())
>>> get_creators(b2)
['Martelli', 'Ravenscroft', 'Holden']
>>> get_creators({'type': 'book', 'pages': 770})
Traceback (most recent call last):
    ...
ValueError: Invalid 'book' record: {'type': 'book', 'pages': 770}
>>> get_creators('Spam, spam, spam')
Traceback (most recent call last):
```

```
    ...
ValueError: Invalid record: 'Spam, spam, spam'
```

Note that the order of the keys in the patterns is irrelevant, even if the subject is an `OrderedDict` as `b2`.

In contrast with sequence patterns, mapping patterns succeed on partial matches. In the doctests, the `b1` and `b2` subjects include a `'title'` key that does not appear in any `'book'` pattern, yet they match.

There is no need to use `**extra` to match extra key-value pairs, but if you want to capture them as a `dict`, you can prefix one variable with `**`. It must be the last in the pattern, and `**_` is forbidden because it would be redundant. A simple example:

```
>>> food = dict(category='ice cream', flavor='vanilla', cost=199)
>>> match food:
...     case {'category': 'ice cream', **details}:
...         print(f'Ice cream details: {details}')
...
Ice cream details: {'flavor': 'vanilla', 'cost': 199}
```

In "Automatic Handling of Missing Keys" we'll study `defaultdict` and other mappings where key lookups via `__getitem__` (i.e. `d[key]`) succeed because missing items are created on the fly. In the context of pattern matching, a match succeeds only if the subject already has the required keys at the top of the `match` statement.

> **TIP**
>
> The automatic handling of missing keys is not triggered because pattern matching always uses the `d.get(key, sentinel)` method—where the default `sentinel` is a special marker value that cannot occur in user data.

Moving on from syntax and structure, let's study the API of mappings.

Standard API of Mapping Types

The `collections.abc` module provides the `Mapping` and `MutableMapping` ABCs describing the interfaces of `dict` and similar types. See Figure 3-1.

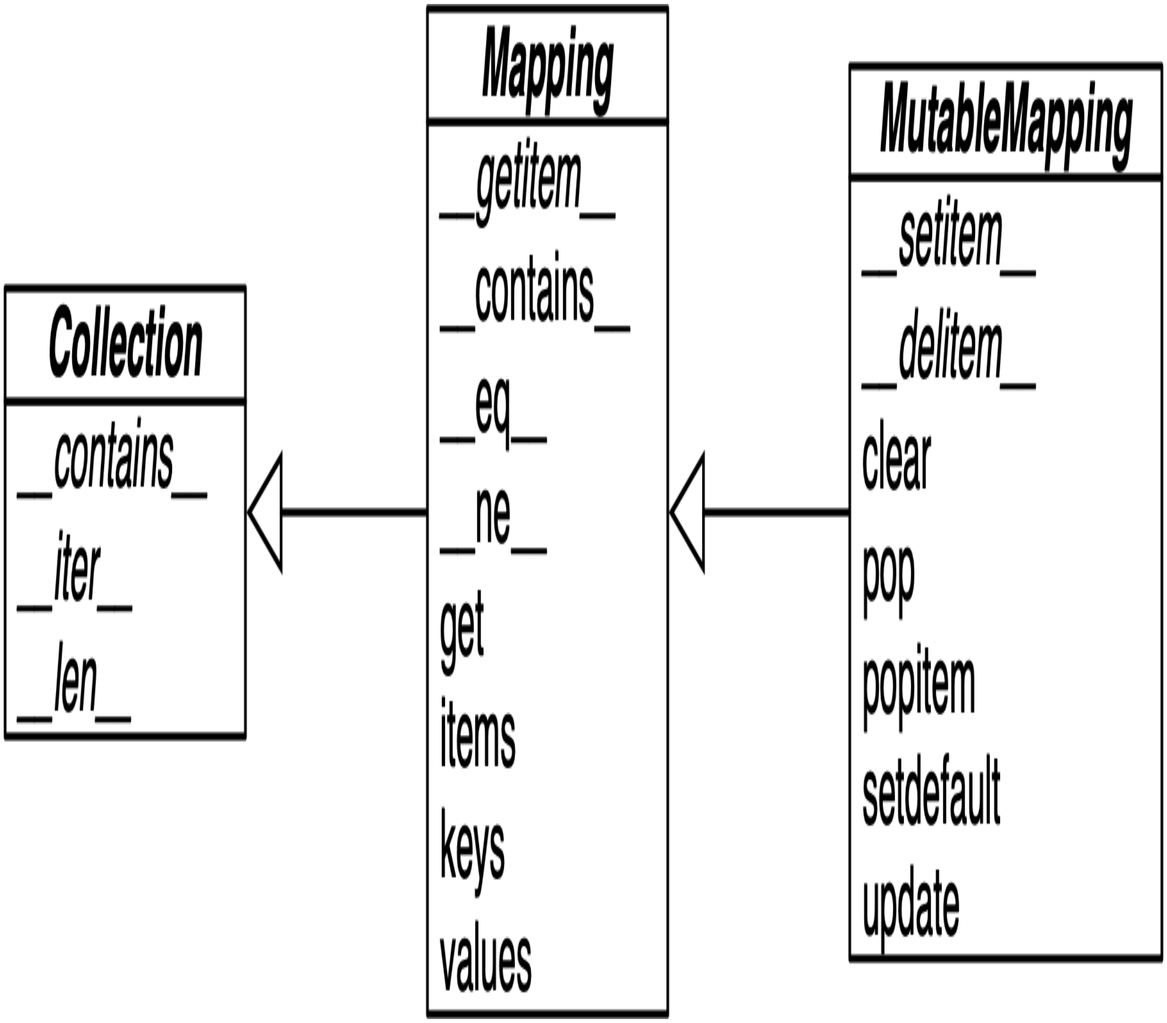


Figure 3-1. Simplified UML class diagram for the MutableMapping and its superclasses from collections.abc (inheritance arrows point from subclasses to superclasses; names in italic are abstract classes and abstract methods)

The main value of the ABCs is documenting and formalizing the standard interfaces for mappings, and serving as criteria for `isinstance` tests in code that needs to support mappings in a broad sense:

```
>>> my_dict = {}
>>> isinstance(my_dict, abc.Mapping)
True
>>> isinstance(my_dict, abc.MutableMapping)
True
```

> **TIP**
>
> Using `isinstance` with an ABC is often better than checking whether a function argument is of the concrete `dict` type, because then alternative mapping types can be used. We'll discuss this in detail in Chapter 13.

To implement a custom mapping, it's easier to extend `collections.UserDict`, or to wrap a `dict` by composition, instead of subclassing these ABCs. The `collections.UserDict` class and all concrete mapping classes in the standard library encapsulate the basic `dict` in their implementation, which in turn is built on a hash table. Therefore, they all share the limitation that the keys must be *hashable* (the values need not be hashable, only the keys). If you need a refresher, the next section explains.

What is Hashable

Here is part of the definition of hashable adapted from the Python Glossary:

> *An object is hashable if it has a hash code which never changes during its lifetime (it needs a `__hash__()` method), and can be compared to other objects (it needs an `__eq__()` method). Hashable objects which compare equal must have the same hash code.*[2]

Numeric types and flat immutable types `str` and `bytes` are all hashable. Container types are hashable if they are immutable and all contained objects are also hashable. A `frozenset` is always hashable, because every element it contains must be hashable by definition. A `tuple` is hashable only if all its items are hashable. See tuples `tt`, `tl`, and `tf`:

```
>>> tt = (1, 2, (30, 40))
>>> hash(tt)
8027212646858338501
>>> tl = (1, 2, [30, 40])
>>> hash(tl)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unhashable type: 'list'
>>> tf = (1, 2, frozenset([30, 40]))
>>> hash(tf)
-4118419923444501110
```

The hash code of an object may be different depending on the version of Python, the machine architecture, and because of a *salt* added to the hash computation for security reasons.[3] The hash code of a correctly implemented object is guaranteed to be constant only within one Python process.

User-defined types are hashable by default because their hash code is their `id()` and the `__eq__()` method inherited from the `object` class simply compares the object ids. If an object implements a custom `__eq__()` which takes into account its internal state, it will be hashable only if its `__hash__()` always returns the same hash code. In practice, this requires that `__eq__()` and `__hash__()` only take into account instance attributes that never change during the life of the object.

Now let's review the API of the most commonly used mapping types in Python: `dict`, `defaultdict` and `OrderedDict`.

Overview of Common Mapping Methods

The basic API for mappings is quite rich. Table 3-1 shows the methods implemented by `dict` and two popular variations: `defaultdict` and `OrderedDict`, both defined in the `collections` module.

Table 3-1. Methods of the mapping types dict, collections.defaultdict, and collections.OrderedDict (co *mmon object methods omitted for brevity); optional arguments are enclosed in […]*

	dict	defaultdict	OrderedDict	
`d.clear()`	●	●	●	Remove all items
`d.__contains__(k)`	●	●	●	`k in d`
`d.copy()`	●	●	●	Shallow copy

`d.__copy__()`		●		Support for `copy.copy(d)`
`d.default_factory`		●		Callable invoked by `__missing__` to set missing values[a]
`d.__delitem__(k)`	●	●	●	`del d[k]`—remove item with key `k`
`d.fromkeys(it, [initial])`	●	●	●	New mapping from keys in iterable, with optional initial value (defaults to `None`)
`d.get(k, [default])`	●	●	●	Get item with key `k`, return `default` or `None` if missing
`d.__getitem__(k)`	●	●	●	`d[k]`—get item with key `k`
`d.items()`	●	●	●	Get *view* over items—`(key, value)` pairs
`d.__iter__()`	●	●	●	Get iterator over keys
`d.keys()`	●	●	●	Get *view* over keys
`d.__len__()`	●	●	●	`len(d)`—number of items
`d.__missing__(k)`		●		Called when `__getitem__` cannot find the key
`d.move_to_end(k, [last])`			●	Move `k` first or last position (`last` is `True` by default)
`d.__or__(other)`	●	●	●	Support for `d1 | d2` to create new `d`

				`ict` merging `d1` and `d2` (Python ≥ 3.9)
`d.__ior__(other)`	●	●	●	Support for `d1 |= d2` to update `d1` with `d2` (Python ≥ 3.9)
`d.pop(k, [default])`	●	●	●	Remove and return value at `k`, or `default` or `None` if missing
`d.popitem()`	●	●	●	Remove and return the last inserted item as `(key, value)` [b]
`d.__reversed__()`	●	●	●	Support for `reverse(d)`—returns iterator for keys from last to first inserted.
`d.__ror__(other)`	●	●	●	Support for `other | dd`—reversed union operator (Python ≥ 3.9)[c]
`d.setdefault(k, [default])`	●	●	●	If `k in d`, return `d[k]`; else set `d[k] = default` and return it
`d.__setitem__(k, v)`	●	●	●	`d[k] = v`—put `v` at `k`
`d.update(m, [**kwargs])`	●	●	●	Update `d` with items from mapping or iterable of `(key, value)` pairs
`d.values()`	●	●	●	Get *view* over values

a `default_factory` is not a method, but a callable attribute set by the end user when a `defaultdict` is instantiated.

b `OrderedDict.popitem(last=False)` removes the first item inserted (FIFO). The `last` keyword argument is not supported in `dict` or `defaultdict` as recently as Python 3.10b3.

c Reversed operators are explained in Chapter 16.

The way `d.update(m)` handles its first argument `m` is a prime example of *duck typing*: it first checks whether `m` has a `keys` method and, if it does, assumes it is a mapping. Otherwise, `update()` falls back to iterating over `m`, assuming its items are `(key, value)` pairs. The constructor for most Python mappings uses the logic of `update()` internally, which means they can be initialized from other mappings or from any iterable object producing `(key, value)` pairs.

A subtle mapping method is `setdefault()`. It avoids redundant key lookups when we need to update the value of an item in-place. The next section shows how to use it.

Inserting or Updating Mutable Values

In line with Python's *fail-fast* philosophy, `dict` access with `d[k]` raises an error when `k` is not an existing key. Pythonistas know that `d.get(k, default)` is an alternative to `d[k]` whenever a default value is more convenient than handling `KeyError`. However, when you retrieve a mutable value and want to update it, there is better way.

Consider a script to index text, producing a mapping where each key is a word and the value is a list of positions where that word occurs, as shown in Example 3-3.

Example 3-3. Partial output from Example 3-4 processing the Zen of Python; each line shows a word and a list of occurrences coded as pairs: (line_number, column_number)

```
$ python3 index0.py zen.txt
a [(19, 48), (20, 53)]
Although [(11, 1), (16, 1), (18, 1)]
ambiguity [(14, 16)]
```

```
and [(15, 23)]
are [(21, 12)]
aren [(10, 15)]
at [(16, 38)]
bad [(19, 50)]
be [(15, 14), (16, 27), (20, 50)]
beats [(11, 23)]
Beautiful [(3, 1)]
better [(3, 14), (4, 13), (5, 11), (6, 12), (7, 9), (8, 11), (17, 8),
(18, 25)]
...
```

Example 3-4, a suboptimal script written to show one case where `dict.get` is not the best way to handle a missing key. I adapted it from an example by Alex Martelli.[4]

Example 3-4. index0.py uses dict.get to fetch and update a list of word occurrences from the index (a better solution is in Example 3-5)

```
"""Build an index mapping word -> list of occurrences"""

import re
import sys

WORD_RE = re.compile(r'\w+')

index = {}
with open(sys.argv[1], encoding='utf-8') as fp:
    for line_no, line in enumerate(fp, 1):
        for match in WORD_RE.finditer(line):
            word = match.group()
            column_no = match.start() + 1
            location = (line_no, column_no)
            # this is ugly; coded like this to make a point
            occurrences = index.get(word, [])  ❶
            occurrences.append(location)       ❷
            index[word] = occurrences          ❸

# display in alphabetical order
for word in sorted(index, key=str.upper):  ❹
    print(word, index[word])
```

❶ Get the list of occurrences for `word`, or `[]` if not found.

❷ Append new location to `occurrences`.

❸

Put changed `occurrences` into `index` dict; this entails a second search through the `index`.

❹ In the `key=` argument of `sorted` I am not calling `str.upper`, just passing a reference to that method so the `sorted` function can use it to normalize the words for sorting.[5]

The three lines dealing with `occurrences` in Example 3-4 can be replaced by a single line using `dict.setdefault`. Example 3-5 is closer to Alex Martelli's code.

Example 3-5. index.py uses dict.setdefault to fetch and update a list of word occurrences from the index in a single line; contrast with Example 3-4

```
"""Build an index mapping word -> list of occurrences"""

import re
import sys

WORD_RE = re.compile(r'\w+')

index = {}
with open(sys.argv[1], encoding='utf-8') as fp:
    for line_no, line in enumerate(fp, 1):
        for match in WORD_RE.finditer(line):
            word = match.group()
            column_no = match.start() + 1
            location = (line_no, column_no)
            index.setdefault(word, []).append(location)  ❶

# display in alphabetical order
for word in sorted(index, key=str.upper):
    print(word, index[word])
```

❶ Get the list of occurrences for `word`, or set it to `[]` if not found; `setdefault` returns the value, so it can be updated without requiring a second search.

In other words, the end result of this line…

```
my_dict.setdefault(key, []).append(new_value)
```

…is the same as running…

```
if key not in my_dict:
    my_dict[key] = []
my_dict[key].append(new_value)
```

…except that the latter code performs at least two searches for key—three if it's not found—while `setdefault` does it all with a single lookup.

A related issue, handling missing keys on any lookup (and not only when inserting), is the subject of the next section.

Automatic Handling of Missing Keys

Sometimes it is convenient to have mappings that return some made-up value when a missing key is searched. There are two main approaches to this: one is to use a `defaultdict` instead of a plain `dict`. The other is to subclass `dict` or any other mapping type and add a `__missing__` method. Both solutions are covered next.

`defaultdict`: Another Take on Missing Keys

A `collections.defaultdict` instance creates items with a default value on demand whenever a missing key is searched using `d[k]` syntax. Example 3-6 uses `defaultdict` to provide another elegant solution to the word index task from Example 3-5.

Here is how it works: when instantiating a `defaultdict`, you provide a callable to produce a default value whenever `__getitem__` is passed a nonexistent key argument.

For example, given a `defaultdict` created as `dd = defaultdict(list)`, if `'new-key'` is not in `dd`, the expression `dd['new-key']` does the following steps:

1. Calls `list()` to create a new list.
2. Inserts the list into `dd` using `'new-key'` as key.

3. Returns a reference to that list.

The callable that produces the default values is held in an instance attribute named `default_factory`.

Example 3-6. index_default.py: using `defaultdict` instead of the `setdefault` method

```
"""Build an index mapping word -> list of occurrences"""

import collections
import re
import sys

WORD_RE = re.compile(r'\w+')

index = collections.defaultdict(list)     ❶
with open(sys.argv[1], encoding='utf-8') as fp:
    for line_no, line in enumerate(fp, 1):
        for match in WORD_RE.finditer(line):
            word = match.group()
            column_no = match.start() + 1
            location = (line_no, column_no)
            index[word].append(location)  ❷

# display in alphabetical order
for word in sorted(index, key=str.upper):
    print(word, index[word])
```

❶ Create a `defaultdict` with the `list` constructor as `default_factory`.

❷ If `word` is not initially in the `index`, the `default_factory` is called to produce the missing value, which in this case is an empty `list` that is then assigned to `index[word]` and returned, so the `.append(location)` operation always succeeds.

If no `default_factory` is provided, the usual `KeyError` is raised for missing keys.

> **WARNING**
>
> The `default_factory` of a `defaultdict` is only invoked to provide default values for `__getitem__` calls, and not for the other methods. For example, if `dd` is a `defaultdict`, and `k` is a missing key, `dd[k]` will call the `default_factory` to create a default value, but `dd.get(k)` still returns `None`, and `k in dd` is `False`.

The mechanism that makes `defaultdict` work by calling `default_factory` is the `__missing__` special method, a feature that we discuss next.

The `__missing__` Method

Underlying the way mappings deal with missing keys is the aptly named `__missing__` method. This method is not defined in the base `dict` class, but `dict` is aware of it: if you subclass `dict` and provide a `__missing__` method, the standard `dict.__getitem__` will call it whenever a key is not found, instead of raising `KeyError`.

> **WARNING**
>
> The `__missing__` method is only called by `__getitem__` (i.e., for the `d[k]` operator). The presence of a `__missing__` method has no effect on the behavior of other methods that look up keys, such as `get` or `__contains__` (which implements the `in` operator). This is why the `default_factory` of `defaultdict` works only with `__getitem__`, as noted in the warning at the end of the previous section.

Suppose you'd like a mapping where keys are converted to `str` when looked up. A concrete use case is a device library for IoT[6], where a programmable board with general purpose I/O pins (e.g., a Raspberry Pi or an Arduino) is represented by a `Board` class with a `my_board.pins` attribute, which is a mapping of physical pin identifiers to pin software objects. The physical pin identifier may be just a number or a string like `"A0"` or `"P9_12"`. For consistency, it is desirable that all keys in `board.pins` are strings, but it is also convenient that looking up a pin by number, as in `my_arduino.pin[13]`, so that beginners are not tripped when they want to blink the LED on pin 13 of their Arduinos. Example 3-7 shows how such a mapping would work.

Example 3-7. When searching for a nonstring key, StrKeyDict0 converts it to str when it is not found

```
Tests for item retrieval using `d[key]` notation::

    >>> d = StrKeyDict0([('2', 'two'), ('4', 'four')])
    >>> d['2']
    'two'
    >>> d[4]
    'four'
    >>> d[1]
    Traceback (most recent call last):
      ...
    KeyError: '1'

Tests for item retrieval using `d.get(key)` notation::

    >>> d.get('2')
    'two'
    >>> d.get(4)
    'four'
    >>> d.get(1, 'N/A')
    'N/A'


Tests for the `in` operator::

    >>> 2 in d
    True
    >>> 1 in d
    False
```

Example 3-8 implements a class `StrKeyDict0` that passes the preceding doctests.

> **TIP**
>
> A better way to create a user-defined mapping type is to subclass `collections.UserDict` instead of `dict` (as we'll do in Example 3-9). Here we subclass `dict` just to show that `__missing__` is supported by the built-in `dict.__getitem__` method.

Example 3-8. StrKeyDict0 converts nonstring keys to str on lookup (see tests in Example 3-7)

```
class StrKeyDict0(dict):  ❶

    def __missing__(self, key):
        if isinstance(key, str):  ❷
            raise KeyError(key)
        return self[str(key)]  ❸

    def get(self, key, default=None):
        try:
            return self[key]  ❹
        except KeyError:
            return default  ❺

    def __contains__(self, key):
        return key in self.keys() or str(key) in self.keys()  ❻
```

❶ `StrKeyDict0` inherits from `dict`.

❷ Check whether `key` is already a `str`. If it is, and it's missing, raise `KeyError`.

❸ Build `str` from `key` and look it up.

❹ The `get` method delegates to `__getitem__` by using the `self[key]` notation; that gives the opportunity for our `__missing__` to act.

❺ If a `KeyError` was raised, `__missing__` already failed, so we return the `default`.

❻ Search for unmodified key (the instance may contain non-`str` keys), then for a `str` built from the key.

Take a moment to consider why the test `isinstance(key, str)` is necessary in the `__missing__` implementation.

Without that test, our `__missing__` method would work OK for any key `k`—`str` or not `str`—whenever `str(k)` produced an existing key. But if `str(k)` is not an existing key, we'd have an infinite recursion. In the last line of `__missing__`, `self[str(key)]` would call `__getitem__` passing that `str` key, which in turn would call `__missing__` again.

The `__contains__` method is also needed for consistent behavior in this example, because the operation `k in d` calls it, but the method inherited from `dict` does not fall back to invoking `__missing__`. There is a subtle detail in our implementation of `__contains__`: we do not check for the key in the usual Pythonic way—`k` in `my_dict`—because `str(key) in self` would recursively call `__contains__`. We avoid this by explicitly looking up the key in `self.keys()`.

> **NOTE**
>
> A search like `k in my_dict.keys()` is efficient in Python 3 even for very large mappings because `dict.keys()` returns a view, which is similar to a set, as we'll see in "Set operations on `dict` views". However, remember that `k in my_dict` does the same job, and is faster because it avoids the attribute lookup to find the `.keys` method. I had a specific reason to use `self.keys()` in the `__contains__` method in Example 3-8.

The check for the unmodified key—`key in self.keys()`—is necessary for correctness because `StrKeyDict0` does not enforce that all keys in the dictionary must be of type `str`. Our only goal with this simple example is to make searching "friendlier" and not enforce types.

So far we have covered the `dict` and `defaultdict` mapping types, but the standard library comes with other mapping implementations, which we discuss next.

Variations of dict

In this section is an overview of mapping types included in the standard library, besides `defaultdict`, already covered in "`defaultdict`: Another Take on Missing Keys".

`collections.OrderedDict`

Now that the built-in `dict` also keeps the keys ordered since Python 3.6, the most common reason to use `OrderedDict` is writing code that is backward-compatible with earlier Python versions. Having said that, Python's documentation lists some remaining differences between `dict` and `OrderedDict`, which I quote here—only reordering the items for relevance in daily use:

- The equality operation for `OrderedDict` checks for matching order.
- The `popitem()` method of `OrderedDict` has a different signature. It accepts an optional argument to specify which item is popped.
- `OrderedDict` has a `move_to_end()` method to efficiently reposition an element to an endpoint.
- The regular `dict` was designed to be very good at mapping operations. Tracking insertion order was secondary.
- `OrderedDict` was designed to be good at reordering operations. Space efficiency, iteration speed, and the performance of update operations were secondary.
- Algorithmically, `OrderedDict` can handle frequent reordering operations better than `dict`. This makes it suitable for tracking recent accesses (for example in an LRU cache).

collections.ChainMap

A `ChainMap` instance holds a list of mappings that can be searched as one. The lookup is performed on each input mapping in the order they appear in the constructor call, and succeeds as soon as the key is found in one of those mappings. For example:

```
>>> d1 = dict(a=1, b=3)
>>> d2 = dict(a=2, b=4, c=6)
>>> from collections import ChainMap
>>> chain = ChainMap(d1, d2)
>>> chain['a']
1
```

```
>>> chain['c']
6
```

The `ChainMap` instance does not copy the input mappings, but holds references to them. A later update to a key in the `ChainMap` will update the first input mapping where that key appears. Continuing the previous example:

```
>>> chain['b'] = -1
>>> d1
{'a': 1, 'b': -1}
>>> d2
{'a': 2, 'b': 4, 'c': 6}
```

`ChainMap` is useful to implement interpreters for languages with nested scopes, where each mapping represents a scope context, from the innermost enclosing scope to the outermost scope. The "ChainMap objects" section of the `collections` docs has several examples of `ChainMap` usage, including this snippet inspired by the basic rules of variable lookup in Python:

```
import builtins
pylookup = ChainMap(locals(), globals(), vars(builtins))
```

`collections.Counter`

A mapping that holds an integer count for each key. Updating an existing key adds to its count. This can be used to count instances of hashable objects or as a multiset (see below). `Counter` implements the `+` and `-` operators to combine tallies, and other useful methods such as `most_common([n])`, which returns an ordered list of tuples with the *n* most common items and their counts; see the documentation. Here is `Counter` used to count letters in words:

```
>>> ct = collections.Counter('abracadabra')
>>> ct
Counter({'a': 5, 'b': 2, 'r': 2, 'c': 1, 'd': 1})
>>> ct.update('aaaaazzz')
>>> ct
Counter({'a': 10, 'z': 3, 'b': 2, 'r': 2, 'c': 1, 'd': 1})
>>> ct.most_common(3)
[('a', 10), ('z', 3), ('b', 2)]
```

Note that the `'b'` and `'r'` keys are tied in third place, but `ct.most_common(3)` shows only three counts.

To use `collections.Counter` as a multiset, pretend each key is an element in the set, and the count is the number of occurrences of that element in the set.

`shelve.Shelf`

The `shelve` module in the standard library provides persistent storage for a mapping of string keys to Python objects serialized in the `pickle` binary format. The curious name of `shelve` makes sense when you realize that pickle jars are stored in shelves.

The `shelve.open` module-level function returns a `shelve.Shelf` instance—a simple key-value DBM database backed by the `dbm` module, with these characteristics:

- `shelve.Shelf` subclasses `abc.MutableMapping`, so it provides the essential methods we expect of a mapping type.
- In addition, `shelve.Shelf` provides a few other I/O management methods, like `sync` and `close`.
- a `Shelf` instance is a context manager, so you can use a `with` block to make sure it is closed after use.
- Keys and values are saved whenever a new value is assigned to a key.
- The keys must be strings.
- The values must be objects that the `pickle` module can serialize.

The documentation for the `shelve`, `dbm`, and `pickle` modules provide more details and some caveats.

WARNING

Python's `pickle` is easy to use in the simplest cases, but has several drawbacks. Read Ned Batchelder's Pickle's nine flaws before adopting any solution involving `pickle`. In his post, Ned mentions other serialization formats to consider.

`OrderedDict`, `ChainMap`, `Counter`, and `Shelf` are ready to use but can also be customized by subclassing. In contrast, `UserDict` is intended only as a base class to be extended.

Subclassing `UserDict` Instead of `dict`

It's better to create a new mapping type by extending `collections.UserDict` rather than `dict`. We realize that when we try to extend our `StrKeyDict0` from Example 3-8 to make sure that any keys added to the mapping are stored as `str`.

The main reason why it's better to subclass `UserDict` rather than `dict` is that the built-in has some implementation shortcuts that end up forcing us to override methods that we can just inherit from `UserDict` with no problems.[7]

Note that `UserDict` does not inherit from `dict`, but uses composition: it has an internal `dict` instance, called `data`, which holds the actual items. This avoids undesired recursion when coding special methods like `__setitem__`, and simplifies the coding of `__contains__`, compared to Example 3-8.

Thanks to `UserDict`, `StrKeyDict` (Example 3-9) is actually shorter than `StrKeyDict0` (Example 3-8), but it does more: it stores all keys as `str`, avoiding unpleasant surprises if the instance is built or updated with data containing nonstring keys.

Example 3-9. StrKeyDict always converts non-string keys to str—on insertion, update, and lookup

```
import collections


class StrKeyDict(collections.UserDict):  ❶

    def __missing__(self, key):  ❷
```

```
        if isinstance(key, str):
            raise KeyError(key)
        return self[str(key)]

    def __contains__(self, key):
        return str(key) in self.data  ❸

    def __setitem__(self, key, item):
        self.data[str(key)] = item   ❹
```

❶ `StrKeyDict` extends `UserDict`.

❷ `__missing__` is exactly as in Example 3-8.

❸ `__contains__` is simpler: we can assume all stored keys are `str` and we can check on `self.data` instead of invoking `self.keys()` as we did in `StrKeyDict0`.

❹ `__setitem__` converts any `key` to a `str`. This method is easier to overwrite when we can delegate to the `self.data` attribute.

Because `UserDict` extends `abc.MutableMapping`, the remaining methods that make `StrKeyDict` a full-fledged mapping are inherited from `UserDict`, `MutableMapping`, or `Mapping`. The latter have several useful concrete methods, in spite of being abstract base classes (ABCs). The following methods are worth noting:

`MutableMapping.update`

This powerful method can be called directly but is also used by `__init__` to load the instance from other mappings, from iterables of `(key, value)` pairs, and keyword arguments. Because it uses `self[key] = value` to add items, it ends up calling our implementation of `__setitem__`.

`Mapping.get`

In `StrKeyDict0` (Example 3-8), we had to code our own `get` to return the same results as `__getitem__`, but in Example 3-9 we inherited

`Mapping.get`, which is implemented exactly like `StrKeyDict0.get` (see Python source code).

> **TIP**
>
> Antoine Pitrou authored PEP 455 — Adding a key-transforming dictionary to collections and a patch to enhance the `collections` module with a `TransformDict`, that is more general than `StrKeyDict` and preserves the keys as they are provided, before tha transformation is applied. PEP 455 was rejected in May 2015—see Raymond Hettinger's rejection message. To experiment with `TransformDict`, I extracted Pitrou's patch from issue18986 into a standalone module (03-dict-set/transformdict.py in the *Fluent Python Second Edition* code repository).

We know there are immutable sequence types, but how about an immutable mapping? Well, there isn't a real one in the standard library, but a stand-in is available. That's next.

Immutable Mappings

The mapping types provided by the standard library are all mutable, but you may need to prevent users from changing a mapping by accident. A concrete use case can be found, again, in a hardware programming library like *Pingo*, mentioned in "The `__missing__` Method": the `board.pins` mapping represents the physical GPIO pins on the device. As such, it's useful to prevent inadvertent updates to `board.pins` because the hardware can't be changed via software, so any change in the mapping would make it inconsistent with the physical reality of the device.

The `types` module provides a wrapper class called `MappingProxyType`, which, given a mapping, returns a `mappingproxy` instance that is a read-only but dynamic proxy for the original mapping. This means that updates to the original mapping can be seen in the `mappingproxy`, but changes cannot be made through it. See Example 3-10 for a brief demonstration.

Example 3-10. MappingProxyType builds a read-only mappingproxy instance from a dict

```
>>> from types import MappingProxyType
>>> d = {1: 'A'}
>>> d_proxy = MappingProxyType(d)
>>> d_proxy
mappingproxy({1: 'A'})
>>> d_proxy[1]  ❶
'A'
>>> d_proxy[2] = 'x'  ❷
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: 'mappingproxy' object does not support item assignment
>>> d[2] = 'B'
>>> d_proxy  ❸
mappingproxy({1: 'A', 2: 'B'})
>>> d_proxy[2]
'B'
>>>
```

❶ Items in `d` can be seen through `d_proxy`.

❷ Changes cannot be made through `d_proxy`.

❸ `d_proxy` is dynamic: any change in `d` is reflected.

Here is how this could be used in practice in the hardware programming scenario: the constructor in a concrete `Board` subclass would fill a private mapping with the pin objects, and expose it to clients of the API via a public `.pins` attribute implemented as a `mappingproxy`. That way the clients would not be able to add, remove, or change pins by accident.

Next, we'll cover views—which allow high-performance oparations on a `dict`, without unnecessary copying of data.

Dictionary views

The `dict` instance methods `.keys()`, `.values()`, and `.items()` return instances of classes called `dict_keys`, `dict_values`, and `dict_items`, respectively. These dictionary views are read-only projections of the internal data structures used in the `dict` implementation. They avoid the memory overhead of the equivalent Python 2 methods that returned lists duplicating data already in the target `dict`, and they also replace the old methods that returned iterators.

Example 3-11 shows some basic operations supported by all dictionary views.

Example 3-11. The `.values()` method returns a view of the values in a `dict`.

```
>>> d = dict(a=10, b=20, c=30)
>>> values = d.values()
>>> values
dict_values([10, 20, 30])  ❶
>>> len(values)  ❷
3
>>> list(values)  ❸
[10, 20, 30]
>>> reversed(values)  ❹
<dict_reversevalueiterator object at 0x10e9e7310>
>>> values[0] ❺
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: 'dict_values' object is not subscriptable
```

❶ The `repr` of a view object shows its content.

❷ We can query the `len` of a view.

❸ Views are iterable, so it's easy to create lists from them.

❹ Views implement `__reversed__`, returning a custom iterator.

❺ We can't use `[]` to get individual items from a view.

A view object is a dynamic proxy. If the source `dict` is updated, you can immediately see the changes through an existing view. Continuing from Example 3-11:

```
>>> d['z'] = 99
>>> d
{'a': 10, 'b': 20, 'c': 30, 'z': 99}
>>> values
dict_values([10, 20, 30, 99])
```

The classes `dict_keys`, `dict_values`, and `dict_items` are internal: they are not available via `__builtins__` or any standard library module, and even if you get a reference to one of them, you can't use it to create a view from scratch in Python code:

```
>>> values_class = type({}.values())
>>> v = values_class()
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: cannot create 'dict_values' instances
```

The `dict_values` class is the simplest dictionary view—it implements only the `__len__`, `__iter__`, and `__reversed__` special methods. In addition to these methods, `dict_keys` and `dict_items` implement several set methods, almost as many as the `frozenset` class. After we cover sets, we'll have more to say about `dict_keys` and `dict_items` in "Set operations on `dict` views".

Now let's see some rules and tips informed by the way `dict` is implemented under the hood.

Practical Consequences of How dict Works

The hash table implementation of Python's `dict` is very efficient, but it's important to understand the practical effects of this design.

- Keys must be hashable objects. They must implement proper `__hash__` and `__eq__` methods as described in "What is Hashable".
- Item access by key is very fast. A `dict` may have millions of keys, but Python can locate a key directly by computing the hash code of the key and deriving an index offset into the hash table, with the possible overhead of a small number of tries to find a matching entry.
- Key ordering is preserved as a side-effect of a more compact memory layout for `dict` in CPython 3.6, which became an official language feature in 3.7.

- Despite its new compact layout, dicts inevitably have a significant memory overhead. The most compact internal data structure for a container would be an array of pointers to the items.[8] Compared to that, a hash table needs to store more data per entry, and Python needs to keep at least ⅓ of the hash table rows empty to remain efficient.

- To save memory, avoid creating instance attributes outside of the `__init__` method.

That tip about instance attributes comes from the fact that Python's default behavior is to store instance attributes in a special `__dict__` attribute which is a `dict` attached to each instance.[9] Since PEP 412—Key-Sharing Dictionary was implemented in Python 3.3, instances of a class can share a common hash table, stored with the class. That common hash table is shared by the `__dict__` of each new instance that has the same attributes names as the first instance of that class when `__init__` returns. Each instance `__dict__` can then hold only its own attribute values as a simple array of pointers. Adding an instance attribute after `__init__` forces Python to create a new hash table just for the `__dict__` of that one instance (which was the default behavior for all instances before Python 3.3). According to PEP 412, this optimization reduces memory use by 10% to 20% for object-oriented programs.

The details of the compact layout and key-sharing optimizations are rather complex. For more, please read *Internals of sets and dicts* at fluentpython.com.

Now let's dive into sets.

Set Theory

Sets are not new in Python, but are still somewhat underused. The `set` type and its immutable sibling `frozenset` first appeared as modules in the Python 2.3 standard library, and were promoted to built-ins in Python 2.6.

> **NOTE**
>
> In this book, I use the word "set" to refer both to `set` and `frozenset`. When talking specifically about the `set` class, I use constant width font: `set`.

A set is a collection of unique objects. A basic use case is removing duplication:

```
>>> l = ['spam', 'spam', 'eggs', 'spam', 'bacon', 'eggs']
>>> set(l)
{'eggs', 'spam', 'bacon'}
>>> list(set(l))
['eggs', 'spam', 'bacon']
```

> **TIP**
>
> If you want to remove duplicates but also preserve the order of the first occurrence of each item, you can now use a plain `dict` to do it, like this:
>
> ```
> >>> dict.fromkeys(l).keys()
> dict_keys(['spam', 'eggs', 'bacon'])
> >>> list(dict.fromkeys(l).keys())
> ['spam', 'eggs', 'bacon']
> ```

Set elements must be hashable. The `set` type is not hashable, so you can't build a `set` with nested `set` instances. But `frozenset` is hashable, so you can have `frozenset` elements inside a `set`.

In addition to enforcing uniqueness, the set types implement many set operations as infix operators, so, given two sets `a` and `b`, `a | b` returns their union, `a & b` computes the intersection, `a - b` the difference, and `a ^ b` the symmetric difference. Smart use of set operations can reduce both the line count and the execution time of Python programs, at the same time making code easier to read and reason about—by removing loops and conditional logic.

For example, imagine you have a large set of email addresses (the `haystack`) and a smaller set of addresses (the `needles`) and you need to count how many `needles` occur in the `haystack`. Thanks to `set` intersection (the `&` operator) you can code that in a simple line (see Example 3-12).

Example 3-12. Count occurrences of needles in a haystack, both of type set

```
found = len(needles & haystack)
```

Without the intersection operator, you'd have write Example 3-13 to accomplish the same task as Example 3-12.

Example 3-13. Count occurrences of needles in a haystack (same end result as Example 3-12)

```
found = 0
for n in needles:
    if n in haystack:
        found += 1
```

Example 3-12 runs slightly faster than Example 3-13. On the other hand, Example 3-13 works for any iterable objects `needles` and `haystack`, while Example 3-12 requires that both be sets. But, if you don't have sets on hand, you can always build them on the fly, as shown in Example 3-14.

Example 3-14. Count occurrences of needles in a haystack; these lines work for any iterable types

```
found = len(set(needles) & set(haystack))

# another way:
found = len(set(needles).intersection(haystack))
```

Of course, there is an extra cost involved in building the sets in Example 3-14, but if either the `needles` or the `haystack` is already a set, the alternatives in Example 3-14 may be cheaper than Example 3-13.

Any one of the preceding examples are capable of searching 1,000 elements in a `haystack` of 10,000,000 items in about 0.3 milliseconds—that's close to 0.3 microseconds per element.

Besides the extremely fast membership test (thanks to the underlying hash table), the `set` and `frozenset` built-in types provide a rich API to create new sets or, in the case of `set`, to change existing ones. We will discuss the operations shortly, but first a note about syntax.

Set Literals

The syntax of `set` literals—`{1}`, `{1, 2}`, etc.—looks exactly like the math notation, with one important exception: there's no literal notation for the empty `set`, so we must remember to write `set()`.

> **SYNTAX QUIRK**
>
> Don't forget: to create an empty `set`, you should use the constructor without an argument: `set()`. If you write `{}`, you're creating an empty `dict`—this hasn't changed in Python 3.

In Python 3, the standard string representation of sets always uses the `{…}` notation, except for the empty set:

```
>>> s = {1}
>>> type(s)
<class 'set'>
>>> s
{1}
>>> s.pop()
1
>>> s
set()
```

Literal `set` syntax like `{1, 2, 3}` is both faster and more readable than calling the constructor (e.g., `set([1, 2, 3])`). The latter form is slower because, to evaluate it, Python has to look up the `set` name to fetch the constructor, then build a list, and finally pass it to the constructor. In contrast, to process a literal like `{1, 2, 3}`, Python runs a specialized `BUILD_SET` bytecode[10].

There is no special syntax to represent `frozenset` literals—they must be created by calling the constructor. The standard string representation in Python 3 looks like a `frozenset` constructor call. Note the output in the console session:

```
>>> frozenset(range(10))
frozenset({0, 1, 2, 3, 4, 5, 6, 7, 8, 9})
```

Speaking of syntax, the idea of listcomps was adapted to build sets as well.

Set Comprehensions

Set comprehensions (*setcomps*) were added way back in Python 2.7, together with the dictcomps that we saw in "dict Comprehensions". Example 3-15 shows how.

Example 3-15. Build a set of Latin-1 characters that have the word “SIGN” in their Unicode names

```
>>> from unicodedata import name  ❶
>>> {chr(i) for i in range(32, 256) if 'SIGN' in name(chr(i),'')}  ❷
{'§', '=', '¢', '#', '¤', '<', '¥', 'µ', '×', '$', '¶', '£', '©',
'°', '+', '÷', '±', '>', '¬', '®', '%'}
```

❶ Import `name` function from `unicodedata` to obtain character names.

❷ Build set of characters with codes from 32 to 255 that have the word `'SIGN'` in their names.

The order of the output changes for each Python process, because of the salted hash mentioned in “What is Hashable”.

Syntax matters aside, let’s now consider the behavior of sets.

Practical Consequences of How Sets Work

The `set` and `frozenset` types are both implemented with a hash table. This has these effects:

- Set elements must be hashable objects. They must implement proper `__hash__` and `__eq__` methods as described in “What is Hashable”.
- Membership testing is very efficient. A set may have millions of elements, but an element can be located directly by computing its hash code and deriving an index offset, with the possible overhead of a small number of tries to find a matching element or exhaust the search.
- Sets have a significant memory overhead, compared to a low-level array a pointers to its elements—which would be more compact but also much slower to search beyond a handful of elements.
- Element ordering depends on insertion order, but not in a useful or reliable way. If two elements are different but have the same hash

code, their position depends on which element is added first.

- Adding elements to a set may change the order of existing elements. That's because the algorithm becomes less efficient if the hash table is more than ⅔ full, so Python may need to move and resize the table as it grows. When this happens, elements are reinserted and and their relative ordering may change.

See *Internals of sets and dicts* at *fluentpython.com* for details.

Let's now review the rich assortment of operations provided by sets.

Set Operations

Figure 3-2 gives an overview of the methods you can use on mutable and immutable sets. Many of them are special methods that overload operators such as `&` and `>=`. Table 3-2 shows the math set operators that have corresponding operators or methods in Python. Note that some operators and methods perform in-place changes on the target set (e.g., `&=`, `difference_update`, etc.). Such operations make no sense in the ideal world of mathematical sets, and are not implemented in `frozenset`.

TIP

The infix operators in Table 3-2 require that both operands be sets, but all other methods take one or more iterable arguments. For example, to produce the union of four collections, `a`, `b`, `c`, and `d`, you can call `a.union(b, c, d)`, where `a` must be a `set`, but `b`, `c`, and `d` can be iterables of any type that produces hashable items. If you need to create a new set with the union of for iterables, instead of updating an existing set, you can write `{*a, *b, *c, *d}` since Python 3.5 thanks to PEP 448—Additional Unpacking Generalizations.

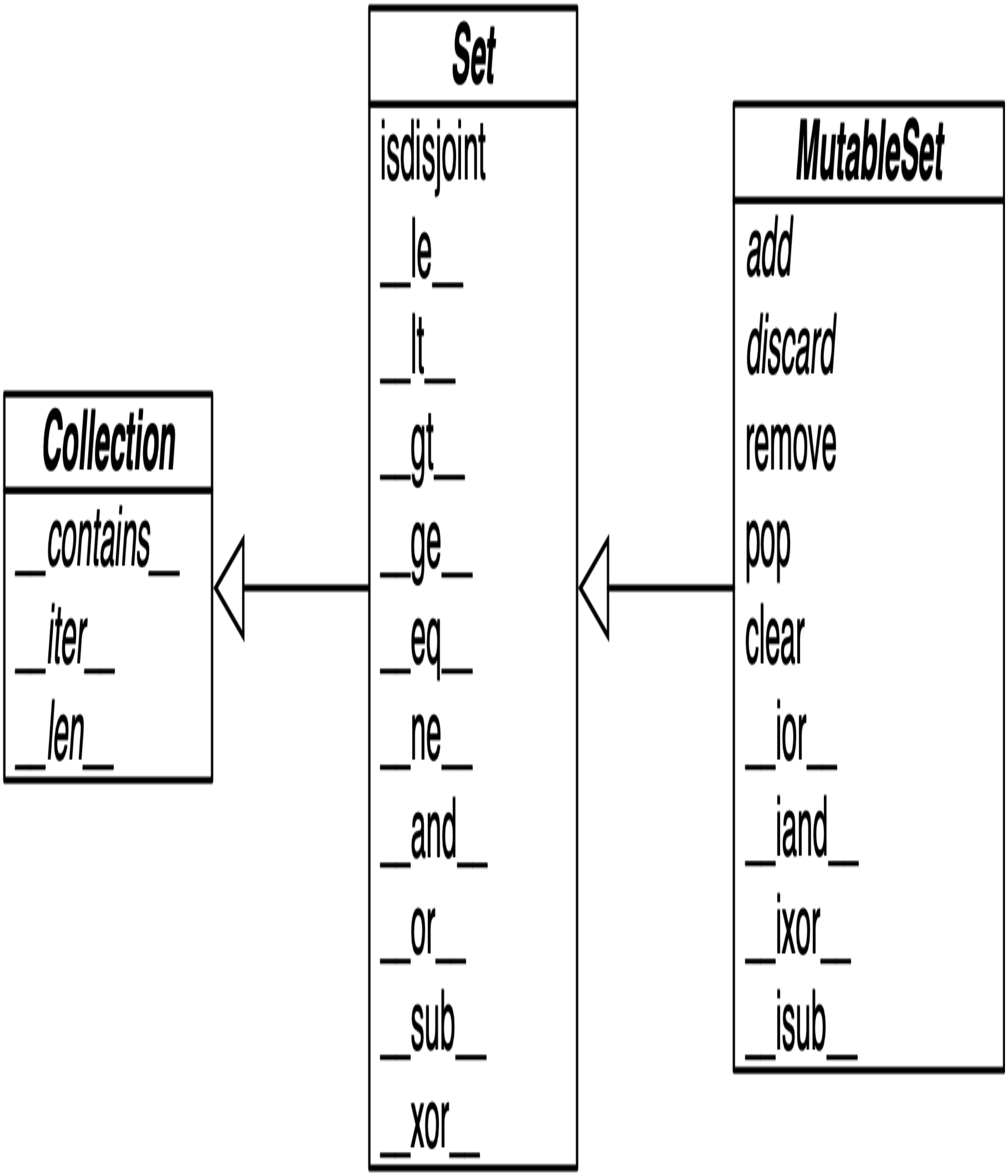


Figure 3-2. Simplified UML class diagram for `MutableSet` and its superclasses from `collections.abc` (names in italic are abstract classes and abstract methods; reverse operator methods omitted for brevity)

Table 3-2. Mathematical set operations: t

h
e
s
e
m
e
t
h
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r
p
r
o
d
u
c
e
a
n
e
w

s
e
t
o
r
u
p
d

ate the target set in place, if it’s mutable

Math symbol	Python operator	Method	Description

<table>
<tr><td>S ∩ Z</td><td>s & z</td><td>s.__and__(z)</td><td>Intersection of s and z</td></tr>
<tr><td></td><td>z & s</td><td>s.__rand__(z)</td><td>Reversed & operator</td></tr>
<tr><td></td><td></td><td>s.intersection(it, …)</td><td>Intersection of s and all sets built from iterables it, etc.</td></tr>
<tr><td></td><td>s &= z</td><td>s.__iand__(z)</td><td>s updated with intersection of s and z</td></tr>
<tr><td></td><td></td><td>s.intersection_update(it, …)</td><td>s updated with intersection of s and all sets built from iterables it, etc.</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td>S ∪ Z</td><td>s | z</td><td>s.__or__(z)</td><td>Union of s and z</td></tr>
<tr><td></td><td>z | s</td><td>s.__ror__(z)</td><td>Reversed |</td></tr>
<tr><td></td><td></td><td>s.union(it, …)</td><td>Union of s and all sets built from iterables it, etc.</td></tr>
<tr><td></td><td>s |= z</td><td>s.__ior__(z)</td><td>s updated with union of s and z</td></tr>
<tr><td></td><td></td><td>s.update(it, …)</td><td>s updated with union of s and all sets built from iterables it, etc.</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td>S \ Z</td><td>s - z</td><td>s.__sub__(z)</td><td>Relative complement or difference between s and z</td></tr>
<tr><td></td><td>z - s</td><td>s.__rsub__(z)</td><td>Reversed - operator</td></tr>
<tr><td></td><td></td><td>s.difference(it, …)</td><td>Difference between s and all sets built from iterables it, etc.</td></tr>
<tr><td></td><td>s -= z</td><td>s.__isub__(z)</td><td>s updated with difference between s and z</td></tr>
<tr><td></td><td></td><td>s.difference_update(it, …)</td><td>s updated with difference between s and all sets built from iterables it, etc.</td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td>S Δ Z</td><td>s ^ z</td><td>s.__xor__(z)</td><td>Symmetric difference (the complement of the intersection s &</td></tr>
</table>

		`z)`
`z ^ s`	`s.__rxor__(z)`	Reversed `^` operator
	`s.symmetric_difference(it)`	Complement of `s & set(it)`
`s ^= z`	`s.__ixor__(z)`	`s` updated with symmetric difference of `s` and `z`
	`s.symmetric_difference_update(it, …)`	`s` updated with symmetric difference of `s` and all sets built from iterables `it`, etc.

Table 3-3 lists set predicates: operators and methods that return `True` or `False`.

Table 3-3. Set comparison operators and me *thods that return a bool*

Math symbol	Python operator	Method	Description
$S \cap Z = \emptyset$		`s.isdisjoint(z)`	`s` and `z` are disjoint (no elements in common)
$e \in S$	`e in s`	`s.__contains__(e)`	Element `e` is a member of `s`
$S \subseteq Z$	`s <= z`	`s.__le__(z)`	`s` is a subset of the `z` set
		`s.issubset(it)`	`s` is a subset of the set built from the iterable `it`
$S \subset Z$	`s < z`	`s.__lt__(z)`	`s` is a proper subset of the `z` set
$S \supseteq Z$	`s >= z`	`s.__ge__(z)`	`s` is a superset of the `z` set

		`s.issuperset(it)`	`s` is a superset of the set built from the iterable `it`
S ⊃ Z	`s > z`	`s.__gt__(z)`	`s` is a proper superset of the `z` set

In addition to the operators and methods derived from math set theory, the set types implement other methods of practical use, summarized in Table 3-4.

Table 3-4. Additional set methods

	set	frozenset	
`s.add(e)`	●		Add element `e` to `s`

`s.clear()`	●		Remove all elements of `s`
`s.copy()`	●	●	Shallow copy of `s`
`s.discard(e)`	●		Remove element `e` from `s` if it is present
`s.__iter__()`	●	●	Get iterator over `s`
`s.__len__()`	●	●	`len(s)`
`s.pop()`	●		Remove and return an element from `s`, raising `KeyError` if `s` is empty
`s.remove(e)`	●		Remove element `e` from `s`, raising `KeyError` if `e not in s`

This completes our overview of the features of sets. As promised in "Dictionary views", we'll now see how two of the dictionary view types behave very much like a `frozenset`.

Set operations on `dict` views

Table 3-5 shows that the view objects returned by the `dict` methods `.keys()` and `.items()` are remarkably similar to `frozenset`.

Table 3-5. Methods implemented by frozen *set, dict_keys, and dict_items.*

	frozenset	dict_keys	dict_items	Description
`s.__and__(z)`	●	●	●	`s & z` (intersection of `s` and `z`)
`s.__rand__(z)`	●	●	●	Reversed & operator
`s.__contains__()`	●	●	●	`e in s`

`s.copy()`	●			Shallow copy of `s`
`s.difference(it, …)`	●			Difference between `s` and iterables `it`, etc.
`s.intersection(it, …)`	●			Intersection of `s` and iterables `it`, etc.
`s.isdisjoint(z)`	●	●	●	`s` and `z` are disjoint (no elements in common)
`s.issubset(it)`	●			`s` is a subset of iterable `it`
`s.issuperset(it)`	●			`s` is a superset of iterable `it`
`s.__iter__()`	●	●	●	Get iterator over `s`
`s.__len__()`	●	●	●	`len(s)`
`s.__or__(z)`	●	●	●	`s | z` (union of `s` and `z`)
`s.__ror__()`	●	●	●	Reversed `|` operator
`s.__reversed__()`		●	●	Get iterator over `s` in reverse order
`s.__rsub__(z)`	●	●	●	Reversed `-` operator
`s.__sub__(z)`	●	●	●	`s - z` (difference between `s` and `z`)
`s.symmetric_difference(it)`	●			Complement of `s & set(it)`
`s.union(it, …)`	●			Union of `s` and iterables `it`, etc.

`s.__xor__()`	●	●	●	`s ^ z` (symmetric difference of `s` and `z`)
`s.__rxor__()`	●	●	●	Reversed `^` operator

In particular, `dict_keys` and `dict_items` implement the special methods to support the powerful set operators `&` (intersection), `|` (union), `-` (difference) and `^` (symmetric difference).

For example, using `&` is easy to get the keys that appear in two dictionaries:

```
>>> d1 = dict(a=1, b=2, c=3, d=4)
>>> d2 = dict(b=20, d=40, e=50)
>>> d1.keys() & d2.keys()
{'b', 'd'}
```

Note that the return value of `&` is a `set`. Even better: the set operators in dictionary views are compatible with `set` instances. Check this out:

```
>>> s = {'a', 'e', 'i'}
>>> d1.keys() & s
{'a'}
>>> d1.keys() | s
{'a', 'c', 'b', 'd', 'i', 'e'}
```

WARNING

A `dict_items` view only works as a set if all values in the `dict` are hashable. Attempting set operations on a `dict_items` view with an unhashable value raises `TypeError: unhashable type 'T'`, with `T` as the type of the offending value.

On the other hand, a `dict_keys` view can always be used as a set, because every key is hashable—by definition.

Using set operators with views will save a lot of loops and ifs when inspecting the contents of dictionaries in your code. Let Python’s efficient implementation in C work for you!

With this, we can wrap up this chapter.

Chapter Summary

Dictionaries are a keystone of Python. Over the years, the familiar `{k1: v1, k2: v2}` literal syntax was enhanced to support unpacking with `**`, pattern matching—as well as `dict` comprehensions.

Beyond the basic `dict`, the standard library offers handy, ready-to-use specialized mappings like `defaultdict`, `ChainMap`, and `Counter`, all defined in the `collections` module. With the new `dict` implementation, `OrderedDict` is not as useful as before, but should remain in the standard library for backward compatibility—and has specific characterstics that `dict` doesn't have—such as taking into account key ordering in `==` comparisons. Also in the `collections` module is the `UserDict`, an easy to use base class to create custom mappings.

Two powerful methods available in most mappings are `setdefault` and `update`. The `setdefault` method can update items holding mutable values—for example, in a `dict` of `list` values—avoiding a second search for the same key. The `update` method allows bulk insertion or overwriting of items from any other mapping, from iterables providing `(key, value)` pairs and from keyword arguments. Mapping constructors also use `update` internally, allowing instances to be initialized from mappings, iterables, or keyword arguments. Since Python 3.9 we can also use the `|=` operator to update a mapping, and the `|` operator to create a new one from the union of two mappings.

A clever hook in the mapping API is the `__missing__` method, which lets you customize what happens when a key is not found when using the `d[k]` syntax which invokes `__getitem__`.

The `collections.abc` module provides the `Mapping` and `MutableMapping` abstract base classes as standard interfaces, useful for run-time type checking. The `MappingProxyType` from the `types` module creates an immutable façade for a mapping you want to protect from accidental change. There are also ABCs for `Set` and `MutableSet`.

Dictionary views were great addition in Python 3, eliminating the memory overhead of the Python 2 `.keys()`, `.values()` and `.items()` methods that built lists duplicating data in the target `dict` instance. In addition, the `dict_keys` and `dict_items` classes support the most useful operators and methods of `frozenset`.

Further Reading

In The Python Standard Library documentation, 8.3. collections — Container datatypes includes examples and practical recipes with several mapping types. The Python source code for the module *Lib/collections/__init__.py* is a great reference for anyone who wants to create a new mapping type or grok the logic of the existing ones. Chapter 1 of *Python Cookbook, Third edition* (O'Reilly) by David Beazley and Brian K. Jones has 20 handy and insightful recipes with data structures—the majority using `dict` in clever ways.

Greg Gandenberger advocates for the continued use of `collections.OrderedDict`, on the grounds that "explicit is better than implicit", backward compatibility, and the fact that some tools and libraries assume the ordering of `dict` keys is irrelevant—his post: Python Dictionaries Are Now Ordered. Keep Using OrderedDict..

PEP 3106 — Revamping dict.keys(), .values() and .items() is where Guido van Rossum presented the dictionary views feature for Python 3. In the abstract, he wrote the idea came from the Java Collections Framework.

PyPy was the first Python interpreter to implement Raymond Hettinger's proposal of compact dicts, and they blogged about it in Faster, more memory efficient and more ordered dictionaries on PyPy, acknowledging that a similar layout was adopted in PHP 7, described in PHP's new hashtable implementation. It's always great when creators cite prior art.

At PyCon 2017, Brandon Rhodes presented The Dictionary Even Mightier, a sequel to his classic animated presentation The Mighty Dictionary—including animated hash collisions! Another up-to-date, but more in-depth video on the internals of Python's `dict` is Modern Dictionaries by Raymond Hettinger, where he tells that after initially failing to sell compact dicts to the CPython core devs, he lobbied the PyPy team, they adopted it, the idea gained traction, and was finally contributed to CPython 3.6 by INADA Naoki. For all details, check out the extensive comments in the CPython code for Objects/dictobject.c and Objects/dict-common.h, as well as the design document Objects/dictnotes.txt.

The rationale for adding sets to Python is documented in PEP 218 — Adding a Built-In Set Object Type. When PEP 218 was approved, no special literal syntax was adopted for sets. The `set` literals were created for Python 3 and backported to Python 2.7, along with `dict` and `set` comprehensions. At PyCon 2019, I presented Set Practice: learning from Python's set types (slides), describing use cases of sets in real programs, covering their API design, and the implementation of `uintset`, a set class for integer elements using a bit vector instead of a hash table, inspired by an example in chapter 6 of the excellent *The Go Programming Language*, by Donovan & Kernighan.

IEEE's Spectrum magazine has a story about Hans Peter Luhn, a prolific inventor who patented a punched card deck to select cocktail recipes depending on ingredients available, among other diverse inventions including… hash tables! See Hans Peter Luhn and the Birth of the Hashing Algorithm.

SOAPBOX

Syntactic sugar

My friend Geraldo Cohen once remarked that Python is “simple and correct.”

Programming language purists like to dismiss syntax as unimportant.

> *Syntactic sugar causes cancer of the semicolon.*
>
> —Alan Perlis

Syntax is the user interface of a programming language, so it does matter in practice.

Before finding Python, I did some Web programming using Perl and PHP. The syntax for mappings in these languages is very useful, and I badly miss it whenever I have to use Java or C.

A good literal syntax for mappings is very convenient for configuration, table-driven implementations, and to hold data for prototyping and testing. That’s one lesson the designers of Go learned from dynamic languages. The lack of a good way to express structured data in code pushed the Java community to adopt the verbose and overly complex XML as a data format.

JSON was proposed as “The Fat-Free Alternative to XML” and became a huge success, replacing XML in many contexts. A concise syntax for lists and dictionaries makes an excellent data interchange format.

PHP and Ruby imitated the hash syntax from Perl, using `=>` to link keys to values. JavaScript uses `:` like Python. Why use two characters when one is readable enough?[11]

JSON came from JavaScript, but it also happens to be an almost exact subset of Python syntax. JSON is compatible with Python except for the spelling of the values `true`, `false`, and `null`.

Armin Ronacher tweeted that he likes to hack Python’s global namespace to add JSON-compatible aliases for Python’s `True`, `False`, and `None` so he can paste JSON directly in the console. The basic idea:

```
>>> true, false, null = True, False, None
>>> fruit = {
...     "type": "banana",
...     "avg_weight": 123.2,
...     "edible_peel": false,
...     "species": ["acuminata", "balbisiana", "paradisiaca"],
...     "issues": null,
... }
>>> fruit
{'type': 'banana', 'avg_weight': 123.2, 'edible_peel': False,
'species': ['acuminata', 'balbisiana', 'paradisiaca'], 'issues':
None}
```

The syntax everybody now uses for exchanging data is Python's `dict` and `list` syntax. Now we have the nice syntax with the convenience of preserved insertion order.

Simple and correct.

---

1 A virtual subclass is any class registered by calling the `.register()` method of an ABC, as explained in "A Virtual Subclass of an ABC". A type implemented via Python/C API is also eligible if a specific marker bit is set. See Py_TPFLAGS_MAPPING.

2 The Python Glossary entry for "hashable" uses the term "hash value" instead of *hash code*. I prefer *hash code* because that is a concept often discussed in the context of mappings, where items are made of keys and values, so it may be confusing to mention the hash code as a value. In this book, I only use *hash code*.

3 See PEP 456—Secure and interchangeable hash algorithm to learn about the security implications and solutions adopted.

4 The original script appears in slide 41 of Martelli's "Re-learning Python" presentation. His script is actually a demonstration of `dict.setdefault`, as shown in our Example 3-5.

5 This is an example of using a method as a first-class function, the subject of Chapter 7.

6 One such library is Pingo.io, no longer under active development.

7 The exact problem with subclassing `dict` and other built-ins is covered in "Subclassing Built-In Types Is Tricky".

8 That's how tuples are stored.

9 Unless the class has a `__slots__` attribute, as explained in "Saving Memory with `__slots__`".

10 This may be interesting, but is not super important. The speed up will happen only when a set literal is evaluated, and that happens at most once per Python process—when a module is initially compiled. If you're curious, import the `dis` function from the `dis` module and use it to

disassemble the bytecodes for a `set` literal—e.g. `dis('{1}')`—and a `set` call—`dis('set([1])')`

11 It’s possible that Brendan Eich studied Python before he created JavaScript. I’ve heard a rumor that Netscape reached out to Guido van Rossum to embed Python in their browser, before Eich spent 10 days creating a language almost completely unlike Java, except for the C-like syntax and the same set of reserved words. In the tale I heard, Guido told Netscape that Python was not suitable. Maybe it’s just an urban legend.

Chapter 4. Text Versus Bytes

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 4th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Humans use text. Computers speak bytes.*[1]
>
> —Esther Nam and Travis Fischer, Character Encoding and Unicode in Python

Python 3 introduced a sharp distinction between strings of human text and sequences of raw bytes. Implicit conversion of byte sequences to Unicode text is a thing of the past. This chapter deals with Unicode strings, binary sequences, and the encodings used to convert between them.

Depending on the kind of work you do with Python, you may think that understanding Unicode is not important. That's unlikely, but anyway there is no escaping the `str` versus `byte` divide. As a bonus, you'll find that the specialized binary sequence types provide features that the "all-purpose" Python 2 `str` type did not have.

In this chapter, we will visit the following topics:

- Characters, code points, and byte representations

- Unique features of binary sequences: `bytes`, `bytearray`, and `memoryview`
- Encodings for full Unicode and legacy character sets
- Avoiding and dealing with encoding errors
- Best practices when handling text files
- The default encoding trap and standard I/O issues
- Safe Unicode text comparisons with normalization
- Utility functions for normalization, case folding, and brute-force diacritic removal
- Proper sorting of Unicode text with `locale` and the PyUCA library
- Character metadata in the Unicode database
- Dual-mode APIs that handle `str` and `bytes`

What's new in this chapter

Support for Unicode in Python 3 has been comprehensive and stable, so the most notable addition is is "Finding characters by name", describing a utility for searching the Unicode database—a great way to find circled digits and smiling cats from the command-line.

One minor change worth mentioning is the Unicode support on Windows, which is better and simpler since Python 3.6, as we'll see in "Beware of Encoding Defaults".

Let's start with the not-so-new, but fundamental concepts of characters, code points, and bytes.

NOTE

For the *Second Edition*, I expanded the section about the `struct` module and published it online at *Parsing binary records with struct*, in the *fluentpython.com* companion Website.

There you will also find *Building Multi-character Emojis*, describing how to make country flags, rainbow flags, people with different skin tones, and diverse family icons by combining Unicode characters.

Character Issues

The concept of “string” is simple enough: a string is a sequence of characters. The problem lies in the definition of “character.”

In 2021, the best definition of “character” we have is a Unicode character. Accordingly, the items we get out of a Python 3 `str` are Unicode characters, just like the items of a `unicode` object in Python 2—and not the raw bytes we got from a Python 2 `str`.

The Unicode standard explicitly separates the identity of characters from specific byte representations:

- The identity of a character—its *code point*—is a number from 0 to 1,114,111 (base 10), shown in the Unicode standard as 4 to 6 hex digits with a “U+” prefix, from U+0000 to U+10FFFF. For example, the code point for the letter A is U+0041, the Euro sign is U+20AC, and the musical symbol G clef is assigned to code point U+1D11E. About 13% of the valid code points have characters assigned to them in Unicode 13.0.0, the standard used in Python 3.10.0b4.

- The actual bytes that represent a character depend on the *encoding* in use. An encoding is an algorithm that converts code points to byte sequences and vice versa. The code point for the letter A (U+0041) is encoded as the single byte `\x41` in the UTF-8 encoding, or as the bytes `\x41\x00` in UTF-16LE encoding. As

> another example, UTF-8 requires three bytes—`\xe2\x82\xac`—to encode the Euro sign (U+20AC) but in UTF-16LE the same code point is encoded as two bytes: `\xac\x20`.

Converting from code points to bytes is *encoding*; converting from bytes to code points is *decoding*. See Example 4-1.

Example 4-1. Encoding and decoding

```
>>> s = 'café'
>>> len(s)  ❶
4
>>> b = s.encode('utf8')  ❷
>>> b
b'caf\xc3\xa9'  ❸
>>> len(b)  ❹
5
>>> b.decode('utf8')  ❺
'café'
```

❶ The `str` `'café'` has four Unicode characters.

❷ Encode `str` to `bytes` using UTF-8 encoding.

❸ `bytes` literals have a `b` prefix.

❹ `bytes` `b` has five bytes (the code point for “é” is encoded as two bytes in UTF-8).

❺ Decode `bytes` to `str` using UTF-8 encoding.

> **TIP**
>
> If you need a memory aid to help distinguish `.decode()` from `.encode()`, convince yourself that byte sequences can be cryptic machine core dumps while Unicode `str` objects are “human” text. Therefore, it makes sense that we *decode* `bytes` to `str` to get human-readable text, and we *encode* `str` to `bytes` for storage or transmission.

Although the Python 3 `str` is pretty much the Python 2 `unicode` type with a new name, the Python 3 `bytes` is not simply the old `str` renamed, and there is also the closely related `bytearray` type. So it is worthwhile to take a look at the binary sequence types before advancing to encoding/decoding issues.

Byte Essentials

The new binary sequence types are unlike the Python 2 `str` in many regards. The first thing to know is that there are two basic built-in types for binary sequences: the immutable `bytes` type introduced in Python 3 and the mutable `bytearray`, added way back in Python 2.6.[2] The Python documentation sometimes uses the generic term "byte string" to refer to both `bytes` and `bytearray`. I avoid that confusing term.

Each item in `bytes` or `bytearray` is an integer from 0 to 255, and not a one-character string like in the Python 2 `str`. However, a slice of a binary sequence always produces a binary sequence of the same type—including slices of length 1. See Example 4-2.

Example 4-2. A five-byte sequence as bytes and as bytearray

```
>>> cafe = bytes('café', encoding='utf_8')  ❶
>>> cafe
b'caf\xc3\xa9'
>>> cafe[0]  ❷
99
>>> cafe[:1]  ❸
b'c'
>>> cafe_arr = bytearray(cafe)
>>> cafe_arr  ❹
bytearray(b'caf\xc3\xa9')
>>> cafe_arr[-1:]  ❺
bytearray(b'\xa9')
```

❶ `bytes` can be built from a `str`, given an encoding.

❷ Each item is an integer in `range(256)`.

❸ Slices of `bytes` are also `bytes`—even slices of a single byte.

❹ There is no literal syntax for `bytearray`: they are shown as `bytearray()` with a `bytes` literal as argument.

❺ A slice of `bytearray` is also a `bytearray`.

> **WARNING**
>
> The fact that `my_bytes[0]` retrieves an `int` but `my_bytes[:1]` returns a `bytes` sequence of length 1 is only surprising because we are used to Python's `str` type, where `s[0] == s[:1]`. For all other sequence types in Python, 1 item is not the same as a slice of length 1.

Although binary sequences are really sequences of integers, their literal notation reflects the fact that ASCII text is often embedded in them. Therefore, four different displays are used, depending on each byte value:

1. For bytes with decimal codes 32 to 126—from space to ~ (tilde)—the ASCII character itself is used.
2. For bytes corresponding to tab, newline, carriage return, and `\`, the escape sequences `\t`, `\n`, `\r`, and `\\` are used.
3. If both string delimiters `'` and `"` appear in the byte sequence, the whole sequence is delimited by `'` and any `'` inside are escaped as `\'`.[3]
4. For other byte values, a hexadecimal escape sequence is used (e.g., `\x00` is the null byte).

That is why in Example 4-2 you see `b'caf\xc3\xa9'`: the first three bytes `b'caf'` are in the printable ASCII range, the last two are not.

Both `bytes` and `bytearray` support every `str` method except those that do formatting (`format`, `format_map`) and a those that depend on

Unicode data, including `casefold`, `isdecimal`, `isidentifier`, `isnumeric`, `isprintable`, and `encode`. This means that you can use familiar string methods like `endswith`, `replace`, `strip`, `translate`, `upper`, and dozens of others with binary sequences—only using `bytes` and not `str` arguments. In addition, the regular expression functions in the `re` module also work on binary sequences, if the regex is compiled from a binary sequence instead of a `str`. Since Python 3.5, the `%` operator works with binary sequences again.[4]

Binary sequences have a class method that `str` doesn't have, called `fromhex`, which builds a binary sequence by parsing pairs of hex digits optionally separated by spaces:

```
>>> bytes.fromhex('31 4B CE A9')
b'1K\xce\xa9'
```

The other ways of building `bytes` or `bytearray` instances are calling their constructors with:

- A `str` and an `encoding` keyword argument.
- An iterable providing items with values from 0 to 255.
- An object that implements the buffer protocol (e.g., `bytes`, `bytearray`, `memoryview`, `array.array`); this copies the bytes from the source object to the newly created binary sequence.

> **WARNING**
>
> Until Python 3.5, it was also possible to call `bytes` or `bytearray` with a single integer to create a binary sequence of that size initialized with null bytes. This signature was deprecated in Python 3.5 and removed in Python 3.6. See PEP 467 — Minor API improvements for binary sequences.)

Building a binary sequence from a buffer-like object is a low-level operation that may involve type casting. See a demonstration in Example 4-

3.

Example 4-3. Initializing bytes from the raw data of an array

```
>>> import array
>>> numbers = array.array('h', [-2, -1, 0, 1, 2])  ❶
>>> octets = bytes(numbers)  ❷
>>> octets
b'\xfe\xff\xff\xff\x00\x00\x01\x00\x02\x00'  ❸
```

❶ Typecode `'h'` creates an `array` of short integers (16 bits).

❷ `octets` holds a copy of the bytes that make up `numbers`.

❸ These are the 10 bytes that represent the five short integers.

Creating a `bytes` or `bytearray` object from any buffer-like source will always copy the bytes. In contrast, `memoryview` objects let you share memory between binary data structures, as we saw in "Memory Views".

After this basic exploration of binary sequence types in Python, let's see how they are converted to/from strings.

Basic Encoders/Decoders

The Python distribution bundles more than 100 *codecs* (encoder/decoder) for text to byte conversion and vice versa. Each codec has a name, like `'utf_8'`, and often aliases, such as `'utf8'`, `'utf-8'`, and `'U8'`, which you can use as the `encoding` argument in functions like `open()`, `str.encode()`, `bytes.decode()`, and so on. Example 4-4 shows the same text encoded as three different byte sequences.

Example 4-4. The string "El Niño" encoded with three codecs producing very different byte sequences

```
>>> for codec in ['latin_1', 'utf_8', 'utf_16']:
...     print(codec, 'El Niño'.encode(codec), sep='\t')
...
latin_1 b'El Ni\xf1o'
```

```
utf_8   b'El Ni\xc3\xb1o'
utf_16  b'\xff\xfeE\x00l\x00 \x00N\x00i\x00\xf1\x00o\x00'
```

Figure 4-1 demonstrates a variety of codecs generating bytes from characters like the letter “A” through the G-clef musical symbol. Note that the last three encodings are variable-length, multibyte encodings.

char.	code point	ascii	latin1	cp1252	cp437	gb2312	utf-8	utf-16le
A	U+0041	41	41	41	41	41	41	41 00
¿	U+00BF	*	BF	BF	A8	*	C2 BF	BF 00
Ã	U+00C3	*	C3	C3	*	*	C3 83	C3 00
á	U+00E1	*	E1	E1	A0	A8 A2	C3 A1	E1 00
Ω	U+03A9	*	*	*	EA	A6 B8	CE A9	A9 03
ڿ	U+06BF	*	*	*	*	*	DA BF	BF 06
“	U+201C	*	*	93	*	A1 B0	E2 80 9C	1C 20
€	U+20AC	*	*	80	*	*	E2 82 AC	AC 20
┌	U+250C	*	*	*	DA	A9 B0	E2 94 8C	0C 25
气	U+6C14	*	*	*	*	C6 F8	E6 B0 94	14 6C
氣	U+6C23	*	*	*	*	*	E6 B0 A3	23 6C
𝄞	U+1D11E	*	*	*	*	*	F0 9D 84 9E	34 D8 1E DD

Figure 4-1. Twelve characters, their code points, and their byte representation (in hex) in seven different encodings (asterisks indicate that the character cannot be represented in that encoding)

All those asterisks in Figure 4-1 make clear that some encodings, like ASCII and even the multibyte GB2312, cannot represent every Unicode character. The UTF encodings, however, are designed to handle every Unicode code point.

The encodings shown in Figure 4-1 were chosen as a representative sample:

`latin1` *a.k.a.* *`iso8859_1`*

Important because it is the basis for other encodings, such as `cp1252` and Unicode itself (note how the `latin1` byte values appear in the `cp1252` bytes and even in the code points).

`cp1252`

A useful `latin1` superset created by Microsoft, adding useful symbols like curly quotes and the € (euro); some Windows apps call it "ANSI," but it was never a real ANSI standard.

`cp437`

The original character set of the IBM PC, with box drawing characters. Incompatible with `latin1`, which appeared later.

`gb2312`

Legacy standard to encode the simplified Chinese ideographs used in mainland China; one of several widely deployed multibyte encodings for Asian languages.

`utf-8`

The most common 8-bit encoding on the Web, by far; as of July 2021, W3Techs: Usage of Character Encodings for Websites claims that 97% of sites use UTF-8, up from 81.4% when I wrote this paragraph in the *First Edition* in September 2014.

`utf-16le`

One form of the UTF 16-bit encoding scheme; all UTF-16 encodings support code points beyond U+FFFF through escape sequences called “surrogate pairs.”

> **WARNING**
>
> UTF-16 superseded the original 16-bit Unicode 1.0 encoding—UCS-2—way back in 1996. UCS-2 is still used in many systems despite being deprecated since the last century because it only supports code points up to U+FFFF. As of 2021, more than 57% of the allocated code points are above U+FFFF, including the all-important emojis.

With this overview of common encodings now complete, we move to handling issues in encoding and decoding operations.

Understanding Encode/Decode Problems

Although there is a generic `UnicodeError` exception, the error reported by Python is usually more specific: either a `UnicodeEncodeError` (when converting `str` to binary sequences) or a `UnicodeDecodeError` (when reading binary sequences into `str`). Loading Python modules may also raise `SyntaxError` when the source encoding is unexpected. We’ll show how to handle all of these errors in the next sections.

> **TIP**
>
> The first thing to note when you get a Unicode error is the exact type of the exception. Is it a `UnicodeEncodeError`, a `UnicodeDecodeError`, or some other error (e.g., `SyntaxError`) that mentions an encoding problem? To solve the problem, you have to understand it first.

Coping with UnicodeEncodeError

Most non-UTF codecs handle only a small subset of the Unicode characters. When converting text to bytes, if a character is not defined in the target encoding, `UnicodeEncodeError` will be raised, unless special handling is provided by passing an `errors` argument to the encoding method or function. The behavior of the error handlers is shown in Example 4-5.

Example 4-5. Encoding to bytes: success and error handling

```
>>> city = 'São Paulo'
>>> city.encode('utf_8')  ❶
b'S\xc3\xa3o Paulo'
>>> city.encode('utf_16')
b'\xff\xfeS\x00\xe3\x00o\x00 \x00P\x00a\x00u\x00l\x00o\x00'
>>> city.encode('iso8859_1')  ❷
b'S\xe3o Paulo'
>>> city.encode('cp437')  ❸
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "/.../lib/python3.4/encodings/cp437.py", line 12, in encode
    return codecs.charmap_encode(input,errors,encoding_map)
UnicodeEncodeError: 'charmap' codec can't encode character '\xe3'
in
position 1: character maps to <undefined>
>>> city.encode('cp437', errors='ignore')  ❹
b'So Paulo'
>>> city.encode('cp437', errors='replace')  ❺
b'S?o Paulo'
>>> city.encode('cp437', errors='xmlcharrefreplace')  ❻
b'S&#227;o Paulo'
```

❶ The UTF encodings handle any `str`.

❷ `iso8859_1` also works for the `'São Paulo'` string.

❸ `cp437` can't encode the `'ã'` ("a" with tilde). The default error handler —`'strict'`—raises `UnicodeEncodeError`.

❹ The `error='ignore'` handler skips characters that cannot be encoded; this is usually a very bad idea, leading to silent data loss.

❺ When encoding, `error='replace'` substitutes unencodable characters with `'?'`; data is also lost, but users will get a clue that something is amiss.

❻

`'xmlcharrefreplace'` replaces unencodable characters with an XML entity. If you can't use UTF, and you can't affort to lose data, this is the only option.

> **NOTE**
>
> The `codecs` error handling is extensible. You may register extra strings for the `errors` argument by passing a name and an error handling function to the `codecs.register_error` function. See the `codecs.register_error` documentation.

ASCII is a common subset to all the encodings that I know about, therefore encoding should always work if the text is made exclusively of ASCII characters. Python 3.7 added a new boolean method `str.isascii()` to check whether your Unicode text is 100% pure ASCII. If it is, you should be able to encode it to bytes in any encoding without raising `UnicodeEncodeError`.

Coping with UnicodeDecodeError

Not every byte holds a valid ASCII character, and not every byte sequence is valid UTF-8 or UTF-16; therefore, when you assume one of these encodings while converting a binary sequence to text, you will get a `UnicodeDecodeError` if unexpected bytes are found.

On the other hand, many legacy 8-bit encodings like `'cp1252'`, `'iso8859_1'`, and `'koi8_r'` are able to decode any stream of bytes, including random noise, without reporting errors. Therefore, if your program assumes the wrong 8-bit encoding, it will silently decode garbage.

> **TIP**
>
> Garbled characters are known as gremlins or mojibake (文字化け—Japanese for "transformed text").

Example 4-6 illustrates how using the wrong codec may produce gremlins or a `UnicodeDecodeError`.

Example 4-6. Decoding from str to bytes: success and error handling

```
>>> octets = b'Montr\xe9al'  ❶
>>> octets.decode('cp1252')  ❷
'Montréal'
>>> octets.decode('iso8859_7')  ❸
'Montrιal'
>>> octets.decode('koi8_r')  ❹
'MontrИal'
>>> octets.decode('utf_8')  ❺
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
UnicodeDecodeError: 'utf-8' codec can't decode byte 0xe9 in
position 5:
invalid continuation byte
>>> octets.decode('utf_8', errors='replace')  ❻
'Montr�al'
```

❶ The word "Montréal" encoded as `latin1`; `'\xe9'` is the byte for "é".

❷ Decoding with Windows 1252 works because it is a superset of `latin1`.

❸ ISO-8859-7 is intended for Greek, so the `'\xe9'` byte is misinterpreted, and no error is issued.

❹ KOI8-R is for Russian. Now `'\xe9'` stands for the Cyrillic letter "И".

❺ The `'utf_8'` codec detects that `octets` is not valid UTF-8, and raises `UnicodeDecodeError`.

❻ Using `'replace'` error handling, the `\xe9` is replaced by "�" (code point U+FFFD), the official Unicode `REPLACEMENT CHARACTER` intended to represent unknown characters.

SyntaxError When Loading Modules with Unexpected Encoding

UTF-8 is the default source encoding for Python 3, just as ASCII was the default for Python 2. If you load a *.py* module containing non-UTF-8 data and no encoding declaration, you get a message like this:

```
SyntaxError: Non-UTF-8 code starting with '\xe1' in file ola.py
on line
  1, but no encoding declared; see
https://python.org/dev/peps/pep-0263/
  for details
```

Because UTF-8 is widely deployed in GNU/Linux and MacOS systems, a likely scenario is opening a *.py* file created on Windows with `cp1252`. Note that this error happens even in Python for Windows, because the default encoding for Python 3 source is UTF-8 across all platforms.

To fix this problem, add a magic `coding` comment at the top of the file, as shown in Example 4-7.

Example 4-7. ola.py: "Hello, World!" in Portuguese

```
# coding: cp1252

print('Olá, Mundo!')
```

> **TIP**
>
> Now that Python 3 source code is no longer limited to ASCII and defaults to the excellent UTF-8 encoding, the best "fix" for source code in legacy encodings like `'cp1252'` is to convert them to UTF-8 already, and not bother with the `coding` comments. If your editor does not support UTF-8, it's time to switch.

Suppose you have a text file, be it source code or poetry, but you don't know its encoding. How do you detect the actual encoding? Answers in the next section.

How to Discover the Encoding of a Byte Sequence

How do you find the encoding of a byte sequence? Short answer: you can't. You must be told.

Some communication protocols and file formats, like HTTP and XML, contain headers that explicitly tell us how the content is encoded. You can be sure that some byte streams are not ASCII because they contain byte values over 127, and the way UTF-8 and UTF-16 are built also limits the possible byte sequences.

LEO’S HACK FOR GUESSING UTF-8 DECODING

(The next paragraphs come from a note left by tech reviewer Leonardo Rochael in the draft of this book.)

The way UTF-8 was designed, it’s almost impossible for a random sequence of bytes, or even a non-random sequence of bytes coming from a non-UTF-8 encoding, to be decoded accidentally as garbage in UTF-8, instead of raising `UnicodeDecodeError`.

The reasons for this are that UTF-8 escape sequences never use ASCII characters, and these escape sequences have bit patterns that make it very hard for random data to be valid UTF-8 by accident.

So if you can decode some bytes containing codes > 127 as UTF-8, it’s probably UTF-8.

In dealing with Brazillian online services, some of which were attached to legacy backends, I’ve had, on occasion, to implement a decoding strategy of trying to decode via UTF-8 and treat a `UnicodeDecodeError` by decoding via `cp1252`. It was ugly but effective.

However, considering that human languages also have their rules and restrictions, once you assume that a stream of bytes is human *plain text* it may be possible to sniff out its encoding using heuristics and statistics. For example, if `b'\x00'` bytes are common, it is probably a 16- or 32-bit encoding, and not an 8-bit scheme, because null characters in plain text are bugs. When the byte sequence `b'\x20\x00'` appears often, it is more likely to be the space character (U+0020) in a UTF-16LE encoding, rather than the obscure U+2000 `EN QUAD` character—whatever that is.

That is how the package Chardet — The Universal Character Encoding Detector works to guess one of more than 30 supported encodings. *Chardet* is a Python library that you can use in your programs, but also includes a command-line utility, `chardetect`. Here is what it reports on the source file for this chapter:

```
$ chardetect 04-text-byte.asciidoc
04-text-byte.asciidoc: utf-8 with confidence 0.99
```

Although binary sequences of encoded text usually don't carry explicit hints of their encoding, the UTF formats may prepend a byte order mark to the textual content. That is explained next.

BOM: A Useful Gremlin

In Example 4-4, you may have noticed a couple of extra bytes at the beginning of a UTF-16 encoded sequence. Here they are again:

```
>>> u16 = 'El Niño'.encode('utf_16')
>>> u16
b'\xff\xfeE\x00l\x00 \x00N\x00i\x00\xf1\x00o\x00'
```

The bytes are `b'\xff\xfe'`. That is a *BOM*—byte-order mark—denoting the "little-endian" byte ordering of the Intel CPU where the encoding was performed.

On a little-endian machine, for each code point the least significant byte comes first: the letter `'E'`, code point U+0045 (decimal 69), is encoded in byte offsets 2 and 3 as 69 and 0:

```
>>> list(u16)
[255, 254, 69, 0, 108, 0, 32, 0, 78, 0, 105, 0, 241, 0, 111, 0]
```

On a big-endian CPU, the encoding would be reversed; `'E'` would be encoded as 0 and 69.

To avoid confusion, the UTF-16 encoding prepends the text to be encoded with the special invisible character `ZERO WIDTH NO-BREAK SPACE` (U+FEFF). On a little-endian system, that is encoded as `b'\xff\xfe'` (decimal 255, 254). Because, by design, there is no U+FFFE character in Unicode, the byte sequence `b'\xff\xfe'` must mean the `ZERO WIDTH NO-BREAK SPACE` on a little-endian encoding, so the codec knows which byte ordering to use.

There is a variant of UTF-16—UTF-16LE—that is explicitly little-endian, and another one explicitly big-endian, UTF-16BE. If you use them, a BOM is not generated:

```
>>> u16le = 'El Niño'.encode('utf_16le')
>>> list(u16le)
[69, 0, 108, 0, 32, 0, 78, 0, 105, 0, 241, 0, 111, 0]
>>> u16be = 'El Niño'.encode('utf_16be')
>>> list(u16be)
[0, 69, 0, 108, 0, 32, 0, 78, 0, 105, 0, 241, 0, 111]
```

If present, the BOM is supposed to be filtered by the UTF-16 codec, so that you only get the actual text contents of the file without the leading `ZERO WIDTH NO-BREAK SPACE`. The Unicode standard says that if a file is UTF-16 and has no BOM, it should be assumed to be UTF-16BE (big-endian). However, the Intel x86 architecture is little-endian, so there is plenty of little-endian UTF-16 with no BOM in the wild.

This whole issue of endianness only affects encodings that use words of more than one byte, like UTF-16 and UTF-32. One big advantage of UTF-8 is that it produces the same byte sequence regardless of machine endianness, so no BOM is needed. Nevertheless, some Windows applications (notably Notepad) add the BOM to UTF-8 files anyway—and Excel depends on the BOM to detect a UTF-8 file, otherwise it assumes the content is encoded with a Windows code page. This UTF-8 encoding with BOM is called UTF-8-SIG in Python’s codec registry. The character

U+FEFF encoded in UTF-8-SIG is the three-byte sequence `b'\xef\xbb\xbf'`. So if a file starts with those three bytes, it is likely to be a UTF-8 file with a BOM.

> **CALEB'S TIP ABOUT UTF-8-SIG**
>
> Caleb Hattingh—one of the tech reviewers—suggests always using the UTF-8-SIG codec when reading UTF-8 files. This is harmless because UTF-8-SIG reads files with or without a BOM correctly, and does not return the BOM itself. When writing, I recommend using UTF-8 for general interoperability. For example, Python scripts can be made executable in Unix systems if they start with the comment: `#!/usr/bin/env python3`. The first two bytes of the file must be `b'#!'` for that to work, but the BOM breaks that convention. If you have a specific requirement to export data to apps that need the BOM, use UTF-8-SIG but be aware that Python's codecs documentation says: "In UTF-8, the use of the BOM is discouraged and should generally be avoided."

We now move on to handling text files in Python 3.

Handling Text Files

The best practice for handling text I/O is the "Unicode sandwich" (Figure 4-2).[5] This means that `bytes` should be decoded to `str` as early as possible on input (e.g., when opening a file for reading). The "filling" of the sandwich is the business logic of your program, where text handling is done exclusively on `str` objects. You should never be encoding or decoding in the middle of other processing. On output, the `str` are encoded to `bytes` as late as possible. Most web frameworks work like that, and we rarely touch `bytes` when using them. In Django, for example, your views should output Unicode `str`; Django itself takes care of encoding the response to `bytes`, using UTF-8 by default.

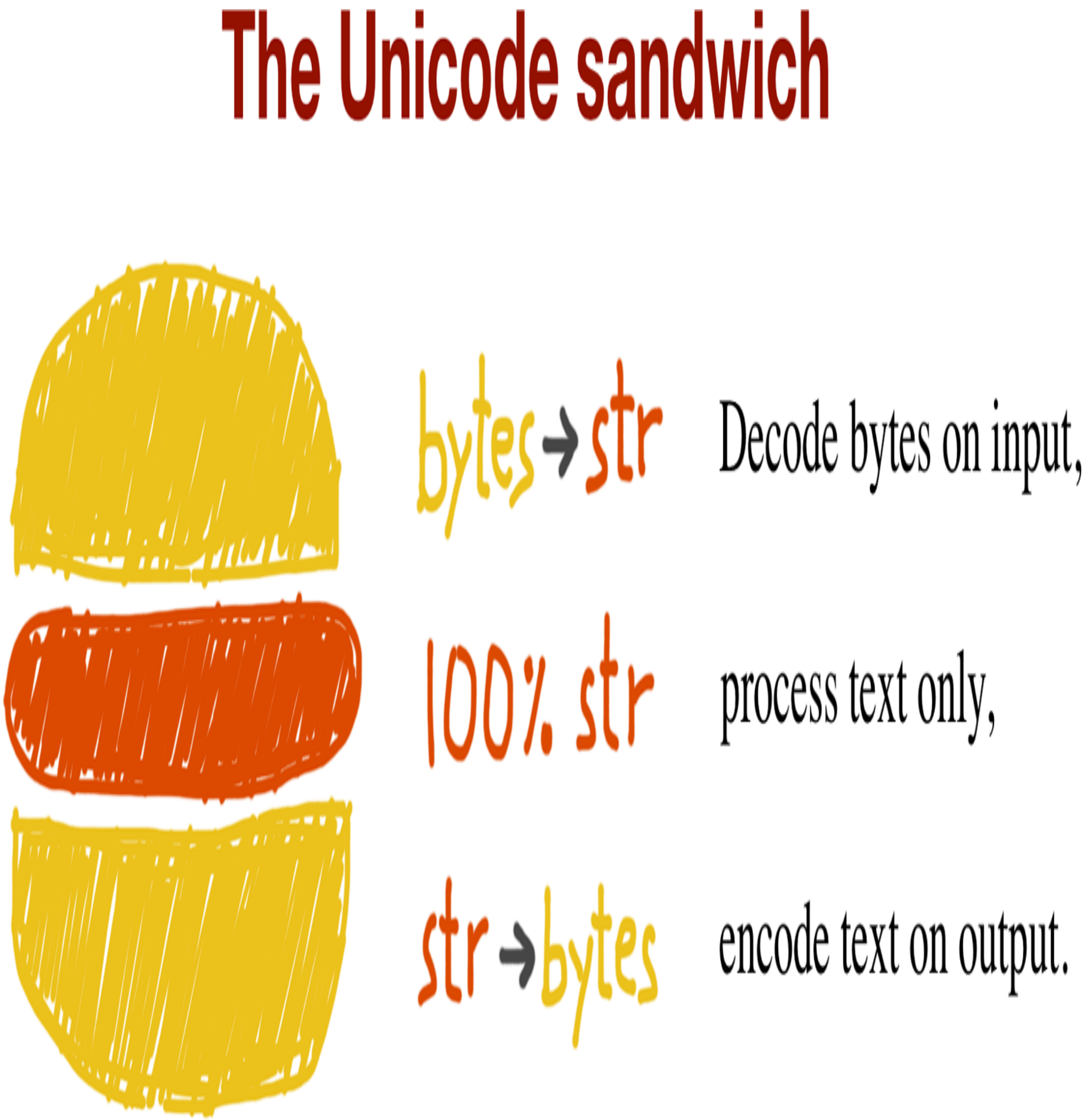

Figure 4-2. Unicode sandwich: current best practice for text processing

Python 3 makes it easier to follow the advice of the Unicode sandwich, because the `open()` built-in does the necessary decoding when reading and encoding when writing files in text mode, so all you get from `my_file.read()` and pass to `my_file.write(text)` are `str` objects.

Therefore, using text files is apparently simple. But if you rely on default encodings you will get bitten.

Consider the console session in Example 4-8. Can you spot the bug?

Example 4-8. A platform encoding issue (if you try this on your machine, you may or may not see the problem)

```
>>> open('cafe.txt', 'w', encoding='utf_8').write('café')
4
>>> open('cafe.txt').read()
'cafÃ©'
```

The bug: I specified UTF-8 encoding when writing the file but failed to do so when reading it, so Python assumed Windows default file encoding—code page 1252—and the trailing bytes in the file were decoded as characters `'Ã©'` instead of `'é'`.

I ran Example 4-8 on Python 3.8.1, 64 bits, on Windows 10 (build 18363). The same statements running on recent GNU/Linux or MacOS work perfectly well because their default encoding is UTF-8, giving the false impression that everything is fine. If the encoding argument was omitted when opening the file to write, the locale default encoding would be used, and we'd read the file correctly using the same encoding. But then this script would generate files with different byte contents depending on the platform or even depending on locale settings in the same platform, creating compatibility problems.

> **TIP**
>
> Code that has to run on multiple machines or on multiple occasions should never depend on encoding defaults. Always pass an explicit `encoding=` argument when opening text files, because the default may change from one machine to the next, or from one day to the next.

A curious detail in Example 4-8 is that the `write` function in the first statement reports that four characters were written, but in the next line five characters are read. Example 4-9 is an extended version of Example 4-8, explaining that and other details.

Example 4-9. Closer inspection of Example 4-8 running on Windows reveals the bug and how to fix it

```
>>> fp = open('cafe.txt', 'w', encoding='utf_8')
>>> fp  ❶
<_io.TextIOWrapper name='cafe.txt' mode='w' encoding='utf_8'>
>>> fp.write('café')  ❷
4
>>> fp.close()
>>> import os
>>> os.stat('cafe.txt').st_size  ❸
5
>>> fp2 = open('cafe.txt')
>>> fp2  ❹
<_io.TextIOWrapper name='cafe.txt' mode='r' encoding='cp1252'>
>>> fp2.encoding  ❺
'cp1252'
>>> fp2.read() ❻
'cafÃ©'
>>> fp3 = open('cafe.txt', encoding='utf_8')  ❼
>>> fp3
<_io.TextIOWrapper name='cafe.txt' mode='r' encoding='utf_8'>
>>> fp3.read() ❽
'café'
>>> fp4 = open('cafe.txt', 'rb')  ❾
>>> fp4                           ❿
<_io.BufferedReader name='cafe.txt'>
>>> fp4.read()  ⓫
b'caf\xc3\xa9'
```

❶ By default, `open` uses text mode and returns a `TextIOWrapper` object with a specific encoding.

❷ The `write` method on a `TextIOWrapper` returns the number of Unicode characters written.

❸ `os.stat` says the file has 5 bytes; UTF-8 encodes `'é'` as 2 bytes, 0xc3 and 0xa9.

❹ Opening a text file with no explicit encoding returns a `TextIOWrapper` with the encoding set to a default from the locale.

❺ A `TextIOWrapper` object has an encoding attribute that you can inspect: `cp1252` in this case.

⑥ In the Windows `cp1252` encoding, the byte 0xc3 is an “Ã” (A with tilde) and 0xa9 is the copyright sign.

⑦ Opening the same file with the correct encoding.

⑧ The expected result: the same four Unicode characters for `'café'`.

⑨ The `'rb'` flag opens a file for reading in binary mode.

⑩ The returned object is a `BufferedReader` and not a `TextIOWrapper`.

⑪ Reading that returns bytes, as expected.

> **TIP**
>
> Do not open text files in binary mode unless you need to analyze the file contents to determine the encoding—even then, you should be using Chardet instead of reinventing the wheel (see “How to Discover the Encoding of a Byte Sequence”). Ordinary code should only use binary mode to open binary files, like raster images.

The problem in Example 4-9 has to do with relying on a default setting while opening a text file. There are several sources for such defaults, as the next section shows.

Beware of Encoding Defaults

Several settings affect the encoding defaults for I/O in Python. See the *default_encodings.py* script in Example 4-10.

Example 4-10. Exploring encoding defaults

```
import locale
import sys

expressions = """
        locale.getpreferredencoding()
        type(my_file)
```

```
        my_file.encoding
        sys.stdout.isatty()
        sys.stdout.encoding
        sys.stdin.isatty()
        sys.stdin.encoding
        sys.stderr.isatty()
        sys.stderr.encoding
        sys.getdefaultencoding()
        sys.getfilesystemencoding()
    """

my_file = open('dummy', 'w')

for expression in expressions.split():
    value = eval(expression)
    print(f'{expression:>30} -> {value!r}')
```

The output of Example 4-10 on GNU/Linux (Ubuntu 14.04 to 19.10) and MacOS (10.9 to 10.14) is identical, showing that `UTF-8` is used everywhere in these systems:

```
  $ python3 default_encodings.py
   locale.getpreferredencoding() -> 'UTF-8'
                   type(my_file) -> <class '_io.TextIOWrapper'>
                my_file.encoding -> 'UTF-8'
             sys.stdout.isatty() -> True
             sys.stdout.encoding -> 'utf-8'
              sys.stdin.isatty() -> True
              sys.stdin.encoding -> 'utf-8'
             sys.stderr.isatty() -> True
             sys.stderr.encoding -> 'utf-8'
        sys.getdefaultencoding() -> 'utf-8'
     sys.getfilesystemencoding() -> 'utf-8'
```

On Windows, however, the output is Example 4-11.

Example 4-11. Default encodings on Windows 10 PowerShell (output is the same on cmd.exe)

```
> chcp  ❶
Active code page: 437
> python default_encodings.py  ❷
 locale.getpreferredencoding() -> 'cp1252'  ❸
                 type(my_file) -> <class '_io.TextIOWrapper'>
              my_file.encoding -> 'cp1252'  ❹
           sys.stdout.isatty() -> True      ❺
```

```
          sys.stdout.encoding -> 'utf-8'    ❻
           sys.stdin.isatty() -> True
           sys.stdin.encoding -> 'utf-8'
          sys.stderr.isatty() -> True
          sys.stderr.encoding -> 'utf-8'
     sys.getdefaultencoding() -> 'utf-8'
  sys.getfilesystemencoding() -> 'utf-8'
```

❶ `chcp` shows the active code page for the console: 437.

❷ Running *default_encodings.py* with output to console.

❸ `locale.getpreferredencoding()` is the most important setting.

❹ Text files use `locale.getpreferredencoding()` by default.

❺ The output is going to the console, so `sys.stdout.isatty()` is `True`.

❻ Now, `sys.stdout.encoding` is not the same as the console code page reported by `chcp`!

Unicode support in Windows itself, and in Python for Windows, got better since I wrote the *First Edition*. Example 4-11 used to report four different encodings in Python 3.4 on Windows 7. The encodings for `stdout`, `stdin`, and `stderr` used to be the same as the active code page reported by the `chcp` command, but now they're all `utf-8` thanks to PEP 528: Change Windows console encoding to UTF-8 implemented in Python 3.6, and Unicode support in PowerShell in cmd.exe (since Windows 1809 from October 2018).[6] It's weird that `chcp` and `sys.stdout.encoding` say different things when `stdout` is writing to the console, but it's great that now we can print Unicode strings without encoding errors on Windows—unless the user redirects output to a file, as we'll soon see. That does not mean all your favorite emojis will appear in the console: that also depends on the font the console is using.

Another change was PEP 529: Change Windows filesystem encoding to UTF-8, also implemented in Python 3.6, which changed the file system encoding (used to represent names of directories and files) from Microsoft's proprietary MBCS to UTF-8.

However, if the output of Example 4-10 is redirected to a file, like this:

```
Z:\>python default_encodings.py > encodings.log
```

Then, the value of `sys.stdout.isatty()` becomes `False`, and `sys.stdout.encoding` is set by `locale.getpreferredencoding()`, `'cp1252'` in that machine—but `sys.stdin.encoding` and `sys.stderr.encoding` remain `utf-8`.

> **TIP**
>
> In Example 4-12 I use the `'\N{}'` escape for Unicode literals, where we write the official name of the character inside the `\N{}`. It's rather verbose, but explicit and safe: Python raises `SyntaxError` if the name doesn't exist—much better than writing an hex number that could be wrong but you'll only find out much later. You'd probably want to write a comment explaining the character codes anyway, so the verbosity of `\N{}` is easy to accept.

This means that a script like Example 4-12 works when printing to the console, but may break when output is redirected to a file.

Example 4-12. `stdout_check.py`

```
import sys
from unicodedata import name

print(sys.version)
print()
print('sys.stdout.isatty():', sys.stdout.isatty())
print('sys.stdout.encoding:', sys.stdout.encoding)
print()

test_chars = [
    '\N{HORIZONTAL ELLIPSIS}',       # exists in cp1252, not in
```

```
cp437
    '\N{INFINITY}',                 # exists in cp437, not in
cp1252
    '\N{CIRCLED NUMBER FORTY TWO}',  # not in cp437 or in cp1252
]

for char in test_chars:
    print(f'Trying to output {name(char)}:')
    print(char)
```

Example 4-12 displays the result of `sys.stdout.isatty()`, the value of `sys.stdout.encoding`, and these three characters:

- `'…'` HORIZONTAL ELLIPSIS—exists in CP 1252 but not in CP 437;
- `'∞'` INFINITY—exists in CP 437 but not in CP 1252;
- `'㊷'` CIRCLED NUMBER FORTY TWO[7]—doesn't exist in CP 1252 or CP 437.

When I run `stdout_check.py` on PowerShell or cmd.exe, it works as captured in Figure 4-3.

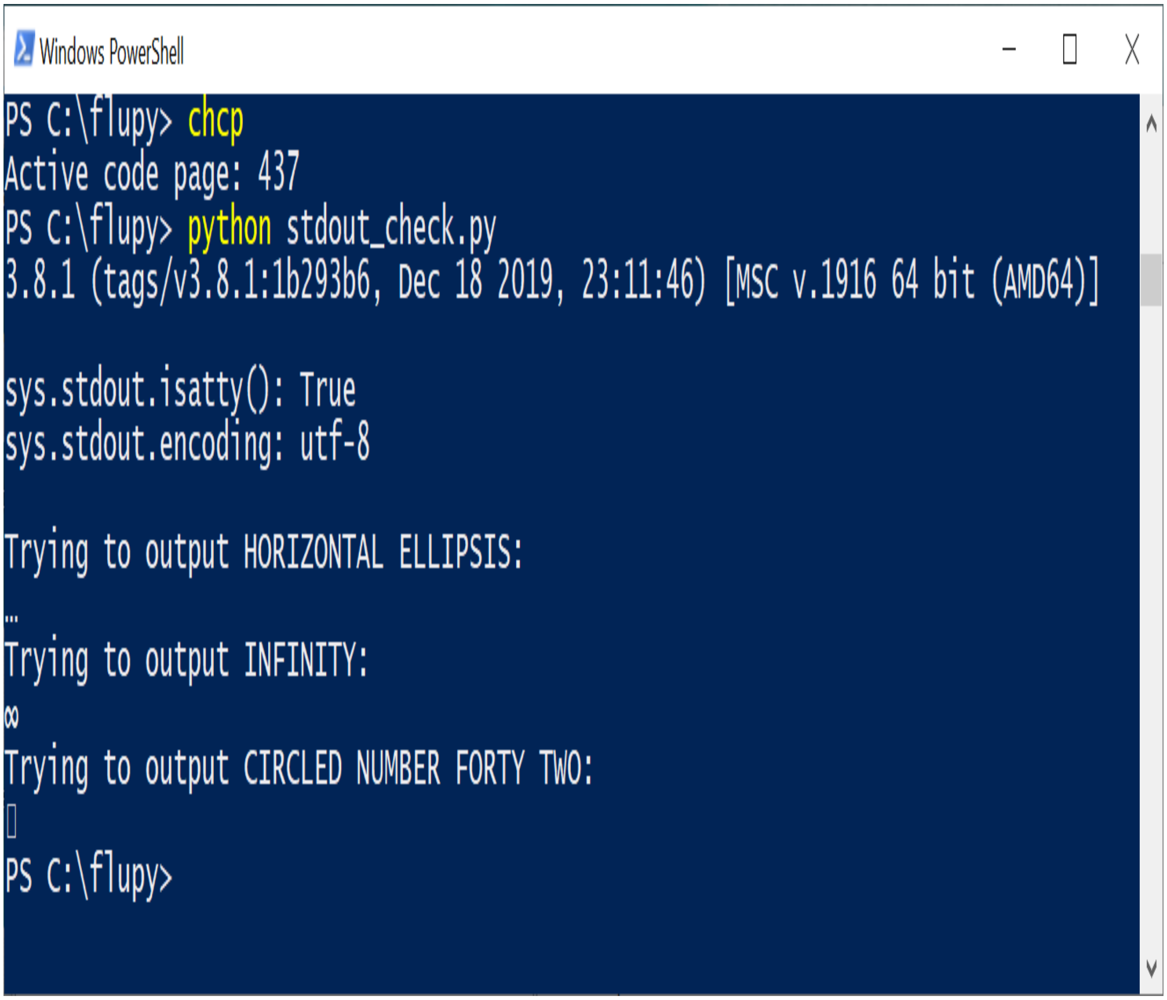

Figure 4-3. Running `stdout_check.py` on PowerShell.

Despite `chcp` reporting the active code as 437, `sys.stdout.encoding` is UTF-8, so the HORIZONTAL ELLIPSIS and INFINITY both output correctly. The CIRCLED NUMBER FORTY TWO is replaced by a rectangle, but no error is raised. Presumably it is recognized as a valid character, but the console font doesn't have the glyph to display it.

However, when I redirect the output of `stdout_check.py` to a file, I get Figure 4-4.

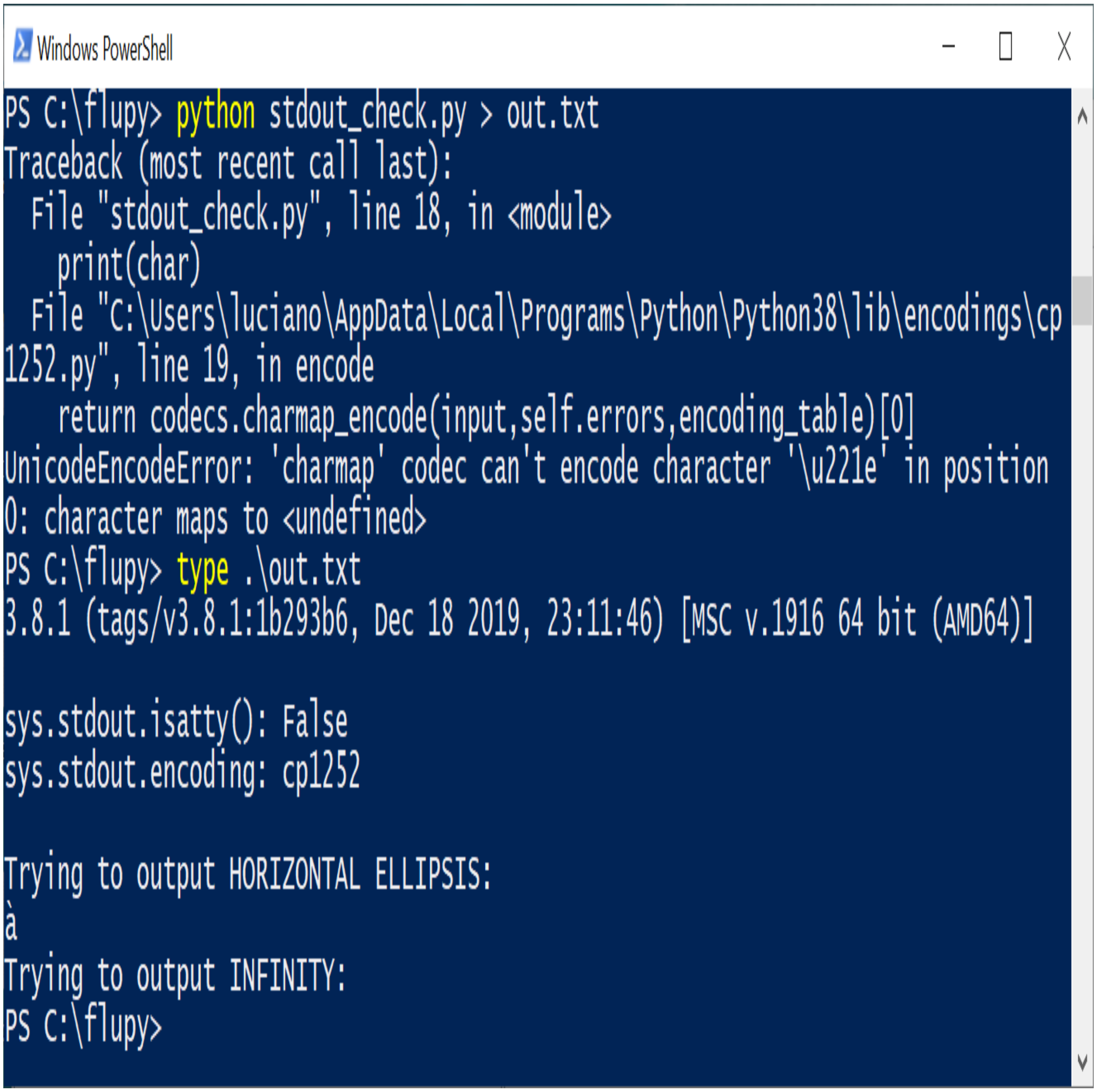

Figure 4-4. Running `stdout_check.py` on PowerShell, redirecting output.

The first problem demonstrated by Figure 4-4 is the `UnicodeEncodeError` mentioning character `'\u221e'`, because `sys.stdout.encoding` is `'cp1252'`—a code page that doesn't have the INFINITY character.

Reading `out.txt` with the `type` command—or a Windows editor like VS Code or Sublime Text—shows that instead of HORIZONTAL ELLIPSIS, I got `'à'` (LATIN SMALL LETTER A WITH GRAVE). As it turns out, the byte value 0x85 in CP 1252 means `'…'`, but in CP 437 the same byte value represents `'à'`. So it seems the active code page does matter, not in a sensible or useful way, but as partial explanation of a bad Unicode experience.

> **NOTE**
>
> I used a laptop configured for the US market, running Windows 10 OEM to run these experiments. Windows versions localized for other countries may have different encoding configurations. For example, in Brazil the Windows console uses code page 850 by default—not 437.

To wrap up this maddening issue of default encodings, let's give a final look at the different encodings in Example 4-11:

- If you omit the `encoding` argument when opening a file, the default is given by `locale.getpreferredencoding()` (`'cp1252'` in Example 4-11).
- The encoding of `sys.stdout|stdin|stderr` used to be set by the `PYTHONIOENCODING` environment variable before Python 3.6—now that variable is ignored, unless `PYTHONLEGACYWINDOWSSTDIO` is set to a non-empty string. Otherwise, the encoding for standard I/O is UTF-8 for interactive I/O, or defined by `locale.getpreferredencoding()` if the output/input is redirected to/from a file.
- `sys.getdefaultencoding()` is used internally by Python in implicit conversions of binary data to/from `str`; this happens less often in Python 3, but still happens.[8] Changing this setting is not supported.[9]
- `sys.getfilesystemencoding()` is used to encode/decode filenames (not file contents). It is used when `open()` gets a `str` argument for the filename; if the filename is given as a `bytes` argument, it is passed unchanged to the OS API.

NOTE

On GNU/Linux and MacOS all of these encodings are set to UTF-8 by default, and have been for several years, so I/O handles all Unicode characters. On Windows, not only are different encodings used in the same system, but they are usually code pages like `'cp850'` or `'cp1252'` that support only ASCII with 127 additional characters that are not the same from one encoding to the other. Therefore, Windows users are far more likely to face encoding errors unless they are extra careful.

To summarize, the most important encoding setting is that returned by `locale.getpreferredencoding()`: it is the default for opening text files and for `sys.stdout/stdin/stderr` when they are redirected to files. However, the documentation reads (in part):

> *`locale.getpreferredencoding(do_setlocale=True)`*
>
> *Return the encoding used for text data, according to user preferences. User preferences are expressed differently on different systems, and might not be available programmatically on some systems, so this function only returns a guess. […]*

Therefore, the best advice about encoding defaults is: do not rely on them.

You will avoid a lot of pain if you follow the advice of the Unicode sandwich and always are explicit about the encodings in your programs. Unfortunately, Unicode is painful even if you get your `bytes` correctly converted to `str`. The next two sections cover subjects that are simple in ASCII-land, but get quite complex on planet Unicode: text normalization (i.e., converting text to a uniform representation for comparisons) and sorting.

Normalizing Unicode for Reliable Comparisons

String comparisons are complicated by the fact that Unicode has combining characters: diacritics and other marks that attach to the preceding character, appearing as one when printed.

For example, the word “café” may be composed in two ways, using four or five code points, but the result looks exactly the same:

```
>>> s1 = 'café'
>>> s2 = 'cafe\N{COMBINING ACUTE ACCENT}'
>>> s1, s2
('café', 'café')
>>> len(s1), len(s2)
(4, 5)
>>> s1 == s2
False
```

Placing `COMBINING ACUTE ACCENT` (U+0301) after “e” renders “é”. In the Unicode standard, sequences like `'é'` and `'e\u0301'` are called “canonical equivalents,” and applications are supposed to treat them as the same. But Python sees two different sequences of code points, and considers them not equal.

The solution is `unicodedata.normalize()`. The first argument to that function is one of four strings: `'NFC'`, `'NFD'`, `'NFKC'`, and `'NFKD'`. Let’s start with the first two.

Normalization Form C (NFC) composes the code points to produce the shortest equivalent string, while NFD decomposes, expanding composed characters into base characters and separate combining characters. Both of these normalizations make comparisons work as expected, as the next example shows.

```
>>> from unicodedata import normalize
>>> s1 = 'café'
>>> s2 = 'cafe\N{COMBINING ACUTE ACCENT}'
>>> len(s1), len(s2)
(4, 5)
>>> len(normalize('NFC', s1)), len(normalize('NFC', s2))
(4, 4)
>>> len(normalize('NFD', s1)), len(normalize('NFD', s2))
```

```
(5, 5)
>>> normalize('NFC', s1) == normalize('NFC', s2)
True
>>> normalize('NFD', s1) == normalize('NFD', s2)
True
```

Keyboard drivers usually generate composed characters, so text typed by users will be in NFC by default. However, to be safe, it may be good to normalize strings with `normalize('NFC', user_text)` before saving. NFC is also the normalization form recommended by the W3C in *Character Model for the World Wide Web: String Matching and Searching*.

Some single characters are normalized by NFC into another single character. The symbol for the ohm (Ω) unit of electrical resistance is normalized to the Greek uppercase omega. They are visually identical, but they compare unequal so it is essential to normalize to avoid surprises:

```
>>> from unicodedata import normalize, name
>>> ohm = '\u2126'
>>> name(ohm)
'OHM SIGN'
>>> ohm_c = normalize('NFC', ohm)
>>> name(ohm_c)
'GREEK CAPITAL LETTER OMEGA'
>>> ohm == ohm_c
False
>>> normalize('NFC', ohm) == normalize('NFC', ohm_c)
True
```

The other two normalization forms are NFKC and NFKD, where the letter K stands for “compatibility.” These are stronger forms of normalization, affecting the so-called “compatibility characters.” Although one goal of Unicode is to have a single “canonical” code point for each character, some characters appear more than once for compatibility with preexisting standards. For example, the `MICRO SIGN`, µ (`U+00B5`), was added to Unicode to support round-trip conversion to `latin1` which includes it, even though the same character is part of the Greek alphabet with code point `U+03BC` (`GREEK SMALL LETTER MU`). So, the micro sign is considered a “compatibility character.”

In the NFKC and NFKD forms, each compatibility character is replaced by a “compatibility decomposition” of one or more characters that are considered a “preferred” representation, even if there is some formatting loss—ideally, the formatting should be the responsibility of external markup, not part of Unicode. To exemplify, the compatibility decomposition of the one half fraction '½' (U+00BD) is the sequence of three characters '1/2', and the compatibility decomposition of the micro sign 'µ' (U+00B5) is the lowercase mu 'μ' (U+03BC).[10]

Here is how the NFKC works in practice:

```
>>> from unicodedata import normalize, name
>>> half = '\N{VULGAR FRACTION ONE HALF}'
>>> print(half)
½
>>> normalize('NFKC', half)
'1⁄2'
>>> for char in normalize('NFKC', half):
...     print(char, name(char), sep='\t')
...
1       DIGIT ONE
⁄       FRACTION SLASH
2       DIGIT TWO
>>> four_squared = '4²'
>>> normalize('NFKC', four_squared)
'42'
>>> micro = 'µ'
>>> micro_kc = normalize('NFKC', micro)
>>> micro, micro_kc
('µ', 'μ')
>>> ord(micro), ord(micro_kc)
(181, 956)
>>> name(micro), name(micro_kc)
('MICRO SIGN', 'GREEK SMALL LETTER MU')
```

Although '1⁄2' is a reasonable substitute for '½', and the micro sign is really a lowercase Greek mu, converting '4²' to '42' changes the meaning. An application could store '4²' as '4²', but the normalize function knows nothing about formatting. Therefore, NFKC or NFKD may lose or distort information, but they can produce convenient intermediate representations for searching and indexing.

Unfortunately, with Unicode everything is always more complicated than it first seems. For the `VULGAR FRACTION ONE HALF`, the NFKC normalization produced 1 and 2 joined by `FRACTION SLASH`, instead of `SOLIDUS`, a.k.a. “slash”—the familiar character with ASCII code decimal 47. Therefore, searching for the 3-character ASCII sequence `'1/2'` would not find the normalized Unicode sequence.

> **WARNING**
>
> NFKC and NFKD normalization cause data loss and should be applied only in special cases like search and indexing, and not for permanent storage of text.

When preparing text for searching or indexing, another operation is useful: case folding, our next subject.

Case Folding

Case folding is essentially converting all text to lowercase, with some additional transformations. It is supported by the `str.casefold()` method.

For any string `s` containing only `latin1` characters, `s.casefold()` produces the same result as `s.lower()`, with only two exceptions—the micro sign `'µ'` is changed to the Greek lowercase mu (which looks the same in most fonts) and the German Eszett or “sharp s” (ß) becomes “ss”:

```
>>> micro = 'µ'
>>> name(micro)
'MICRO SIGN'
>>> micro_cf = micro.casefold()
>>> name(micro_cf)
'GREEK SMALL LETTER MU'
>>> micro, micro_cf
('µ', 'μ')
>>> eszett = 'ß'
>>> name(eszett)
'LATIN SMALL LETTER SHARP S'
>>> eszett_cf = eszett.casefold()
```

```
>>> eszett, eszett_cf
('ß', 'ss')
```

There are nearly 300 code points for which `str.casefold()` and `str.lower()` return different results.

As usual with anything related to Unicode, case folding is a hard issue with plenty of linguistic special cases, but the Python core team made an effort to provide a solution that hopefully works for most users.

In the next couple of sections, we’ll put our normalization knowledge to use developing utility functions.

Utility Functions for Normalized Text Matching

As we’ve seen, NFC and NFD are safe to use and allow sensible comparisons between Unicode strings. NFC is the best normalized form for most applications. `str.casefold()` is the way to go for case-insensitive comparisons.

If you work with text in many languages, a pair of functions like `nfc_equal` and `fold_equal` in Example 4-13 are useful additions to your toolbox.

Example 4-13. normeq.py: normalized Unicode string comparison

```
"""
Utility functions for normalized Unicode string comparison.

Using Normal Form C, case sensitive:

    >>> s1 = 'café'
    >>> s2 = 'cafe\u0301'
    >>> s1 == s2
    False
    >>> nfc_equal(s1, s2)
    True
    >>> nfc_equal('A', 'a')
    False

Using Normal Form C with case folding:

    >>> s3 = 'Straße'
```

```
    >>> s4 = 'strasse'
    >>> s3 == s4
    False
    >>> nfc_equal(s3, s4)
    False
    >>> fold_equal(s3, s4)
    True
    >>> fold_equal(s1, s2)
    True
    >>> fold_equal('A', 'a')
    True

"""

from unicodedata import normalize

def nfc_equal(str1, str2):
    return normalize('NFC', str1) == normalize('NFC', str2)

def fold_equal(str1, str2):
    return (normalize('NFC', str1).casefold() ==
            normalize('NFC', str2).casefold())
```

Beyond Unicode normalization and case folding—which are both part of the Unicode standard—sometimes it makes sense to apply deeper transformations, like changing `'café'` into `'cafe'`. We'll see when and how in the next section.

Extreme "Normalization": Taking Out Diacritics

The Google Search secret sauce involves many tricks, but one of them apparently is ignoring diacritics (e.g., accents, cedillas, etc.), at least in some contexts. Removing diacritics is not a proper form of normalization because it often changes the meaning of words and may produce false positives when searching. But it helps coping with some facts of life: people sometimes are lazy or ignorant about the correct use of diacritics, and spelling rules change over time, meaning that accents come and go in living languages.

Outside of searching, getting rid of diacritics also makes for more readable URLs, at least in Latin-based languages. Take a look at the URL for the Wikipedia article about the city of São Paulo:

```
https://en.wikipedia.org/wiki/S%C3%A3o_Paulo
```

The `%C3%A3` part is the URL-escaped, UTF-8 rendering of the single letter “ã” (“a” with tilde). The following is much easier to recognize, even if it is not the right spelling:

```
https://en.wikipedia.org/wiki/Sao_Paulo
```

To remove all diacritics from a `str`, you can use a function like Example 4-14.

Example 4-14. simplify.py: Function to remove all combining marks.

```
import unicodedata
import string


def shave_marks(txt):
    """Remove all diacritic marks"""
    norm_txt = unicodedata.normalize('NFD', txt)  ❶
    shaved = ''.join(c for c in norm_txt
                     if not unicodedata.combining(c))  ❷
    return unicodedata.normalize('NFC', shaved)  ❸
```

❶ Decompose all characters into base characters and combining marks.

❷ Filter out all combining marks.

❸ Recompose all characters.

Example 4-15 shows a couple of uses of `shave_marks`.

Example 4-15. Two examples using shave_marks from Example 4-14

```
>>> order = '“Herr Voß: • ½ cup of Œtker™ caffè latte • bowl of
açaí.”'
>>> shave_marks(order)
'“Herr Voß: • ½ cup of Œtker™ caffe latte • bowl of acai.”'  ❶
>>> Greek = 'Ζέφυρος, Zéfiro'
>>> shave_marks(Greek)
'Ζεφυρος, Zefiro'  ❷
```

❶ Only the letters “è”, “ç”, and “í” were replaced.

❷ Both “έ” and “é” were replaced.

The function `shave_marks` from Example 4-14 works all right, but maybe it goes too far. Often the reason to remove diacritics is to change Latin text to pure ASCII, but `shave_marks` also changes non-Latin characters—like Greek letters—which will never become ASCII just by losing their accents. So it makes sense to analyze each base character and to remove attached marks only if the base character is a letter from the Latin alphabet. This is what Example 4-16 does.

Example 4-16. Function to remove combining marks from Latin characters (import statements are omitted as this is part of the simplify.py module from Example 4-14)

```
def shave_marks_latin(txt):
    """Remove all diacritic marks from Latin base characters"""
    norm_txt = unicodedata.normalize('NFD', txt)  ❶
    latin_base = False
    preserve = []
    for c in norm_txt:
        if unicodedata.combining(c) and latin_base:   ❷
            continue  # ignore diacritic on Latin base char
        preserve.append(c)                            ❸
        # if it isn't a combining char, it's a new base char
        if not unicodedata.combining(c):              ❹
            latin_base = c in string.ascii_letters
    shaved = ''.join(preserve)
    return unicodedata.normalize('NFC', shaved)  ❺
```

❶ Decompose all characters into base characters and combining marks.

❷ Skip over combining marks when base character is Latin.

❸ Otherwise, keep current character.

❹ Detect new base character and determine if it’s Latin.

❺ Recompose all characters.

An even more radical step would be to replace common symbols in Western texts (e.g., curly quotes, em dashes, bullets, etc.) into `ASCII` equivalents. This is what the function `asciize` does in Example 4-17.

Example 4-17. Transform some Western typographical symbols into ASCII (this snippet is also part of simplify.py from Example 4-14)

```
single_map = str.maketrans("""‚ƒ„ˆ‹‘’“”•–—˜›""",  ❶
                           """'f"^<''""---~>""")

multi_map = str.maketrans({  ❷
    '€': 'EUR',
    '…': '...',
    'Æ': 'AE',
    'æ': 'ae',
    'Œ': 'OE',
    'œ': 'oe',
    '™': '(TM)',
    '‰': '<per mille>',
    '†': '**',
    '‡': '***',
})

multi_map.update(single_map)  ❸


def dewinize(txt):
    """Replace Win1252 symbols with ASCII chars or sequences"""
    return txt.translate(multi_map)  ❹


def asciize(txt):
    no_marks = shave_marks_latin(dewinize(txt))     ❺
    no_marks = no_marks.replace('ß', 'ss')          ❻
    return unicodedata.normalize('NFKC', no_marks)  ❼
```

❶ Build mapping table for char-to-char replacement.

❷ Build mapping table for char-to-string replacement.

❸ Merge mapping tables.

❹ `dewinize` does not affect `ASCII` or `latin1` text, only the Microsoft additions in to `latin1` in `cp1252`.

❺ Apply `dewinize` and remove diacritical marks.

❻ Replace the Eszett with “ss” (we are not using case fold here because we want to preserve the case).

❼ Apply NFKC normalization to compose characters with their compatibility code points.

Example 4-18 shows `asciize` in use.

Example 4-18. Two examples using asciize from Example 4-17

```
>>> order = '“Herr Voß: • ½ cup of Œtker™ caffè latte • bowl of
açaí.”'
>>> dewinize(order)
'"Herr Voß: - ½ cup of OEtker(TM) caffè latte - bowl of açaí."'  ❶
>>> asciize(order)
'"Herr Voss: - 1⁄2 cup of OEtker(TM) caffe latte - bowl of acai."'
❷
```

❶ `dewinize` replaces curly quotes, bullets, and ™ (trademark symbol).

❷ `asciize` applies `dewinize`, drops diacritics, and replaces the `'ß'`.

> **WARNING**
>
> Different languages have their own rules for removing diacritics. For example, Germans change the `'ü'` into `'ue'`. Our `asciize` function is not as refined, so it may or not be suitable for your language. It works acceptably for Portuguese, though.

To summarize, the functions in *simplify.py* go way beyond standard normalization and perform deep surgery on the text, with a good chance of changing its meaning. Only you can decide whether to go so far, knowing the target language, your users, and how the transformed text will be used.

This wraps up our discussion of normalizing Unicode text.

Now let’s sort out Unicode sorting.

Sorting Unicode Text

Python sorts sequences of any type by comparing the items in each sequence one by one. For strings, this means comparing the code points. Unfortunately, this produces unacceptable results for anyone who uses non-ASCII characters.

Consider sorting a list of fruits grown in Brazil:

```
>>> fruits = ['caju', 'atemoia', 'cajá', 'açaí', 'acerola']
>>> sorted(fruits)
['acerola', 'atemoia', 'açaí', 'caju', 'cajá']
```

Sorting rules vary for different locales, but in Portuguese and many languages that use the Latin alphabet, accents and cedillas rarely make a difference when sorting.[11] So "cajá" is sorted as "caja," and must come before "caju."

The sorted `fruits` list should be:

```
['açaí', 'acerola', 'atemoia', 'cajá', 'caju']
```

The standard way to sort non-ASCII text in Python is to use the `locale.strxfrm` function which, according to the `locale` module docs, "transforms a string to one that can be used in locale-aware comparisons."

To enable `locale.strxfrm`, you must first set a suitable locale for your application, and pray that the OS supports it. The sequence of commands in Example 4-19 may work for you.

Example 4-19. `locale_sort.py`: using the locale.strxfrm function as sort key

```
import locale
my_locale = locale.setlocale(locale.LC_COLLATE, 'pt_BR.UTF-8')
print(my_locale)
fruits = ['caju', 'atemoia', 'cajá', 'açaí', 'acerola']
sorted_fruits = sorted(fruits, key=locale.strxfrm)
print(sorted_fruits)
```

Running Example 4-19 on GNU/Linux (Ubuntu 19.10) with the `pt_BR.UTF-8` locale installed, I get the correct result:

```
'pt_BR.UTF-8'
['açaí', 'acerola', 'atemoia', 'cajá', 'caju']
```

So you need to call `setlocale(LC_COLLATE, «your_locale»)` before using `locale.strxfrm` as the key when sorting.

There are some caveats, though:

- Because locale settings are global, calling `setlocale` in a library is not recommended. Your application or framework should set the locale when the process starts, and should not change it afterwards.
- The locale must be installed on the OS, otherwise `setlocale` raises a `locale.Error: unsupported locale setting` exception.
- You must know how to spell the locale name.
- The locale must be correctly implemented by the makers of the OS. I was successful on Ubuntu 19.10, but not on MacOS 10.14. On MacOS, the call `setlocale(LC_COLLATE, 'pt_BR.UTF-8')` returns the string `'pt_BR.UTF-8'` with no complaints. But `sorted(fruits, key=locale.strxfrm)` produced the same incorrect result as `sorted(fruits)` did. I also tried the `fr_FR`, `es_ES`, and `de_DE` locales on MacOS, but `locale.strxfrm` never did its job.[12]

So the standard library solution to internationalized sorting works, but seems to be well supported only on GNU/Linux (perhaps also on Windows, if you are an expert). Even then, it depends on locale settings, creating deployment headaches.

Fortunately, there is a simpler solution: the PyUCA library, available on *PyPI*.

Sorting with the Unicode Collation Algorithm

James Tauber, prolific Django contributor, must have felt the pain and created _PyUCA_, a pure-Python implementation of the Unicode Collation Algorithm (UCA). Example 4-20 shows how easy it is to use.

Example 4-20. Using the pyuca.Collator.sort_key method

```
>>> import pyuca
>>> coll = pyuca.Collator()
>>> fruits = ['caju', 'atemoia', 'cajá', 'açaí', 'acerola']
>>> sorted_fruits = sorted(fruits, key=coll.sort_key)
>>> sorted_fruits
['açaí', 'acerola', 'atemoia', 'cajá', 'caju']
```

This is simple and works on GNU/Linux, MacOS, and Windows, at least with my small sample.

PyUCA does not take the locale into account. If you need to customize the sorting, you can provide the path to a custom collation table to the `Collator()` constructor. Out of the box, it uses `allkeys.txt`, which is bundled with the project. That's just a copy of the Default Unicode Collation Element Table from Unicode.org.

PYICU: MIRO'S RECOMMENDATION FOR UNICODE SORTING

(Tech reviewer Miroslav Šedivý is a polyglot and an expert on Unicode. This is what he wrote about PyUCA.)

PyUCA has one sorting algorithm that does not respect the sorting order in individual languages. For instance, Ä in German is between A and B, while in Swedish it comes after Z. Have a look at PyICU that works like locale without changing the locale of the process. It is also needed if you want to change the case of iİ/ıI in Turkish. *PyICU* includes an extension that must be compiled, so it may be harder to install in some systems than *PyUCA*, which is just Python.

By the way, that collation table is one of the many data files that comprise the Unicode database, our next subject.

The Unicode Database

The Unicode standard provides an entire database—in the form of several structured text files—that includes not only the table mapping code points to character names, but also metadata about the individual characters and how they are related. For example, the Unicode database records whether a character is printable, is a letter, is a decimal digit, or is some other numeric symbol. That's how the `str` methods `isalpha`, `isprintable`, `isdecimal`, and `isnumeric` work. `str.casefold` also uses information from a Unicode table.

> **NOTE**
>
> The `unicodedata.category(char)` function returns the two-letter category of `char` from the Unicode database. The higher level `str` methods are easier to use. For example, `label.isalpha()` returns `True` if every character in `label` belongs to one of these categories: `Lm`, `Lt`, `Lu`, `Ll`, or `Lo`. To learn what those codes mean, see General Category in the English Wikipedia's Unicode character property article.

Finding characters by name

The `unicodedata` module has functions to retrieve character metadata, including `unicodedata.name()`, which returns a character's official name in the standard. Figure 4-5 demonstrates that function.[13]

```
>>> from unicodedata import name
>>> name('A')
'LATIN CAPITAL LETTER A'
>>> name('ã')
'LATIN SMALL LETTER A WITH TILDE'
>>> name('♛')
'BLACK CHESS QUEEN'
>>> name('😸')
'GRINNING CAT FACE WITH SMILING EYES'
```

Figure 4-5. Exploring unicodedata.name() in the Python console

You can use the `name()` function to build apps that let users search for characters by name. Figure 4-6 demonstrates the `cf.py` command-line script that takes one or more words as arguments, and lists the characters that have those words in their official Unicode names. The full source code for `cf.py` is in Example 4-21.

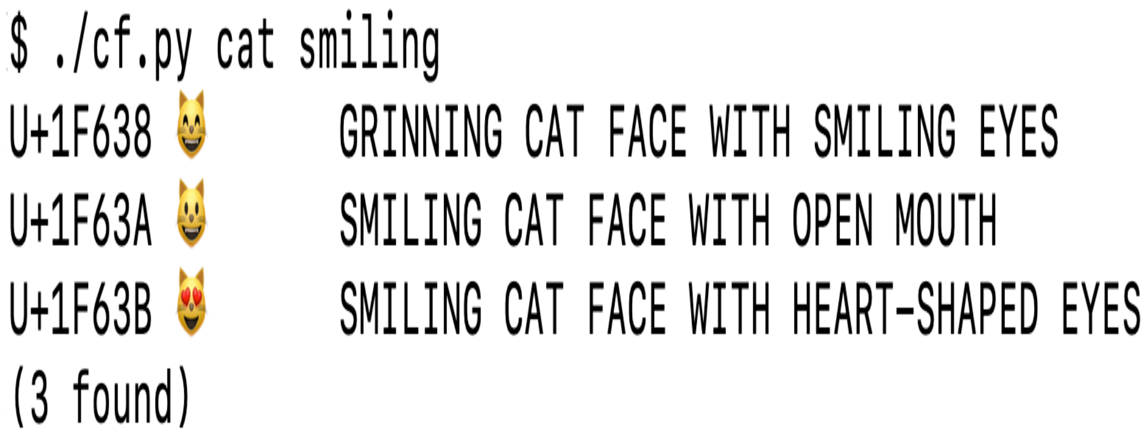

Figure 4-6. Using cf.py to find smiling cats.

> **WARNING**
>
> Emoji support varies widely across operating systems and apps. In recent years the MacOS terminal offers the best support for emojis, followed by modern GNU/Linux graphic terminals. Windows cmd.exe and PowerShell now support Unicode output, but as I write this section in January 2020, they still don't display emojis—at least not "out of the box". Tech reviewer Leonardo Rochael told me about a new, Open Source Windows Terminal by Microsoft, which may have better Unicode support than the older Microsoft consoles. I did not have time to try it.

In Example 4-21, note the `if` statement in the `find` function using the `.issubset()` method to quickly test whether all the words in the `query` set appear in the list of words built from the character's name. Thanks to Python's rich set API, we don't need a nested `for` loop and another `if` to implement this check.

Example 4-21. cf.py: the character finder utility

```
#!/usr/bin/env python3
import sys
import unicodedata

START, END = ord(' '), sys.maxunicode + 1           ❶

def find(*query_words, start=START, end=END):       ❷
    query = {w.upper() for w in query_words}        ❸
    for code in range(start, end):
        char = chr(code)                            ❹
```

```
        name = unicodedata.name(char, None)          ❺
        if name and query.issubset(name.split()):    ❻
            print(f'U+{code:04X}\t{char}\t{name}')   ❼

def main(words):
    if words:
        find(*words)
    else:
        print('Please provide words to find.')

if __name__ == '__main__':
    main(sys.argv[1:])
```

❶ Set defaults for the range of code points to search.

❷ `find` accepts `query_words` and optional keyword-only arguments to limit the range of the search, to facilitate testing.

❸ Convert `query_words` into a set of uppercased strings.

❹ Get Unicode character for `code`.

❺ Get name of character, or `None` if the code point is unassigned.

❻ If there is a name, split it into a list words, then check the `query` set is a subset of that list.

❼ Print out line with code point in `U+9999` format, the character and its name.

The `unicodedata` module has other interesting functions. Next we'll see a few that are related to getting information from characters that have numeric meaning.

Numeric meaning of characters

The `unicodedata` module includes functions to check whether a Unicode character represents a number and, if so, its numeric value for humans—as opposed to its code point number. Example 4-22 shows the use of `unicodedata.name()` and `unicodedata.numeric()` along with the `.isdecimal()` and `.isnumeric()` methods of `str`.

Example 4-22. Demo of Unicode database numerical character metadata (callouts describe each column in the output)

```
import unicodedata
import re

re_digit = re.compile(r'\d')

sample = '1\xbc\xb2\u0969\u136b\u216b\u2466\u2480\u3285'

for char in sample:
    print(f'U+{ord(char):04x}',                       ❶
          char.center(6),                             ❷
          're_dig' if re_digit.match(char) else '-',  ❸
          'isdig' if char.isdigit() else '-',         ❹
          'isnum' if char.isnumeric() else '-',       ❺
          f'{unicodedata.numeric(char):5.2f}',        ❻
          unicodedata.name(char),                     ❼
          sep='\t')
```

❶ Code point in `U+0000` format.

❷ Character centralized in a `str` of length 6.

❸ Show `re_dig` if character matches the `r'\d'` regex.

❹ Show `isdig` if `char.isdigit()` is `True`.

❺ Show `isnum` if `char.isnumeric()` is `True`.

❻ Numeric value formatted with width 5 and 2 decimal places.

❼ Unicode character name.

Running Example 4-22 gives you Figure 4-7, if your terminal font has all those glyphs.

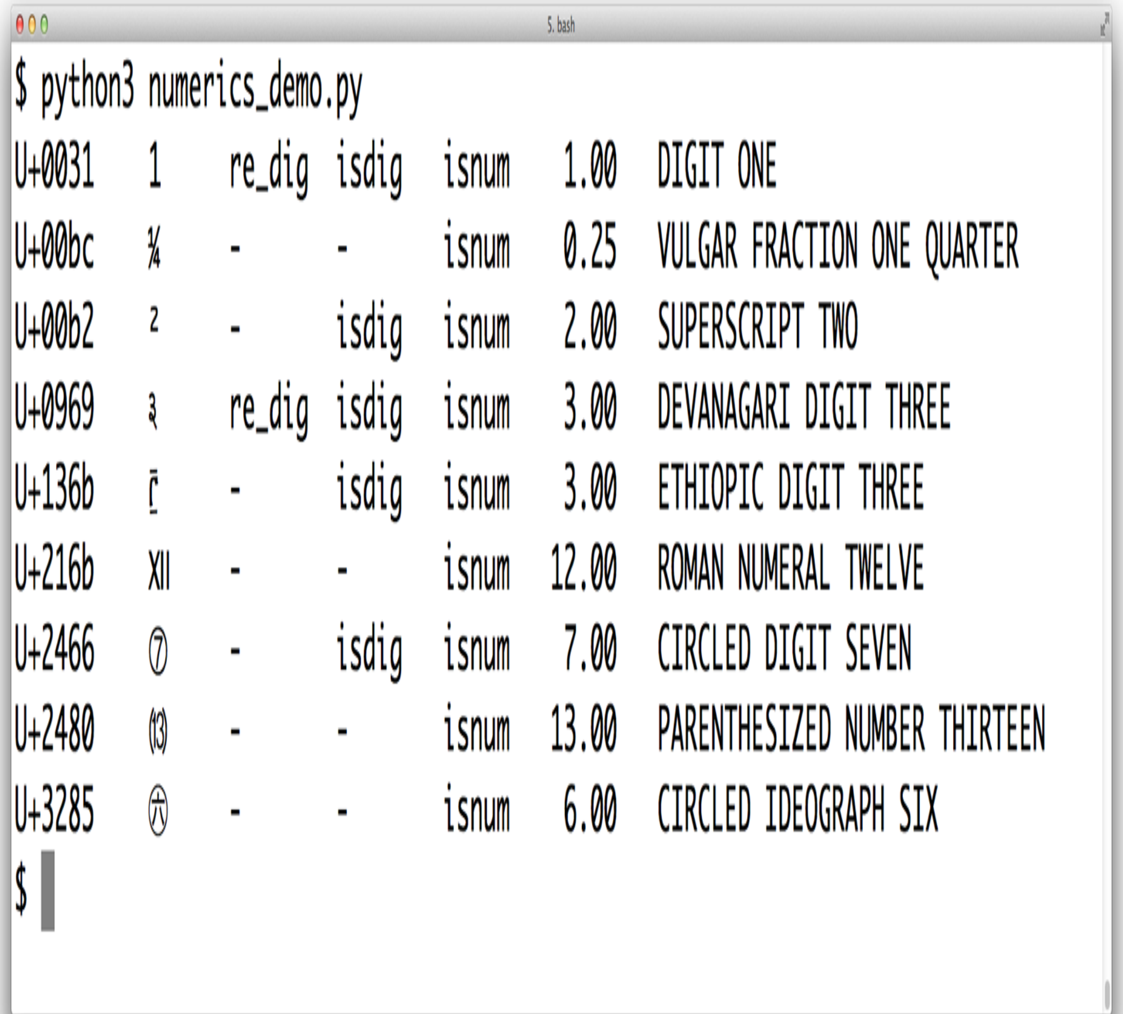

Figure 4-7. MacOS terminal showing numeric characters and metadata about them; re_dig means the character matches the regular expression `r'\d'`

The sixth column of Figure 4-7 is the result of calling `unicodedata.numeric(char)` on the character. It shows that Unicode knows the numeric value of symbols that represent numbers. So if you want to create a spreadsheet application that supports Tamil digits or Roman numerals, go for it!

Figure 4-7 shows that the regular expression `r'\d'` matches the digit "1" and the Devanagari digit 3, but not some other characters that are considered digits by the `isdigit` function. The `re` module is not as savvy about Unicode as it could be. The new `regex` module available on PyPI was designed to eventually replace `re` and provides better Unicode support.[14] We'll come back to the `re` module in the next section.

Throughout this chapter we've used several `unicodedata` functions, but there are many more we did not cover. See the standard library documentation for the `unicodedata` module.

Next we'll take a quick look at dual-mode APIs offering functions that accept `str` or `bytes` arguments with special handling depending on the type.

Dual-Mode str and bytes APIs

Python's standard library has functions that accept `str` or `bytes` arguments and behave differently depending on the type. Some examples are in the `re` and `os` modules.

str Versus bytes in Regular Expressions

If you build a regular expression with `bytes`, patterns such as `\d` and `\w` only match ASCII characters; in contrast, if these patterns are given as `str`, they match Unicode digits or letters beyond ASCII. Example 4-23 and Figure 4-8 compare how letters, ASCII digits, superscripts, and Tamil digits are matched by `str` and `bytes` patterns.

Example 4-23. ramanujan.py: compare behavior of simple str and bytes regular expressions

```
import re

re_numbers_str = re.compile(r'\d+')      ❶
re_words_str = re.compile(r'\w+')
re_numbers_bytes = re.compile(rb'\d+')   ❷
re_words_bytes = re.compile(rb'\w+')

text_str = ("Ramanujan saw \u0be7\u0bed\u0be8\u0bef"   ❸
            " as 1729 = 1³ + 12³ = 9³ + 10³.")         ❹
```

```
text_bytes = text_str.encode('utf_8')  ❺

print(f'Text\n  {text_str!r}')
print('Numbers')
print('  str  :', re_numbers_str.findall(text_str))      ❻
print('  bytes:', re_numbers_bytes.findall(text_bytes))  ❼
print('Words')
print('  str  :', re_words_str.findall(text_str))        ❽
print('  bytes:', re_words_bytes.findall(text_bytes))    ❾
```

❶ The first two regular expressions are of the `str` type.

❷ The last two are of the `bytes` type.

❸ Unicode text to search, containing the Tamil digits for 1729 (the logical line continues until the right parenthesis token).

❹ This string is joined to the previous one at compile time (see "2.4.2. String literal concatenation" in *The Python Language Reference*).

❺ A `bytes` string is needed to search with the `bytes` regular expressions.

❻ The `str` pattern `r'\d+'` matches the Tamil and ASCII digits.

❼ The `bytes` pattern `rb'\d+'` matches only the ASCII bytes for digits.

❽ The `str` pattern `r'\w+'` matches the letters, superscripts, Tamil, and ASCII digits.

❾ The `bytes` pattern `rb'\w+'` matches only the ASCII bytes for letters and digits.

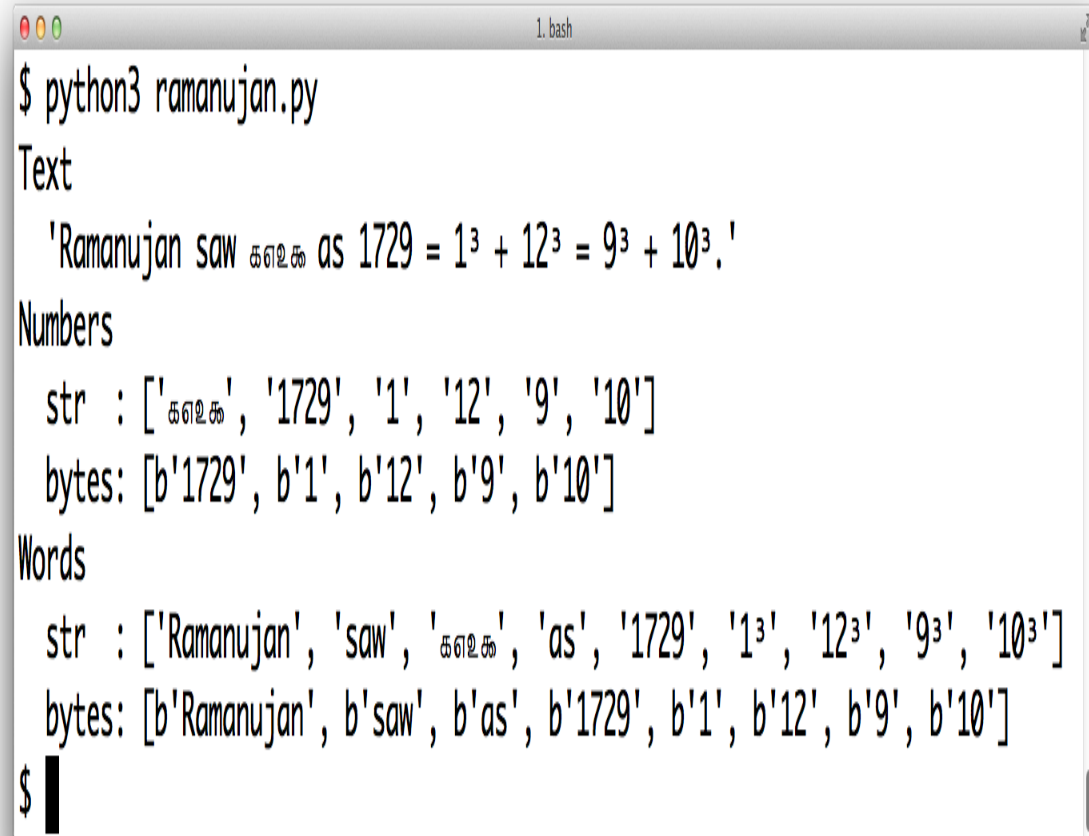

Figure 4-8. Screenshot of running ramanujan.py from Example 4-23

Example 4-23 is a trivial example to make one point: you can use regular expressions on `str` and `bytes`, but in the second case bytes outside the ASCII range are treated as nondigits and nonword characters.

For `str` regular expressions, there is a `re.ASCII` flag that makes `\w`, `\W`, `\b`, `\B`, `\d`, `\D`, `\s`, and `\S` perform ASCII-only matching. See the documentation of the `re` module for full details.

Another important dual-mode module is `os`.

str Versus bytes in os Functions

The GNU/Linux kernel is not Unicode savvy, so in the real world you may find filenames made of byte sequences that are not valid in any sensible encoding scheme, and cannot be decoded to `str`. File servers with clients using a variety of OSes are particularly prone to this problem.

In order to work around this issue, all `os` module functions that accept filenames or pathnames take arguments as `str` or `bytes`. If one such function is called with a `str` argument, the argument will be automatically converted using the codec named by `sys.getfilesystemencoding()`, and the OS response will be decoded with the same codec. This is almost always what you want, in keeping with the Unicode sandwich best practice.

But if you must deal with (and perhaps fix) filenames that cannot be handled in that way, you can pass `bytes` arguments to the `os` functions to get `bytes` return values. This feature lets you deal with any file or pathname, no matter how many gremlins you may find. See Example 4-24.

Example 4-24. listdir with str and bytes arguments and results

```
>>> os.listdir('.')  ❶
['abc.txt', 'digits-of-π.txt']
>>> os.listdir(b'.')  ❷
[b'abc.txt', b'digits-of-\xcf\x80.txt']
```

❶ The second filename is “digits-of-π.txt” (with the Greek letter pi).

❷ Given a `byte` argument, `listdir` returns filenames as bytes: `b'\xcf\x80'` is the UTF-8 encoding of the Greek letter pi).

To help with manual handling of `str` or `bytes` sequences that are file or path names, the `os` module provides special encoding and decoding functions `os.fsencode(name_or_path)` and `os.fsdecode(name_or_path)`. Both of these functions accept an argument of type `str`, `bytes`, or-an object implementing the `os.PathLike` interface since Python 3.6.

Unicode is a deep rabbit hole. Time to wrap up our exploration of `str` and `bytes`.

Chapter Summary

We started the chapter by dismissing the notion that `1 character == 1 byte`. As the world adopts Unicode, we need to keep the concept of text strings separated from the binary sequences that represent them in files, and Python 3 enforces this separation.

After a brief overview of the binary sequence data types—`bytes`, `bytearray`, and `memoryview`—we jumped into encoding and decoding, with a sampling of important codecs, followed by approaches to prevent or deal with the infamous `UnicodeEncodeError`, `UnicodeDecodeError`, and the `SyntaxError` caused by wrong encoding in Python source files.

We then considered the theory and practice of encoding detection in the absence of metadata: in theory, it can't be done, but in practice the Chardet package pulls it off pretty well for a number of popular encodings. Byte order marks were then presented as the only encoding hint commonly found in UTF-16 and UTF-32 files—sometimes in UTF-8 files as well.

In the next section, we demonstrated opening text files, an easy task except for one pitfall: the `encoding=` keyword argument is not mandatory when you open a text file, but it should be. If you fail to specify the encoding, you end up with a program that manages to generate "plain text" that is incompatible across platforms, due to conflicting default encodings. We then exposed the different encoding settings that Python uses as defaults and how to detect them. A sad realization for Windows users is that these settings often have distinct values within the same machine, and the values are mutually incompatible; GNU/Linux and MacOS users, in contrast, live in a happier place where `UTF-8` is the default pretty much everywhere.

Unicode provides multiple ways of representing some characters, so normalizing is a prerequisite for text matching. In addition to explaining normalization and case folding, we presented some utility functions that you may adapt to your needs, including drastic transformations like removing all accents. We then saw how to sort Unicode text correctly by leveraging the standard `locale` module—with some caveats—and an alternative that does not depend on tricky locale configurations: the external PyUCA package.

We leveraged the Unicode database to program a command-line utility to search for characters by name–in 28 lines of code, thanks to the power of Python. We glanced at other Unicode metadata, and had a brief overview of dual-mode APIs where some functions can be called with `str` or `bytes` arguments, producing different results.

Further Reading

Ned Batchelder's 2012 PyCon US talk "Pragmatic Unicode–or–How Do I Stop the Pain?" was outstanding. Ned is so professional that he provides a full transcript of the talk along with the slides and video.

"Character encoding and Unicode in Python: How to (╯°□°)╯︵ ┻━┻ with dignity" (slides, video) was the excellent PyCon 2014 talk by Esther Nam and Travis Fischer where I found this chapter's pithy epigraph: "Humans use text. Computers speak bytes."

Lennart Regebro—one of the technical reviewers for the *First Edition*--shares his "Useful Mental Model of Unicode (UMMU)" in the short post "Unconfusing Unicode: What Is Unicode?". Unicode is a complex standard, so Lennart's UMMU is a really useful starting point.

The official Unicode HOWTO in the Python docs approaches the subject from several different angles, from a good historic intro to syntax details, codecs, regular expressions, filenames, and best practices for Unicode-aware I/O (i.e., the Unicode sandwich), with plenty of additional reference links from each section. Chapter 4, "Strings", of Mark Pilgrim's awesome book *Dive into Python 3* also provides a very good intro to Unicode support in Python 3. In the same book, Chapter 15 describes how the Chardet library was ported from Python 2 to Python 3, a valuable case study given that the switch from the old `str` to the new `bytes` is the cause of most migration pains, and that is a central concern in a library designed to detect encodings.

If you know Python 2 but are new to Python 3, Guido van Rossum's What's New in Python 3.0 has 15 bullet points that summarize what changed, with lots of links. Guido starts with the blunt statement: "Everything you thought you knew about binary data and Unicode has changed." Armin Ronacher's blog post "The Updated Guide to Unicode on Python" is deep and highlights some of the pitfalls of Unicode in Python 3 (Armin is not a big fan of Python 3).

Chapter 2, "Strings and Text," of the *Python Cookbook, Third Edition* (O'Reilly), by David Beazley and Brian K. Jones, has several recipes dealing with Unicode normalization, sanitizing text, and performing text-oriented operations on byte sequences. Chapter 5 covers files and I/O, and it includes "Recipe 5.17. Writing Bytes to a Text File," showing that underlying any text file there is always a binary stream that may be accessed directly when needed. Later in the cookbook, the `struct` module is put to use in "Recipe 6.11. Reading and Writing Binary Arrays of Structures."

Nick Coghlan's Python Notes blog has two posts very relevant to this chapter: "Python 3 and ASCII Compatible Binary Protocols" and "Processing Text Files in Python 3". Highly recommended.

A list of encodings supported by Python is available at Standard Encodings in the `codecs` module documentation. If you need to get that list programmatically, see how it's done in the */Tools/unicode/listcodecs.py* script that comes with the CPython source code.

The books *Unicode Explained* by Jukka K. Korpela (O'Reilly) and *Unicode Demystified* by Richard Gillam (Addison-Wesley) are not Python-specific but were very helpful as I studied Unicode concepts. *Programming with Unicode* by Victor Stinner is a free, self-published book (Creative Commons BY-SA) covering Unicode in general as well as tools and APIs in the context of the main operating systems and a few programming languages, including Python.

The W3C pages Case Folding: An Introduction and Character Model for the World Wide Web: String Matching and Searching cover normalization concepts, with the former being a gentle introduction and the latter a working group note written in dry standard-speak—the same tone of the Unicode Standard Annex #15 — Unicode Normalization Forms. The Frequently Asked Questions / Normalization from Unicode.org is more readable, as is the NFC FAQ by Mark Davis—author of several Unicode algorithms and president of the Unicode Consortium at the time of this writing.

In 2016, the Museum of Modern Art (MoMA) in New York added to its collection The Original Emoji, the 176 emojis designed by Shigetaka Kurita in 1999 for NTT DOCOMO—the Japanese mobile carrier. Going further back in history, Emojipedia published Correcting the Record on the First Emoji Set, crediting Japan's SoftBank for the earliest known emoji set, deployed in cell phones in 1997. SoftBank's set is the source of 90 emojis now in Unicode, including U+1F4A9 (PILE OF POO). Matthew Rothenberg's emojitracker.com is a live dashboard showing counts of emoji usage on Twitter, updated in real time. As I write this, FACE WITH TEARS OF JOY (U+1F602) is the most popular emoji on Twitter, with more than 3,313,667,315 recorded occurrences.

SOAPBOX

Non-ASCII Names in Source Code: Should You Use Them?

Python 3 allows non-ASCII identifiers in source code:

```
>>> ação = 'PBR'  # ação = stock
>>> ε = 10**-6    # ε = epsilon
```

Some people dislike the idea. The most common argument to stick with ASCII identifiers is to make it easy for everyone to read and edit code. That argument misses the point: you want your source code to be readable and editable by its intended audience, and that may not be "everyone." If the code belongs to a multinational corporation or is open source and you want contributors from around the world, the identifiers should be in English, and then all you need is ASCII.

But if you are a teacher in Brazil, your students will find it easier to read code that uses Portuguese variable and function names, correctly spelled. And they will have no difficulty typing the cedillas and accented vowels on their localized keyboards.

Now that Python can parse Unicode names and UTF-8 is the default source encoding, I see no point in coding identifiers in Portuguese without accents, as we used to do in Python 2 out of necessity—unless you need the code to run on Python 2 also. If the names are in Portuguese, leaving out the accents won't make the code more readable to anyone.

This is my point of view as a Portuguese-speaking Brazilian, but I believe it applies across borders and cultures: choose the human language that makes the code easier to read by the team, then use the characters needed for correct spelling.

What Is "Plain Text"?

For anyone who deals with non-English text on a daily basis, "plain text" does not imply "ASCII." The Unicode Glossary defines *plain text* like this:

> *Computer-encoded text that consists only of a sequence of code points from a given standard, with no other formatting or structural information.*

That definition starts very well, but I don't agree with the part after the comma. HTML is a great example of a plain-text format that carries formatting and structural information. But it's still plain text because every byte in such a file is there to represent a text character, usually using UTF-8. There are no bytes with nontext meaning, as you can find in a *.png* or *.xls* document where most bytes represent packed binary values like RGB values and floating-point numbers. In plain text, numbers are represented as sequences of digit characters.

I am writing this book in a plain-text format called—ironically—AsciiDoc, which is part of the toolchain of O'Reilly's excellent Atlas book publishing platform. AsciiDoc source files are plain text, but they are UTF-8, not ASCII. Otherwise, writing this chapter would have been really painful. Despite the name, AsciiDoc is just great.

The world of Unicode is constantly expanding and, at the edges, tool support is not always there. Not all characters I wanted to show were available in the fonts used to render the book. That's why I had to use images instead of listings in several examples in this chapter. On the other hand, the Ubuntu and MacOS terminals display most Unicode text very well—including the Japanese characters for the word "mojibake": 文字化け.

How Are str Represented in RAM?

The official Python docs avoid the issue of how the code points of a `str` are stored in memory. It is really an implementation detail. In theory, it doesn't matter: whatever the internal representation, every `str` must be encoded to `bytes` on output.

In memory, Python 3 stores each `str` as a sequence of code points using a fixed number of bytes per code point, to allow efficient direct access to any character or slice.

Since Python 3.3, when creating a new `str` object, the interpreter checks the characters in it and chooses the most economic memory layout that is suitable for that particular `str`: if there are only characters in the `latin1` range, that `str` will use just one byte per code point. Otherwise, 2 or 4 bytes per code point may be used, depending on the `str`. This is a simplification; for the full details, look up PEP 393 — Flexible String Representation.

The flexible string representation is similar to the way the `int` type works in Python 3: if the integer fits in a machine word, it is stored in one machine word. Otherwise, the interpreter switches to a variable-length representation like that of the Python 2 `long` type. It is nice to see the spread of good ideas.

However, we can always count on Armin Ronacher to find problems in Python 3. He explained to me why that was not such as great idea in practice: it takes a single RAT (U+1F400) to inflate an otherwise all-ASCII text into a memory-hogging array using 4 bytes per character, when one 1 byte would suffice for each character except the RAT. In addition, because of all the ways Unicode characters combine, the ability to quickly retrieve an arbitrary character by position is overrated —and extracting arbitrary slices from Unicode text is naïve at best, and often wrong, producing mojibake. As emojis become more popular, these problems will only get worse.

---

1 Slide 12 of PyCon 2014 talk “Character Encoding and Unicode in Python” (slides, video).

2 Python 2.6 and 2.7 also had `bytes`, but it was just an alias to the `str` type.

3 Trivia: the ASCII “single quote” character that Python uses by default as the string delimiter is actually named APOSTROPHE in the Unicode standard. The real single quotes are asymmetric: left is U+2018 and right is U+2019

4 It did not work in Python 3.0 to 3.4, causing much pain to developers dealing with binary data. The reversal is documented in PEP 461 — Adding % formatting to bytes and bytearray.

5 I first saw the term “Unicode sandwich” in Ned Batchelder’s excellent “Pragmatic Unicode” talk at US PyCon 2012.

6 Source: Windows Command-Line: Unicode and UTF-8 Output Text Buffer.

7 The CIRCLED NUMBER FORTY TWO character is not rendering correctly in the PDF generated by O’Reilly’s toolchain as of July, 2021. Its pictograph is a black circular outline with the number 42 inside.

8 While researching this subject, I did not find a list of situations when Python 3 internally converts `bytes` to `str`. Python core developer Antoine Pitrou says on the `comp.python.devel` list that CPython internal functions that depend on such conversions “don’t get a lot of use in py3k.”

9 The Python 2 `sys.setdefaultencoding` function was misused and is no longer documented in Python 3. It was intended for use by the core developers when the internal default encoding of Python was still undecided. In the same `comp.python.devel` thread, Marc-André Lemburg states that the `sys.setdefaultencoding` must never be called by user code and the only values supported by CPython are `'ascii'` in Python 2 and `'utf-8'` in Python 3.

10 Curiously, the micro sign is considered a “compatibility character” but the ohm symbol is not. The end result is that NFC doesn’t touch the micro sign but changes the ohm symbol to capital omega, while NFKC and NFKD change both the ohm and the micro into Greek characters.

11 Diacritics affect sorting only in the rare case when they are the only difference between two words—in that case, the word with a diacritic is sorted after the plain word.

12 Again, I could not find a solution, but did find other people reporting the same problem. Alex Martelli, one of the tech reviewers, had no problem using `setlocale` and `locale.strxfrm` on his Mac with MacOS 10.9. In summary: your mileage may vary.

13 That’s an image—not a code listing—because emojis are not well supported by O’Reilly’s digital publishing toolchain as I write this.

14 Although it was not better than `re` at identifying digits in this particular sample.

Chapter 5. Data Class Builders

> **A NOTE FOR EARLY RELEASE READERS**
>
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>
> This will be the 5th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Data classes are like children. They are okay as a starting point, but to participate as a grownup object, they need to take some responsibility.*[1]
>
> —Martin Fowler and Kent Beck

Python offers a few ways to build a simple class that is just a collection of fields, with little or no extra functionality. That pattern is known as a "data class"—and `dataclasses` is one of the packages that supports this pattern. This chapter covers three different class builders that you may use as shortcuts to write data classes:

- `collections.namedtuple`: the simplest way—available since Python 2.6;
- `typing.NamedTuple`: an alternative that requires type hints on the fields—since Python 3.5, with `class` syntax added in 3.6;
- `@dataclasses.dataclass`: a class decorator that allows more customization than previous alternatives, adding lots of

options and potential complexity—since Python 3.7.

After covering those class builders, we will discuss why *Data Class* is also the name of a code smell: a coding pattern that may be a symptom of poor object-oriented design.

> **NOTE**
>
> `typing.TypedDict` may seem like another data class builder. It uses similar syntax and is described right after `typing.NamedTuple` in the `typing` module documentation for Python 3.9.
>
> However, `TypedDict` does not build concrete classes that you can instantiate. It's just syntax to write type hints for function parameters and variables that will accept mapping values used as records, with keys as field names. We'll see them in Chapter 15, "TypedDict".

What's new in this chapter

This chapter is new in *Fluent Python Second Edition*. The section "Classic Named Tuples" appeared in chapter 2 of the *First Edition*, but the rest of the chapter is completely new.

We begin with a high level overview of the three class builders.

Overview of data class builders

Consider a simple class to represent a geographic coordinate pair:

Example 5-1. `class/coordinates.py`

```
class Coordinate:

    def __init__(self, lat, lon):
        self.lat = lat
        self.lon = lon
```

That `Coordinate` class does the job of holding latitude and longitude attributes. Writing the `__init__` boilerplate becomes old real fast, especially if your class has more than a couple of attributes: each of them is mentioned three times! And that boilerplate doesn't buy us basic features we'd expect from a Python object:

```
>>> from coordinates import Coordinate
>>> moscow = Coordinate(55.76, 37.62)
>>> moscow
<coordinates.Coordinate object at 0x107142f10>  ❶
>>> location = Coordinate(55.76, 37.62)
>>> location == moscow  ❷
False
>>> (location.lat, location.lon) == (moscow.lat, moscow.lon)  ❸
True
```

❶ `__repr__` inherited from `object` is not very helpful.

❷ Meaningless `==`; the `__eq__` method inherited from `object` compares object ids.

❸ Comparing two coordinates requires explicit comparison of each attribute.

The data class builders covered in this chapter provide the necessary `__init__`, `__repr__`, and `__eq__` methods automatically, as well as other useful features.

> **NOTE**
>
> None of the class builders discussed here depend on inheritance to do their work. Both `collections.namedtuple` and `typing.NamedTuple` build classes that are `tuple` subclasses. `@dataclass` is a class decorator that does not affect the class hierarchy in any way. Each of them uses different metaprogramming techniques to inject methods and data attributes into the class under construction.

Here is a `Coordinate` class built with `namedtuple`—a factory function that builds a subclass of `tuple` with the name and fields you specify:

```
>>> from collections import namedtuple
>>> Coordinate = namedtuple('Coordinate', 'lat lon')
>>> issubclass(Coordinate, tuple)
True
>>> moscow = Coordinate(55.756, 37.617)
>>> moscow
Coordinate(lat=55.756, lon=37.617)  ❶
>>> moscow == Coordinate(lat=55.756, lon=37.617)  ❷
True
```

❶ Useful `__repr__`.

❷ Meaningful `__eq__`.

The newer `typing.NamedTuple` provides the same functionality, adding a type annotation to each field:

```
>>> import typing
>>> Coordinate = typing.NamedTuple('Coordinate', [('lat', float),
('lon', float)])
>>> issubclass(Coordinate, tuple)
True
>>> typing.get_type_hints(Coordinate)
{'lat': <class 'float'>, 'lon': <class 'float'>}
```

> **TIP**
>
> A typed named tuple can also be constructed with the fields given as keyword arguments, like this:
>
> ```
> Coordinate = typing.NamedTuple('Coordinate', lat=float,
> lon=float)
> ```
>
> This is more readable, and also lets you provide the mapping of fields and types as `**fields_and_types`.

Since Python 3.6, `typing.NamedTuple` can also be used in a `class` statement, with type annotations written as described in PEP 526—Syntax for Variable Annotations. This is much more readable, and makes it easy to override methods or add new ones. Example 5-2 is the same `Coordinate` class, with a pair of `float` attributes and a custom `__str__` to display a coordinate formatted like 55.8°N, 37.6°E:

Example 5-2. `typing_namedtuple/coordinates.py`

```
from typing import NamedTuple

class Coordinate(NamedTuple):
    lat: float
    lon: float

    def __str__(self):
        ns = 'N' if self.lat >= 0 else 'S'
        we = 'E' if self.lon >= 0 else 'W'
        return f'{abs(self.lat):.1f}°{ns}, {abs(self.lon):.1f}°
{we}'
```

WARNING

Although `NamedTuple` appears in the `class` statement as a superclass, it's actually not. `typing.NamedTuple` uses the advanced functionality of a metaclass[2] to customize the creation of the user's class. Check this out:

```
>>> issubclass(Coordinate, typing.NamedTuple)
False
>>> issubclass(Coordinate, tuple)
True
```

In the `__init__` method generated by `typing.NamedTuple`, the fields appear as parameters in the same order they appear in the `class` statement.

Like `typing.NamedTuple`, the `dataclass` decorator supports PEP 526 syntax to declare instance attributes. The decorator reads the variable annotations and automatically generates methods for your class. For comparison, check out the equivalent `Coordinate` class written with the help of the `dataclass` decorator:

Example 5-3. `dataclass/coordinates.py`

```
from dataclasses import dataclass

@dataclass(frozen=True)
class Coordinate:
    lat: float
    lon: float

    def __str__(self):
        ns = 'N' if self.lat >= 0 else 'S'
        we = 'E' if self.lon >= 0 else 'W'
        return f'{abs(self.lat):.1f}°{ns}, {abs(self.lon):.1f}°
{we}'
```

Note that the body of the classes in Example 5-2 and Example 5-3 are identical—the difference is in the `class` statement itself. The `@dataclass` decorator does not depend on inheritance or a metaclass, so it should not interfere with your own use of these mechanisms.[3] The `Coordinate` class in Example 5-3 is a subclass of `object`.

Main features

The different data class builders have a lot in common. Table 5-1 summarizes.

Table 5-1. Selected features compared a

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	namedtuple	NamedTuple	dataclass
mutable instances	NO	NO	YES
class statement syntax	NO	YES	YES
construct dict	x._asdict()	x._asdict()	dataclasses.asdict(x)
get field names	x._fields	x._fields	[f.name for f in dataclasses.fields(x)]
get defaults	x._field_defaults	x._field_defaults	[f.default for f in dataclasses.fields(x)]
get field types	N/A	x.__annotations__	x.__annotations__
new instance with changes	x._replace(…)	x._replace(…)	dataclasses.replace(x, …)
new class at runtime	namedtuple(…)	NamedTuple(…)	dataclasses.make_dataclass(…)

WARNING

The classes built by `typing.NamedTuple` and `@dataclass` have an `__annotations__` attribute holding the type hints for the fields. However, the best practice is not to read from `__annotations__` directly, but use `typing.get_type_hints(my_data_class)` to obtain that information. That's because `get_type_hints` provides extra services, like resolving forward references in type hints. We get back to this issue much later in the book, in "Problems with Annotations at Runtime".

Now let's discuss those main features.

Mutable instances

A key difference between these class builders is that `collections.namedtuple` and `typing.NamedTuple` build `tuple` subclasses, therefore the instances are immutable. By default, `@dataclass` produces mutable classes. But the decorator accepts a keyword argument `frozen`—shown in Example 5-3. When `frozen=True`, the class will raise an exception if you try to assign a value to a field after the instance is initialized.

Class statement syntax

Only `typing.NamedTuple` and `dataclass` support the regular `class` statement syntax, making it easier to add methods and docstrings to the class you are creating.

Construct dict

Both named tuple variants provide an instance method (`._asdict`) to construct a `dict` object from the fields in a data class instance. The `dataclasses` module provides a function to do it: `dataclasses.asdict`.

Get field names and default values

All three class builders let you get the field names and default values that may be configured for them. In named tuple classes, that metadata is in the `._fields` and `._fields_defaults` class attributes. You can get the same metadata from a `dataclass` decorated class using the `fields` function from the `dataclasses` module. It returns a tuple of `Field` objects which have several attributes, including `name` and `default`.

Get field types

Classes defined with the help of `typing.NamedTuple` and `@dataclass` have a mapping of field names to type annotations the `__annotations__` class attribute. As mentioned, use the `typing.get_type_hints` function instead of readint `__annotations__` directly.

New instance with changes

Given a named tuple instance `x`, the call `x._replace(**kwargs)` returns a new instance with some attribute values replaced according to the keyword arguments given. The `dataclasses.replace(x, **kwargs)` module-level function does the same for an instance of a `dataclass` decorated class.

New class at runtime

Although the `class` statement syntax is more readable, it is hard-coded. A framework may need to build data classes on the fly, at runtime. For that, you can use the default function call syntax of `collections.namedtuple`, which is likewise supported by `typing.NamedTuple`. The `dataclasses` module provides a `make_dataclass` function for the same purpose.

After this overview of the main features of the data class builders, let's focus on each of them in turn, starting with the simplest.

Classic Named Tuples

The `collections.namedtuple` function is a factory that builds subclasses of `tuple` enhanced with field names, a class name, and an informative `__repr__`. Classes built with `namedtuple` can be used anywhere where `tuples` are needed, and in fact many functions of the Python standard library that used to return tuples now return named tuples for convenience, without affecting user's code at all.

> **TIP**
>
> Each instance of a class built by `namedtuple` takes exactly the same amount of memory as a tuple because the field names are stored in the class.

Example 5-4 shows how we could define a named tuple to hold information about a city.

Example 5-4. Defining and using a named tuple type

```
>>> from collections import namedtuple
>>> City = namedtuple('City', 'name country population
coordinates')  ❶
>>> tokyo = City('Tokyo', 'JP', 36.933, (35.689722, 139.691667))  ❷
>>> tokyo
City(name='Tokyo', country='JP', population=36.933, coordinates=
(35.689722,
139.691667))
>>> tokyo.population  ❸
36.933
>>> tokyo.coordinates
(35.689722, 139.691667)
>>> tokyo[1]
'JP'
```

❶ Two parameters are required to create a named tuple: a class name and a list of field names, which can be given as an iterable of strings or as a single space-delimited string.

❷ Field values must be passed as separate positional arguments to the constructor (in contrast, the `tuple` constructor takes a single iterable).

❸ You can access the fields by name or position.

As a `tuple` subclass, `City` inherits useful methods such as `__eq__` and the special methods for comparison operators—including `__lt__` which allows sorting lists of `City` instances.

A named tuple offers a few attributes and methods in addition to those inherited from `tuple`. Example 5-5 shows the most useful: the `_fields` class attribute, the class method `_make(iterable)`, and the `_asdict()` instance method.

Example 5-5. Named tuple attributes and methods (continued from the previous example)

```
>>> City._fields  ❶
('name', 'country', 'population', 'location')
>>> Coordinate = namedtuple('Coordinate', 'lat lon')
>>> delhi_data = ('Delhi NCR', 'IN', 21.935, Coordinate(28.613889,
77.208889))
>>> delhi = City._make(delhi_data)  ❷
>>> delhi._asdict()  ❸
{'name': 'Delhi NCR', 'country': 'IN', 'population': 21.935,
'location': Coordinate(lat=28.613889, lon=77.208889)}
>>> import json
>>> json.dumps(delhi._asdict())  ❹
'{"name": "Delhi NCR", "country": "IN", "population": 21.935,
"location": [28.613889, 77.208889]}'
```

❶ `._fields` is a tuple with the field names of the class.

❷ `._make()` builds `City` from an iterable; `City(*delhi_data)` would do the same.

❸ `._asdict()` returns a `dict` built from the named tuple instance.

❹ `._asdict()` is useful to serialize the data in JSON format, for example.

> **WARNING**
>
> The `_asdict` method returned an `OrderedDict` until Python 3.7. Since Python 3.8, it returns a simple `dict`—which is OK now that we can rely on key insertion order. If you must have an `OrderedDict`, the `_asdict` documentation recommends building one from the result: `OrderedDict(x._asdict())`.

Since Python 3.7, `namedtuple` accepts the `defaults` keyword-only argument providing an iterable of N default values for each of the N rightmost fields of the class. Example 5-6 shows how to define a `Coordinate` named tuple with a default value for a `reference` field:

Example 5-6. Named tuple attributes and methods, continued from Example 5-5.

```
>>> Coordinate = namedtuple('Coordinate', 'lat lon reference',
defaults=['WGS84'])
>>> Coordinate(0, 0)
Coordinate(lat=0, lon=0, reference='WGS84')
>>> Coordinate._field_defaults
{'reference': 'WGS84'}
```

In “Class statement syntax” I mentioned it’s easier to code methods with the class syntax supported by `typing.NamedTuple` and `@dataclass`. You can also add methods to a `namedtuple`, but it’s a hack. Skip the following box if you’re not interested in hacks.

HACKING A NAMEDTUPLE TO INJECT A METHOD

Recall how we built the `Card` class in Example 1-1 in Chapter 1:

```
Card = collections.namedtuple('Card', ['rank', 'suit'])
```

Later in Chapter 1 I wrote a `spades_high` function for sorting. It would be nice if that logic was encapsulated in a method of `Card`, but adding `spades_high` to `Card` without the benefit of a `class` statement requires a quick hack: define the function and then assign it to a class attribute. Example 5-7 shows how.

Example 5-7. `frenchdeck.doctest`: Adding a class attribute and a method to `Card`, the `namedtuple` from "A Pythonic Card Deck"

```
>>> Card.suit_values = dict(spades=3, hearts=2, diamonds=1,
clubs=0)  ❶
>>> def spades_high(card):
❷
...     rank_value = FrenchDeck.ranks.index(card.rank)
...     suit_value = card.suit_values[card.suit]
...     return rank_value * len(card.suit_values) + suit_value
...
>>> Card.overall_rank = spades_high
❸
>>> lowest_card = Card('2', 'clubs')
>>> highest_card = Card('A', 'spades')
>>> lowest_card.overall_rank()
❹
0
>>> highest_card.overall_rank()
51
```

❶ Attach a class attribute with values for each suit.

❷ `spades_high` will become a method; the first argument doesn't need to be named `self`. Anyway, it will get the receiver when called as a method.

❸

Attach the function to the `Cards` class as a method named `overall_rank`.

❹ It works!

For readability and future maintenance, it's much better to code methods inside a `class` statement. But it's good to know this hack is possible, because it may come in handy.[4]

This was a small detour to showcase the power of a dynamic language.

Now let's check out the `typing.NamedTuple` variation.

Typed Named Tuples

The `Coordinate` class with a default field from Example 5-6 can be written like this using `typing.NamedTuple`:

Example 5-8. `typing_namedtuple/coordinates2.py`

```
from typing import NamedTuple

class Coordinate(NamedTuple):
    lat: float                ❶
    lon: float
    reference: str = 'WGS84'  ❷
```

❶ Every instance field must be annotated with a type.

❷ The `reference` instance field is annotated with a type and a default value

Classes built by `typing.NamedTuple` don't have any methods beyond those that `collections.namedtuple` also generates—and those that are inherited from `tuple`. The only difference is the presence of the `__annotations__` class attribute—which Python completely ignores at runtime.

Given that the main feature of `typing.NamedTuple` are the type annotations, we'll take a brief look at them before resuming our exploration of data class builders.

Type hints 101

Type hints—a.k.a. type annotations—are ways to declare the expected type of function arguments, return values, variables, and attributes.

> **NOTE**
>
> This is a very brief introduction to type hints, just enough to make sense of the syntax and meaning of the annotations used `typing.NamedTuple` and `@dataclass` declarations. We will cover type hints for function signatures in Chapter 8 and more advanced annotations in Chapter 15. Here we'll mostly see hints with simple built-in types, such as `str`, `int`, and `float`, which are probably the most common types used to annotate fields of data classes.

The first thing you need to know about type hints is that they are not enforced at all by the Python bytecode compiler and interpreter.

No runtime effect

A good way to understand Python type hints is to think of them as "documentation that can be verified by IDEs and type checkers."

That's because type hints have no impact on the runtime behavior of Python programs. Check this out:

Example 5-9. Python does not enforce type hints at runtime.

```
>>> import typing
>>> class Coordinate(typing.NamedTuple):
...     lat: float
...     lon: float
...
>>> trash = Coordinate('Ni!', None)
>>> print(trash)
Coordinate(lat='Ni!', lon=None)    ❶
```

❶ I told you: no type checking at runtime!

If you type the code of Example 5-9 in a Python module, it will run and display a meaningless `Coordinate`, with no error or warning:

```
$ python3 nocheck_demo.py
Coordinate(lat='Ni!', lon=None)
```

The type hints are intended primarily to support third-party type checkers, like Mypy or the PyCharm IDE built-in type checker. These are static analysis tools: they check Python source code “at rest”, not running code.

To see the effect of type hints, you must run one of those tools on your code—like a linter. For instance, here is what Mypy has to say about the previous example:

```
$ mypy nocheck_demo.py
nocheck_demo.py:8: error: Argument 1 to "Coordinate" has
incompatible type "str"; expected "float"
nocheck_demo.py:8: error: Argument 2 to "Coordinate" has
incompatible type "None"; expected "float"
```

As you can see, given the definition of `Coordinate`, Mypy knows that both arguments to create an instance must be of type `float`, but the assignment to `trash` uses a `str` and `None`.[5]

Now let’s talk about the syntax and meaning of type hints.

Variable annotation syntax

Both `typing.NamedTuple` and `@dataclass` use the syntax of variable annotations defined in PEP 526. This is a quick introduction to that syntax in the context defining attributes in `class` statements.

The basic syntax of variable annotation is:

```
var_name: some_type
```

Section Acceptable type hints in PEP 484 explains what are acceptable types, but in the context of defining a data class, these types are more likely to be useful:

- a concrete class, for example `str` or `FrenchDeck`;
- a parameterized collection type, like `list[int]`, `tuple[str, float]` etc.
- `typing.Optional`, for example `Optional[str]`—to declare a field that can be a `str` or `None`.

You can also initialize the variable with a value. In a `typing.NamedTuple` or `@dataclass` declaration, that value will become the default for that attribute, if the corresponding argument is omitted in the constructor call.

```
var_name: some_type = a_value
```

The meaning of variable annotations

We saw in "No runtime effect" that type hints have no effect at runtime. But at import time—when a module is loaded—Python does read them to build the `__annotations__` dictionary that `typing.NamedTuple` and `@dataclass` then use to enhance the class.

We'll start this exploration with a simple class, so that we can later see what extra features are added by `typing.NamedTuple` and `@dataclass`.

Example 5-10. meaning/demo_plain.py: a plain class with type hints

```
class DemoPlainClass:
    a: int          ❶
    b: float = 1.1  ❷
    c = 'spam'      ❸
```

❶ `a` becomes an entry in `__annotations__`, but is otherwise discarded: no attribute named `a` is created in the class.

❷ `b` is saved as an annotation, and also becomes a class attribute with value `1.1`.

❸ `c` is just a plain old class attribute, not an annotation.

We can verify that in the console, first reading the `__annotations__` of the `DemoPlainClass`, then trying to get its attributes named `a`, `b`, and `c`:

```
>>> from demo_plain import DemoPlainClass
>>> DemoPlainClass.__annotations__
{'a': <class 'int'>, 'b': <class 'float'>}
>>> DemoPlainClass.a
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: type object 'DemoPlainClass' has no attribute 'a'
>>> DemoPlainClass.b
1.1
>>> DemoPlainClass.c
'spam'
```

Note that the `__annotations__` special attribute is created by the interpreter to record the type hints that appear in the source code—even in a plain class.

The `a` survives only as an annotation. It doesn't become a class attribute because no value is bound to it.[6] The `b` and `c` are stored as class attributes because they are bound to values.

None of those three attributes will be in a new instance of `DemoPlainClass`. If you create an object `o = DemoPlainClass()`, `o.a` will raise `AttributeError`, while `o.b` and `o.c` will retrieve the class attributes with values `1.1` and `'spam'`—that's just normal Python object behavior.

Inspecting a `typing.NamedTuple`

Now let's examine a class built with `typing.NamedTuple`, using the same attributes and annotations as `DemoPlainClass` from Example 5-

10.

Example 5-11. meaning/demo_nt.py: a class built with `typing.NamedTuple`.

```
import typing

class DemoNTClass(typing.NamedTuple):
    a: int           ❶
    b: float = 1.1   ❷
    c = 'spam'       ❸
```

❶ `a` becomes an annotation and also an instance attribute.

❷ `b` is another annotation, and also becomes an instance attribute with default value `1.1`.

❸ `c` is just a plain old class attribute; no annotation will refer to it.

Inspecting the `DemoNTClass`, we get:

```
>>> from demo_nt import DemoNTClass
>>> DemoNTClass.__annotations__
{'a': <class 'int'>, 'b': <class 'float'>}
>>> DemoNTClass.a
<_collections._tuplegetter object at 0x101f0f940>
>>> DemoNTClass.b
<_collections._tuplegetter object at 0x101f0f8b0>
>>> DemoNTClass.c
'spam'
```

Here we have the same annotations for `a` and `b` as we saw in Example 5-10. But `typing.NamedTuple` creates `a` and `b` class attributes. The `c` attribute is just a plain class attribute with the value `'spam'`.

The `a` and `b` class attributes are *descriptors*—an advanced feature covered in Chapter 24. For now, think of them as similar to property getters: methods that don’t require the explicit call operator `()` to retrieve an instance attribute. In practice, this means `a` and `b` will work as read-only instance attributes—which makes sense when we recall that `DemoNTClass` instances are just fancy tuples, and tuples are immutable.

`DemoNTClass` also gets a custom docstring:

```
>>> DemoNTClass.__doc__
'DemoNTClass(a, b)'
```

Let's inspect an instance of `DemoNTClass`:

```
>>> nt = DemoNTClass(8)
>>> nt.a
8
>>> nt.b
1.1
>>> nt.c
'spam'
```

To construct `nt`, we need to give at least the `a` argument to `DemoNTClass`. The constructor also takes a `b` argument, but it has a default value of `1.1`, so it's optional. The `nt` object has the `a` and `b` attributes as expected; it doesn't have a `c` attribute, but Python retrieves it from the class, as usual.

If you try to assign values to `nt.a`, `nt.b`, `nt.c` or even `nt.z` you'll get `AttributeError` exceptions, with subtly different error messages. Try that and reflect on the messages.

Inspecting a class decorated with `dataclass`

Now we'll examine Example 5-12:

Example 5-12. meaning/demo_dc.py: a class decorated with `@dataclass`

```
from dataclasses import dataclass

@dataclass
class DemoDataClass:
    a: int           ❶
    b: float = 1.1   ❷
    c = 'spam'       ❸
```

❶ `a` becomes an annotation and also an instance attribute controlled by a descriptor.

❷ `b` is another annotation, and also becomes an instance attribute with a descriptor and a default value `1.1`.

❸ `c` is just a plain old class attribute; no annotation will refer to it.

Now let's check out `__annotations__`, `__doc__`, and the `a`, `b`, `c` attributes on `DemoDataClass`:

```
>>> from demo_dc import DemoDataClass
>>> DemoDataClass.__annotations__
{'a': <class 'int'>, 'b': <class 'float'>}
>>> DemoDataClass.__doc__
'DemoDataClass(a: int, b: float = 1.1)'
>>> DemoDataClass.a
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: type object 'DemoDataClass' has no attribute 'a'
>>> DemoDataClass.b
1.1
>>> DemoDataClass.c
'spam'
```

The `__annotations__` and `__doc__` are not surprising. However, there is no attribute named `a` in `DemoDataClass`—in contrast with `DemoNTClass` from Example 5-11, which has a descriptor to get `a` from the instances as read-only attributes (that mysterious `<_collections._tuplegetter>`). That's because the `a` attribute will only exist in instances of `DemoDataClass`. It will be a public attribute that we can get and set, unless the class is frozen. But `b` and `c` exist as class attributes, with `b` holding the default value for the `b` instance attribute, while `c` is just a class attribute that will not be bound to the instances.

Now let's see how a `DemoDataClass` instance looks like:

```
>>> dc = DemoDataClass(9)
>>> dc.a
9
>>> dc.b
1.1
>>> dc.c
'spam'
```

Again, `a` and `b` are instance attributes, and `c` is a class attribute we get via the instance.

As mentioned, `DemoDataClass` instances are mutable—and no type checking is done at runtime:

```
>>> dc.a = 10
>>> dc.b = 'oops'
```

We can do even sillier assignments:

```
>>> dc.c = 'whatever'
>>> dc.z = 'secret stash'
```

Now the `dc` instance has a `c` attribute—but that does not change the `c` class attribute. And we can add a new `z` attribute. This is normal Python behavior: regular instances can have their own attributes that don't appear in the class.[7]

More about @dataclass

We've only seen simple examples of `@dataclass` use so far. The decorator accepts several keyword arguments. This is its signature:

```
@dataclass(*, init=True, repr=True, eq=True, order=False,
              unsafe_hash=False, frozen=False)
```

The `*` in the first position means the remaining parameters are keyword-only. Table 5-2 describes them.

Table 5-2. Keyword parameters accepte

d

by the `@dataclass` decorator

option	meaning	default	notes
init	generate `__init__`	True	Ignored if `__init__` is implemented by user.
repr	generate `__repr__`	True	Ignored if `__repr__` is implemented by user.

eq	generate `__eq__`	True	Ignored if `__eq__` is implemented by user.
order	generate `__lt__`, `__le__`, `__gt__`, `__ge__`	False	If `True`, raises exceptions if `eq=False`, or if any of the comparison methods that would be generated are defined or inherited.
unsafe_hash	generate `__hash__`	False	Complex semantics and several caveats—see: dataclass documentation.
frozen	make instances “immutable”	False	instances will be reasonably safe from accidental change, but not really immutable.[a]

a `@dataclass` emulates immutability by generating `__setattr__` and `__delattr__` which raise `dataclass.FrozenInstanceError`—a subclass of `AttributeError`—when the user attempts to set or delete a field.

The defaults are really the most useful settings for common use cases. The options you are more likely to change from the defaults are:

- `frozen=True`: to protect against accidental changes to the class instances;
- `order=True`: to allow sorting of instances of the data class.

Given the dynamic nature of Python objects, it’s not too hard for a nosy programmer to go around the protection afforded by `frozen=True`. But the necessary tricks should be easy to spot on a code review.

If the `eq` and `frozen` arguments are both `True`, `@dataclass` produces a suitable `__hash__` method, so the instances will be hashable. The generated `__hash__` will use data from all fields that are not individually excluded using a field option we’ll see in “Field options”. If `frozen=False` (the default), `@dataclass` will set `__hash__` to `None`, signalling that the instances are unhashable, therefore overriding `__hash__` from any superclass.

PEP 557—Data Classes has this to say about `unsafe_hash`:

> *Although not recommended, you can force Data Classes to create a `__hash__` method with `unsafe_hash=True`. This might be the case if your class is logically immutable but can nonetheless be mutated. This is a specialized use case and should be considered carefully.*

I will leave `unsafe_hash` at that. If you feel you must use that option, check the `dataclasses.dataclass` documentation.

Further customization of the generated data class can be done at a field level.

Field options

We've already seen the most basic field option: providing or not a default value with the type hint. The instance fields you declare will become parameters in the generated `__init__`. Python does not allow parameters without defaults after parameters with defaults, therefore after you declare a field with a default value, all remaining fields must also have default values.

Mutable default values are a common source of bugs for beginning Python developers. In function definitions, a mutable default value is easily corrupted when one invocation of the function mutates the default, changing the behavior of further invocations—an issue we'll explore in "Mutable Types as Parameter Defaults: Bad Idea" (Chapter 6). Class attributes are often used as default attribute values for instances, including in data classes. And `@dataclass` uses the default values in the type hints to generate parameters with defaults for `__init__`. To prevent bugs, `@dataclass` rejects the class definition in Example 5-13.

Example 5-13. `dataclass/club_wrong.py`: this class raises `ValueError`

```
@dataclass
class ClubMember:
    name: str
    guests: list = []
```

If you load the module with that `ClubMember` class, this is what you get:

```
$ python3 club_wrong.py
Traceback (most recent call last):
  File "club_wrong.py", line 4, in <module>
    class ClubMember:
  ...several lines ommitted...
ValueError: mutable default <class 'list'> for field guests is
not allowed:
use default_factory
```

The `ValueError` message explains the problem and suggests a solution: use `default_factory`. This is how to correct `ClubMember`:

Example 5-14. `dataclass/club.py`: this `ClubMember` definition works.

```python
from dataclasses import dataclass, field


@dataclass
class ClubMember:
    name: str
    guests: list = field(default_factory=list)
```

In the `guests` field of Example 5-14, instead of a literal list, the default value is set by calling the `dataclasses.field` function with `default_factory=list`.

The `default_factory` parameter lets you provide a function, class, or any other callable, which will be invoked with zero arguments to build a default value each time an instance of the data class is created. This way, each instance of `ClubMember` will have its own `list`—instead of all instances sharing the same `list` from the class, which is rarely what we want and is often a bug.

WARNING

It’s good that `@dataclass` rejects class definitions with a `list` default value in a field. However, be aware that it is a partial solution that only applies to `list`, `dict` and `set`. Other mutable values used as defaults will not be flagged by `@dataclass`. It’s up to you to understand the problem and remember to use a default factory to set mutable default values.

If you browse the `dataclasses` module documentation, you’ll see a `list` field defined with a novel syntax, as in Example 5-15.

Example 5-15. `dataclass/club_generic.py`: this `ClubMember` definition is more precise

```
from dataclasses import dataclass, field

@dataclass
class ClubMember:
    name: str
    guests: list[str] = field(default_factory=list)  ❶
```

❶ `list[str]` means “a list of str”.

The new syntax `list[str]` is a parameterized generic type: since Python 3.9, the `list` built-in accepts that bracket notation to specify the type of the list items.

WARNING

Prior to Python 3.9, the built-in collections did not support generic type notation. As a temporary workaround, there are corresponding collection types in the `typing` module. If you need a parameterized `list` type hint in Python 3.8 or earlier, you must import the `List` type from `typing` and use it: `List[str]`. For more about this issue, see “Legacy Support and Deprecated Collection Types”.

We’ll cover generics in Chapter 8. For now, note that both Example 5-14 and Example 5-15 are correct, and the Mypy type checker does not complain about either of those class definitions.

The difference is that `guests: list` means that `guests` can be a `list` of objects of any kind, while `guests: list[str]` says that `guests` must be a `list` in which every item is a `str`. This will allow the type checker to find (some) bugs in code that puts invalid items in the list, or that read items from it.

The `default_factory` is likely to be the most common option of the `field` function, but there are several others, listed in Table 5-3.

Table 5-3. Keyword arguments accepted

by the `field` *function*

option	meaning	default
default	default value for field	_MISSING_TYPE [a]
default_factory	0-parameter function used to produce a default	_MISSING_TYPE
init	include field in parameters to `__init__`	True
repr	include field in `__repr__`	True
compare	use field in comparison methods `__eq__`, `__lt__` etc.	True
hash	include field in `__hash__` calculation	None[b]
metadata	mapping with user-defined data; ignored by the `@dataclass`	None

a `dataclass._MISSING_TYPE` is a sentinel value indicating the option was not provided. It exists so we can set `None` as an actual default value, a common use case.

b The option `hash=None` means the field will be used in `__hash__` only if `compare=True`.

The `default` option exists because the `field` call takes the place of the default value in the field annotation. If you want to create an `athlete` field with default value of `False`, and also omit that field from the `__repr__` method, you'd write this:

```
@dataclass
class ClubMember:
    name: str
    guests: list = field(default_factory=list)
    athlete: bool = field(default=False, repr=False)
```

Post-init processing

The `__init__` method generated by `@dataclass` only takes the arguments passed and assigns them—or their default values, if missing—to the instance attributes that are instance fields. But you may need to do more than that to initialize the instance. If that's the case, you can provide a `__post_init__` method. When that method exists, `@dataclass` will add code to the generated `__init__` to call `__post_init__` as the last step.

Common use cases for `__post_init__` are validation and computing field values based on other fields. We'll study a simple example that uses `__post_init__` for both of these reasons.

First, let's look at the expected behavior of a `ClubMember` subclass named `HackerClubMember`, as described by doctests in Example 5-16.

Example 5-16. `dataclass/hackerclub.py`: doctests for `HackerClubMember`

```
"""
``HackerClubMember`` objects accept an optional ``handle``
```

```
argument::

    >>> anna = HackerClubMember('Anna Ravenscroft',
handle='AnnaRaven')
    >>> anna
    HackerClubMember(name='Anna Ravenscroft', guests=[],
handle='AnnaRaven')

If ``handle`` is ommitted, it's set to the first part of the
member's name::

    >>> leo = HackerClubMember('Leo Rochael')
    >>> leo
    HackerClubMember(name='Leo Rochael', guests=[], handle='Leo')

Members must have a unique handle. The following ``leo2`` will not
be created,
because its ``handle`` would be 'Leo', which was taken by ``leo``::

    >>> leo2 = HackerClubMember('Leo DaVinci')
    Traceback (most recent call last):
      ...
    ValueError: handle 'Leo' already exists.

To fix, ``leo2`` must be created with an explicit ``handle``::

    >>> leo2 = HackerClubMember('Leo DaVinci', handle='Neo')
    >>> leo2
    HackerClubMember(name='Leo DaVinci', guests=[], handle='Neo')
"""
```

Note that we must provide `handle` as a keyword argument, because `HackerClubMember` inherits `name` and `guests` from `ClubMember`, and adds the `handle` field. The generated docstring for `HackerClubMember` shows the order of the fields in the constructor call:

```
>>> HackerClubMember.__doc__
"HackerClubMember(name: str, guests: list = <factory>, handle:
str = '')"
```

Here, `<factory>` is a short way of saying that some callable will produce the default value for `guests` (in our case, the factory is the `list` class).

The point is: to provide a `handle` but no `guests`, we must pass `handle` as a keyword argument.

The Inheritance section of the `dataclasses` module documentation explains how the order of the fields is computed when there are several levels of inheritance.

> **NOTE**
>
> In Chapter 14 we'll talk about misusing inheritance, particularly when the superclasses are not abstract. Creating a hierarchy of data classes is usually a bad idea, but it served us well here to make Example 5-17 shorter, focusing on the `handle` field declaration and `__post_init__` validation.

Example 5-17 is the implementation:

Example 5-17. `dataclass/hackerclub.py`: code for `HackerClubMember`.

```
from dataclasses import dataclass
from club import ClubMember

@dataclass
class HackerClubMember(ClubMember):                         ❶
    all_handles = set()                                     ❷
    handle: str = ''                                        ❸

    def __post_init__(self):
        cls = self.__class__                                ❹
        if self.handle == '':                               ❺
            self.handle = self.name.split()[0]
        if self.handle in cls.all_handles:                  ❻
            msg = f'handle {self.handle!r} already exists.'
            raise ValueError(msg)
        cls.all_handles.add(self.handle)                    ❼
```

❶ `HackerClubMember` extends `ClubMember`.

❷ `all_handles` is a class attribute.

❸

`handle` is an instance field of type `str` with empty string as its default value; this makes it optional.

❹ Get the class of the instance.

❺ If `self.handle` is the empty string, set it to the first part of `name`.

❻ If `self.handle` is in `cls.all_handles`, raise `ValueError`.

❼ Add the new `handle` to `cls.all_handles`.

Example 5-17 works as intended, but is not satisfactory to a static type checker. Next, we'll see why, and how to fix it.

Typed class attributes

If we typecheck Example 5-17 with Mypy, we are reprimanded:

```
$ mypy hackerclub.py
hackerclub.py:37: error: Need type annotation for "all_handles"
(hint: "all_handles: Set[<type>] = ...")
Found 1 error in 1 file (checked 1 source file)
```

Unfortunately, the hint provided by Mypy (version 0.910 as I review this) is not helpful in the context of `@dataclass` usage. First, it suggests using `Set`, but I am using Python 3.9 so I can use `set`—and avoid importing `Set` from `typing`. More importantly, if we add a type hint like `set[…]` to `all_handles`, `@dataclass` will find that annotation and make `all_handles` an instance field. We saw this happening in "Inspecting a class decorated with `dataclass`".

The workaround defined in PEP 526—Syntax for Variable Annotations is ugly. To code a class variable with a type hint`, we need to use a pseudo-type named `typing.ClassVar`, which leverages the generics `[]` notation to set the type of the variable and also declare it a class attribute.

To make the type checker and `@dataclass` happy, this is how we are supposed to declare `all_handles` in Example 5-17:

```
all_handles: ClassVar[set[str]] = set()
```

That type hint is saying:

> *`all_handles` is a class attribute of type `set`-of-`str`, with an empty `set` as its default value.*

To code that annotation, we must import `ClassVar` from the `typing` module.

The `@dataclass` decorator doesn't care about the types in the annotations, except in two cases, and this is one of them: if the type is `ClassVar`, an instance field will not be generated for that attribute.

The other case where the type of the field is relevant to `@dataclass` is when declaring *init-only variables*, our next topic.

Initialization variables that are not fields

Sometimes you may need to pass arguments to `__init__` that are not instance fields. Such arguments are called *init-only variables* by the `dataclasses` documentation. To declare an argument like that, `dataclasses` module provides the pseudo-type `InitVar`, which uses the same syntax of `typing.ClassVar`. The example given in the documentation is a data class that has a field initialized from a database, and the database object must be passed to the constructor.

This is the code that illustrates the Init-only variables section:

Example 5-18. Example from the `dataclasses` module documentation.

```
@dataclass
class C:
    i: int
    j: int = None
    database: InitVar[DatabaseType] = None
```

```
    def __post_init__(self, database):
        if self.j is None and database is not None:
            self.j = database.lookup('j')

c = C(10, database=my_database)
```

Note how the `database` attribute is declared. `InitVar` will prevent `@dataclass` from treating `database` as a regular field. It will not be set as an instance attribute, and the `dataclasses.fields` function will not list it. However, `database` will be one of the arguments that the generated `__init__` will accept, and it will be also passed to `__post_init__`—if you write that method, you must add a corresponding argument to the method signature, as shown in Example 5-18

This rather long overview of `@dataclass` covered the most useful features—some of them appeared in previous sections, like "Main features" where we covered all three data class builders in parallel. The `dataclasses` documentation and PEP 526 — Syntax for Variable Annotations have all details.

In the next section, I present a longer example with `@dataclass`.

@dataclass Example: Dublin Core Resource Record

Often, classes built with `@dataclass` will have more fields than the very short examples presented so far. Dublin Core provides the foundation for a more typical `@dataclass` example.

> *The Dublin Core Schema is a small set of vocabulary terms that can be used to describe digital resources (video, images, web pages, etc.), as well as physical resources such as books or CDs, and objects like artworks.*[8]
>
> —Dublin Core on Wikipedia

The standard defines 15 optional fields, the `Resource` class in Example 5-19 uses 8 of them.

Example 5-19. `dataclass/resource.py`: code for `Resource`, a class based on Dublin Core terms.

```python
from dataclasses import dataclass, field
from typing import Optional
from enum import Enum, auto
from datetime import date


class ResourceType(Enum):  ❶
    BOOK = auto()
    EBOOK = auto()
    VIDEO = auto()


@dataclass
class Resource:
    """Media resource description."""
    identifier: str                                    ❷
    title: str = '<untitled>'                          ❸
    creators: list[str] = field(default_factory=list)
    date: Optional[date] = None                        ❹
    type: ResourceType = ResourceType.BOOK             ❺
    description: str = ''
    language: str = ''
    subjects: list[str] = field(default_factory=list)
```

❶ This `Enum` will provide type-safe values for the `Resource.type` field.

❷ `identifier` is the only required field.

❸ `title` is the first field with a default. This forces all fields below to provide defaults.

❹ The value of `date` can be a `datetime.date` instance, or `None`.

❺ The `type` field default is `ResourceType.BOOK`.

Example 5-20 is a doctest to demonstrate how a `Resource` record appears in code:

Example 5-20. `dataclass/resource.py`: code for `Resource`, a class based on Dublin Core terms.

```
    >>> description = 'Improving the design of existing code'
    >>> book = Resource('978-0-13-475759-9', 'Refactoring, 2nd
Edition',
    ...     ['Martin Fowler', 'Kent Beck'], date(2018, 11, 19),
    ...     ResourceType.BOOK, description, 'EN',
    ...     ['computer programming', 'OOP'])
    >>> book  # doctest: +NORMALIZE_WHITESPACE
    Resource(identifier='978-0-13-475759-9', title='Refactoring,
2nd Edition',
    creators=['Martin Fowler', 'Kent Beck'],
date=datetime.date(2018, 11, 19),
    type=<ResourceType.BOOK: 1>, description='Improving the design
of existing code',
    language='EN', subjects=['computer programming', 'OOP'])
```

The `__repr__` generated by `@dataclass` is OK, but we can make it more readable. This is the format we want from `repr(book)`:

```
>>> book  # doctest: +NORMALIZE_WHITESPACE
Resource(
    identifier = '978-0-13-475759-9',
    title = 'Refactoring, 2nd Edition',
    creators = ['Martin Fowler', 'Kent Beck'],
    date = datetime.date(2018, 11, 19),
    type = <ResourceType.BOOK: 1>,
    description = 'Improving the design of existing code',
    language = 'EN',
    subjects = ['computer programming', 'OOP'],
)
```

Example 5-21 is the code of `__repr__` to produce the format above. This example uses `dataclass.fields` to get the names of the data class fields.

Example 5-21. `dataclass/resource_repr.py`: code for `__repr__` method implemented in the `Resource` class from Example 5-19.

```
    def __repr__(self):
        cls = self.__class__
        cls_name = cls.__name__
        indent = ' ' * 4
        res = [f'{cls_name}(']                              ❶
        for f in fields(cls):                               ❷
            value = getattr(self, f.name)                   ❸
```

```
            res.append(f'{indent}{f.name} = {value!r},')  ❹

        res.append(')')                                    ❺
        return '\n'.join(res)                              ❻
```

❶ Start the `res` list to build the output string with the class name and open parenthesis.

❷ For each field `f` in the class…

❸ Get the named attribute from the instance.

❹ Append an indented line with the name of the field and `repr(value)`—that's what the `!r` does.

❺ Append closing parenthesis.

❻ Build multiline string from `res` and return it.

With this example inspired by the soul of Dublin, Ohio, we conclude our tour of Python's data class builders.

Data classes are handy, but your project may suffer if you overuse them. The next section explains.

Data class as a code smell

Whether you implement a data class writing all the code yourself or leveraging one of the class builders described in this chapter, be aware that it may signal a problem in your design.

In *Refactoring, Second Edition*, Martin Fowler and Kent Beck present a catalog of "code smells"—patterns in code that may indicate the need for refactoring. The entry titled *Data Class* starts like this:

> *These are classes that have fields, getting and setting methods for fields, and nothing else. Such classes are dumb data holders and are often being manipulated in far too much detail by other classes.*

In Fowler's personal Web site there's an illuminating post titled Code Smell. The post is very relevant to our discussion because he uses *data class* as one example of a code smell and suggests how to deal with it. Here is the post, reproduced in full.[9]

CODE SMELL

By Martin Fowler

A code smell is a surface indication that usually corresponds to a deeper problem in the system. The term was first coined by Kent Beck while helping me with my Refactoring book.

The quick definition above contains a couple of subtle points. Firstly a smell is by definition something that's quick to spot—or sniffable as I've recently put it. A long method is a good example of this—just looking at the code and my nose twitches if I see more than a dozen lines of Java.

The second is that smells don't always indicate a problem. Some long methods are just fine. You have to look deeper to see if there is an underlying problem there—smells aren't inherently bad on their own—they are often an indicator of a problem rather than the problem themselves.

The best smells are something that's easy to spot and most of time lead you to really interesting problems. Data classes (classes with all data and no behavior) are good examples of this. You look at them and ask yourself what behavior should be in this class. Then you start refactoring to move that behavior in there. Often simple questions and initial refactorings can be the vital step in turning anemic objects into something that really has class.

One of the nice things about smells is that it's easy for inexperienced people to spot them, even if they don't know enough to evaluate if there's a real problem or to correct them. I've heard of lead developers who will pick a "smell of the week" and ask people to look for the smell and bring it up with the senior members of the team. Doing it one smell at a time is a good way of gradually teaching people on the team to be better programmers.

The main idea of Object Oriented Programming is to place behavior and data together in the same code unit: a class. If a class is widely used but has no significant behavior of its own, it's possible that code dealing with its instances is scattered (and even duplicated) in methods and functions throughout the system—a recipe for maintenance headaches. That's why Fowler's refactorings to deal with a data class involve bringing responsibilities back into it.

Taking that into account, there are a couple of common scenarios where it makes sense to have a data class with little or no behavior.

Data class as scaffolding

In this scenario, the data class is an initial, simplistic implementation of a class to jump start a new project or module. With time, the class should get its own methods, instead of relying on methods of other classes to operate on its instances. Scaffolding is temporary; eventually your custom class may become fully independent from the builder you used to start it.

Python is also used for quick problem solving and experimentation, and then it's OK to leave the scaffolding in place.

Data class as intermediate representation

A data class can be useful to build records about to be exported to JSON or some other interchange format, or to hold data that was just imported, crossing some system boundary. Python's data class builders all provide a method or function to convert an instance to a plain `dict`, and you can always invoke the constructor with a `dict` used as keyword arguments expanded with `**`. Such a `dict` is very close to a JSON record.

In this scenario, the data class instances should be handled as immutable objects—even if the fields are mutable, you should not change them while they are in this intermediate form. If you do, you're losing the key benefit of having data and behavior close together. When importing/exporting requires changing values, you should implement your own builder methods instead of using the given “as dict” methods or standard constructors.

Now we change the subject to see how to write patterns that match instances of arbitrary classes, and not just the sequences and mappings we’ve seen in the pattern matching sections of Chapter 2 and Chapter 3.

Pattern Matching Class Instances

Class patterns are designed to match class instances by type and—optionally—by attributes. The subject of a class pattern can be any class instance, not only instances of data classes.[10]

There are three variations of class patterns: simple, keyword, and positional. We’ll study them in that order.

Simple Class Patterns

We’ve already seen an example with simple class patterns used as subpatterns in “Pattern Matching with Sequences”:

```
        case [str(name), _, _, (float(lat), float(lon))]:
```

That pattern matches a 4-item sequence where the first item must be an instance of `str`, and the last item must be a 2-tuple with two instances of `float`.

The syntax for class patterns looks like a constructor invocation. Below is a class pattern which matches `float` values, without binding a variable (the case body can refer to `x` directly if needed):

```
    match x:
        case float():
            do_something_with(x)
```

But this is likely to be a bug in your code:

```
match x:
    case float:  # DANGER!!!
        do_something_with(x)
```

In the example above, `case float:` matches any subject, because Python sees `float` as a variable, which is then bound to the subject.

The simple pattern syntax of `float()` or `float(x)` is a special case that applies only to nine blessed built-in types, listed at the end of the *Class patterns* section of *PEP 634—Structural Pattern Matching: Specification*:

```
bytes   dict   float   frozenset   int   list   set   str   tuple
```

In those classes, the variable that looks like a constructor argument—e.g. `x` in `float(x)`—is bound to the whole subject instance or the part of the subject that matches a subpattern, as exemplified by `str(name)` in the sequence pattern we saw earlier:

```
case [str(name), _, _, (float(lat), float(lon))]:
```

If the class is not one of those nine blessed built-ins, then the argument-like variables or constants represent different attributes of the class, as if they were keyword arguments or positional arguments.

Keyword Class Patterns

To understand how to use keyword class patterns, consider the following `City` class and five instances:

Example 5-22. City class and a few instances.

```
import typing

class City(typing.NamedTuple):
    continent: str
    name: str
    country: str


cities = [
```

```python
    City('Asia', 'Tokyo', 'JP'),
    City('Asia', 'Delhi', 'IN'),
    City('North America', 'Mexico City', 'MX'),
    City('North America', 'New York', 'US'),
    City('South America', 'São Paulo', 'BR'),
]
```

Given those definitions the following function would return a list of Asian cities:

```python
def match_asian_cities():
    results = []
    for city in cities:
        match city:
            case City(continent='Asia'):
                results.append(city)
    return results
```

The pattern `City(continent='Asia')` matches any `City` instance where the `continent` attribute value is equal to `'Asia'`, regardless of the values of the other attributes.

If you want to collect the value of the country attribute, you could write:

```python
def match_asian_countries():
    results = []
    for city in cities:
        match city:
            case City(continent='Asia', country=cc):
                results.append(cc)
    return results
```

The pattern `City(continent='Asia', country=cc)` matches the same Asian cities as before, but now the `cc` variable is bound to the `country` attribute of the instance. This also works if the pattern variable is called `country` as well:

```python
        match city:
            case City(continent='Asia', country=country):
                results.append(country)
```

Keyword class patterns are very readable, and work with any class that has public instance attributes, but they are somewhat verbose.

Positional class patterns are more convenient in some cases, but they require explicit support by the class of the subject, as we'll see next.

Positional Class Patterns

Given the definitions from Example 5-22, the following function would return a list of Asian cities, using a positional class pattern:

```
def match_asian_cities_pos():
    results = []
    for city in cities:
        match city:
            case City('Asia'):
                results.append(city)
    return results
```

The pattern `City('Asia')` matches any `City` instance where the first attribute value is `'Asia'`, regardless of the values of the other attributes.

If you want to collect the value of the country attribute, you could write:

```
def match_asian_countries_pos():
    results = []
    for city in cities:
        match city:
            case City('Asia', _, country):
                results.append(country)
    return results
```

The pattern `City('Asia', _, country)` matches the same cities as before, but now the `country` variable is bound to the third attribute of the instance.

I've mentioned "first" or "third" attribute, but what does that really mean?

What makes `City` or any class work with positional patterns is the presence of a special class attribute named `__match_args__`, which the class builders in this chapter automatically create. This is value of `__match_args__` in the `City` class:

```
>>> City.__match_args__
('continent', 'name', 'country')
```

As you can see, `__match_args__` declares the names of the attributes in the order they will be used in positional patterns.

In Chapter 11 we’ll write code to define `__match_args__` for a class we’ll create without the help of a class builder.

> **TIP**
>
> You can combine keyword and positional arguments in a pattern. Some but not all of the instance attributes available for matching may be listed in `__match_args__`. Therefore, sometimes you may need to use keyword arguments in addition to positional arguments in a pattern.

Time for a chapter summary.

Chapter Summary

The main topic of this chapter were the data class builders `collections.namedtuple`, `typing.NamedTuple` and `dataclasses.dataclass`. We saw that each of them generate data classes from descriptions provided as arguments to a factory function or from `class` statements with type hints—in the case of the latter two. In particular, both named tuple variants produce `tuple` subclasses, adding only the ability to access fields by name, and providing a `_fields` class attribute listing the field names as a tuple of strings.

Next we studied the main features of the three class builders side by side, including how to extract instance data as a `dict`, how to get the names and default values of fields, and how to make a new instance from an existing one.

This prompted our first look into type hints, particularly those used to annotate attributes in a `class` statement, using the notation introduced in Python 3.6 with PEP 526—Syntax for Variable Annotations. Probably the most surprising aspect of type hints in general is the fact that they have no effect at all at runtime. Python remains a dynamic language. External tools, like Mypy, are needed to take advantage of typing information to detect errors via static analysis of the source code. After a basic overview of the syntax from PEP 526, we studied the effect of annotations in a plain class and in classes built by `typing.NamedTuple` and `@dataclass`.

Next we covered the most commonly used features provided by `@dataclass` and the `default_factory` option of the `dataclasses.field` function. We also looked into the special pseudo-type hints `typing.ClassVar` and `dataclasses.InitVar` that are important in the context of data classes. This main topic concluded with an example based on the Dublin Core Schema, which illustrated how to use `dataclasses.fields` to iterate over the attributes of a `Resource` instance in a custom `__repr__`.

“Data class as a code smell” came after that, warning against possible abuse of data classes defeating a basic principle of Object Oriented Programming: data and the functions that touch it should be together in the same class. Classes with no logic may be a sign of misplaced logic.

In the last section, we saw how pattern matching works with subjects that are instances of any class—not just classes built with the tools presented in this chapter.

Further Reading

Python’s standard documentation for the data class builders we covered is very good, and has quite a few small examples.

For `@dataclass` in particular, most of PEP 557—Data Classes was copied into the `dataclasses` module documentation. But PEP 557 has a few very informative sections that were not copied, including Why not just use namedtuple?, Why not just use typing.NamedTuple? and the Rationale section which concludes with this Q&A:

> *Where is it not appropriate to use Data Classes?*
>
> *API compatibility with tuples or dicts is required. Type validation beyond that provided by PEPs 484 and 526 is required, or value validation or conversion is required.*
>
> —Eric V. Smith, PEP 557 Rationale

Over at RealPython.com, Geir Arne Hjelle wrote a very complete Ultimate Guide to Data Classes in Python 3.7.

At PyCon US 2018, Raymond Hettinger presented Dataclasses: The code generator to end all code generators (video).

For more features and advanced functionality, including validation, the *attrs* project led by Hynek Schlawack appeared years before `dataclasses`, and offers more features, promising to “bring back the joy of writing classes by relieving you from the drudgery of implementing object protocols (aka dunder methods).” The influence of *attrs* on `@dataclass` is acknowledged by Eric V. Smith in PEP 557. This probably includes Smith’s most important API decision: the use of a class decorator instead of a base class and/or a metaclass to do the job.

Glyph—founder of the Twisted project—wrote an excellent introduction to *attrs* in The One Python Library Everyone Needs. The *attrs* documentation includes a discussion of alternatives.

Book author, instructor, and mad computer scientist Dave Beazley wrote *cluegen*, yet another data class generator. If you’ve seen any of Dave’s talks, you know he is a master of metaprograming Python from first principles. So, I found it inspiring to learn from the *cluegen README.md* file the concrete use case that motivated him to write an alternative to Python’s `@dataclass`, and his philosophy of presenting an approach to solve the problem, in contrast to providing a tool: the tool may be quicker to use at first, but the approach is more flexible and can take you as far as you want to go.

Regarding *Data Class* as a code smell, the best source I found was Martin Fowler’s book *Refactoring, Second Edition*. This newest version is missing the quote from the epigraph of this chapter, “Data classes are like children…”, but otherwise it’s the best edition of Fowler’s most famous book, particularly for Pythonistas because the examples are in modern JavaScript, which is closer to Python than Java—the language of the first edition.

The Web site Refactoring Guru also has a description of the Data Class code smell.

SOAPBOX

The entry for "Guido" in the Jargon file is about Guido van Rossum. It says, among other things:

> *Mythically, Guido's most important attribute besides Python itself is Guido's time machine, a device he is reputed to possess because of the unnerving frequency with which user requests for new features have been met with the response "I just implemented that last night…"*

For the longest time, one of the missing pieces in Python's syntax has been a quick, standard way to declare instance attributes in a class. Many Object-Oriented languages have that. Here is part of a `Point` class definition in Smalltalk:

```
Object subclass: #Point
    instanceVariableNames: 'x y'
    classVariableNames: ''
    package: 'Kernel-BasicObjects'
```

The second line lists the names of the instance attributes `x` and `y`. If there were class attributes, they would be in the third line.

Python has always offered an easy way to declare class attributes, if they have an initial value. But instance attributes are much more common, and Python coders have been forced to look into the `__init__` method to find them, always afraid that there may be instance attributes created elsewhere in the class—or even created by external functions or methods of other classes.

Now we have `@dataclass`, yay!

But they bring their own problems.

First: when you use `@dataclass`, type hints are not optional. We've been promised for the last 7 years since PEP 484—Type Hints that they would always be optional. Now we have a major new language feature that requires them. If you don't like the whole static typing trend, you may want to use `attrs` instead.

Second: the PEP 526 syntax for annotating instance and class attributes reverses the established convention of `class` statements: everything declared at the top-level of a `class` block was a class attribute (methods are class attributes too). With PEP 526 and `@dataclass`, any attribute declared at the top level with a type hint becomes an instance attribute:

```
@dataclass
class Spam:
    repeat: int  # instance attribute
```

Below, `repeat` is also an instance attribute:

```
@dataclass
class Spam:
    repeat: int = 99  # instance attribute
```

But if there are no type hints, suddenly you are back in the good old times when declarations at the top-level of the class belong to the class only:

```
@dataclass
class Spam:
    repeat = 99  # class attribute!
```

Finally, if you want to annotate that class attribute with a type, you can't use regular types because then it will become an instance attribute. You must resort to that pseudo-type `ClassVar` annotation:

```
@dataclass
class Spam:
    repeat: ClassVar[int] = 99  # aargh!
```

Here we are talking about the exception to the exception to the rule. This seems rather unpythonic to me.

I did not take part in the discussions leading to PEP 526 or PEP 557—Data Classes, but here is an alternative syntax that I'd like to see:

```
@dataclass
class HackerClubMember:
    .name: str                                  ❶
    .guests: list = field(default_factory=list)
    .handle: str = ''

    all_handles = set()                         ❷
```

❶ Instance attributes must be declared with a `.` prefix.

❷ Any attribute name that doesn't have a `.` prefix is a class attribute (as they always have been).

The language grammar would have to change to accept that. I find this quite readable, and it avoids the exception-to-the-exception issue.

I wish I could borrow Guido's time machine to go back to 2017 and sell this idea to the core team.

---

1 From *Refactoring*, *First Edition*, chapter 3, *Bad Smells in Code*, *Data Class* section, page 87.

2 Metaclasses are one of the subjects covered in Chapter 25—*Class Metaprogramming*.

3 Class decorators are covered in Chapter 25—*Class Metaprogramming*, along with metaclasses. Both are ways of customizing class behavior beyond what is possible with inheritance.

4 If you know Ruby, you know that injecting methods is a well-known but controversial technique among Rubyists. In Python, it's not as common, because it doesn't work with any built-in type—`str`, `list`, etc. I consider this limitation of Python a blessing.

5 In the context of type hints, `None` is not the `NoneType` singleton, but an alias for `NoneType` itself. This is strange when we stop to think about it, but appeals to our intuition and makes function return annotations easier to read in the common case of functions that return `None`.

6 Python has no concept of *undefined*, one of the silliest mistakes in the design of JavaScript. Thank Guido!

7 However, almost always when I see this in real code it's a bad idea. I once spent hours chasing a bug that was caused by attributes sneakily stashed in instances, like contraband across module borders. Also, setting an attribute after `__init__` defeats the `__dict__` key-sharing memory optimization mentioned in "Practical Consequences of How dict Works".

8 Source: Dublin Core article in the English Wikipedia.

9 I am fortunate to have Martin Fowler as a colleague at Thoughtworks, so it took just 20 minutes to get his permission.

10 I put this content here because it is the earliest chapter focusing on user-defined classes, and I thought pattern matching with classes was too important to wait until part III of the book. My philosophy: it's more important to know how to use classes than to define classes.

Chapter 6. Object References, Mutability, and Recycling

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 6th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *‘You are sad,’ the Knight said in an anxious tone: ‘let me sing you a song to comfort you. […] The name of the song is called “HADDOCKS’ EYES”.’*
>
> *‘Oh, that’s the name of the song, is it?’ Alice said, trying to feel interested.*
>
> *‘No, you don’t understand,’ the Knight said, looking a little vexed. ‘That’s what the name is CALLED. The name really IS “THE AGED AGED MAN."’ (adapted from Chapter VIII. ‘It’s my own Invention’).*
>
> —Lewis Carroll, Through the Looking-Glass, and What Alice Found There

Alice and the Knight set the tone of what we will see in this chapter. The theme is the distinction between objects and their names. A name is not the object; a name is a separate thing.

We start the chapter by presenting a metaphor for variables in Python: variables are labels, not boxes. If reference variables are old news to you, the analogy may still be handy if you need to explain aliasing issues to others.

We then discuss the concepts of object identity, value, and aliasing. A surprising trait of tuples is revealed: they are immutable but their values may change. This leads to a discussion of shallow and deep copies. References and function parameters are our next theme: the problem with mutable parameter defaults and the safe handling of mutable arguments passed by clients of our functions.

The last sections of the chapter cover garbage collection, the `del` command, and a selection of tricks that Python plays with immutable objects.

This is a rather dry chapter, but its topics lie at the heart of many subtle bugs in real Python programs.

What's new in this chapter

The topics covered here are very fundamental and stable. There were no changes worth mentioning in this *Second Edition*.

I added an example of using `is` to test for a sentinel object, and a warning about misuses of the `is` operator at the end of "Choosing Between == and `is`".

This chapter used to be in Part IV, but I decided to bring it up earlier because it works better as an ending to Part II—*Data Structures*—than an opening to *Object-Oriented Idioms*.

> **NOTE**
>
> The section on *Weak References* from the *First Edition* is now a post at fluentpython.com.

Let's start by unlearning that a variable is like a box where you store data.

Variables Are Not Boxes

In 1997, I took a summer course on Java at MIT. The professor, Lynn Stein[1] made the point that the usual "variables as boxes" metaphor actually hinders the understanding of reference variables in OO languages. Python variables are like reference variables in Java, a better metaphor is to think of variables as labels with names attached to objects. The next example and figure will help you understand why.

Example 6-1 is a simple interaction that the "variables as boxes" idea cannot explain. Figure 6-1 illustrates why the box metaphor is wrong for Python, while sticky notes provide a helpful picture of how variables actually work.

Example 6-1. Variables a and b hold references to the same list, not copies of the list

```
>>> a = [1, 2, 3]   ❶
>>> b = a           ❷
>>> a.append(4)     ❸
>>> b               ❹
[1, 2, 3, 4]
```

❶ Create a list `[1, 2, 3]` and bind the variable `a` to it

❷ Bind the variable `b` to the same value that `a` is referencing.

❸ Modify the list referenced by `a`, by appending another item.

❹ You can see the effect via the `b` variable. If we think of `b` as box that stored a copy of the `[1, 2, 3]` from the `a` box, this behavior is makes no sense.

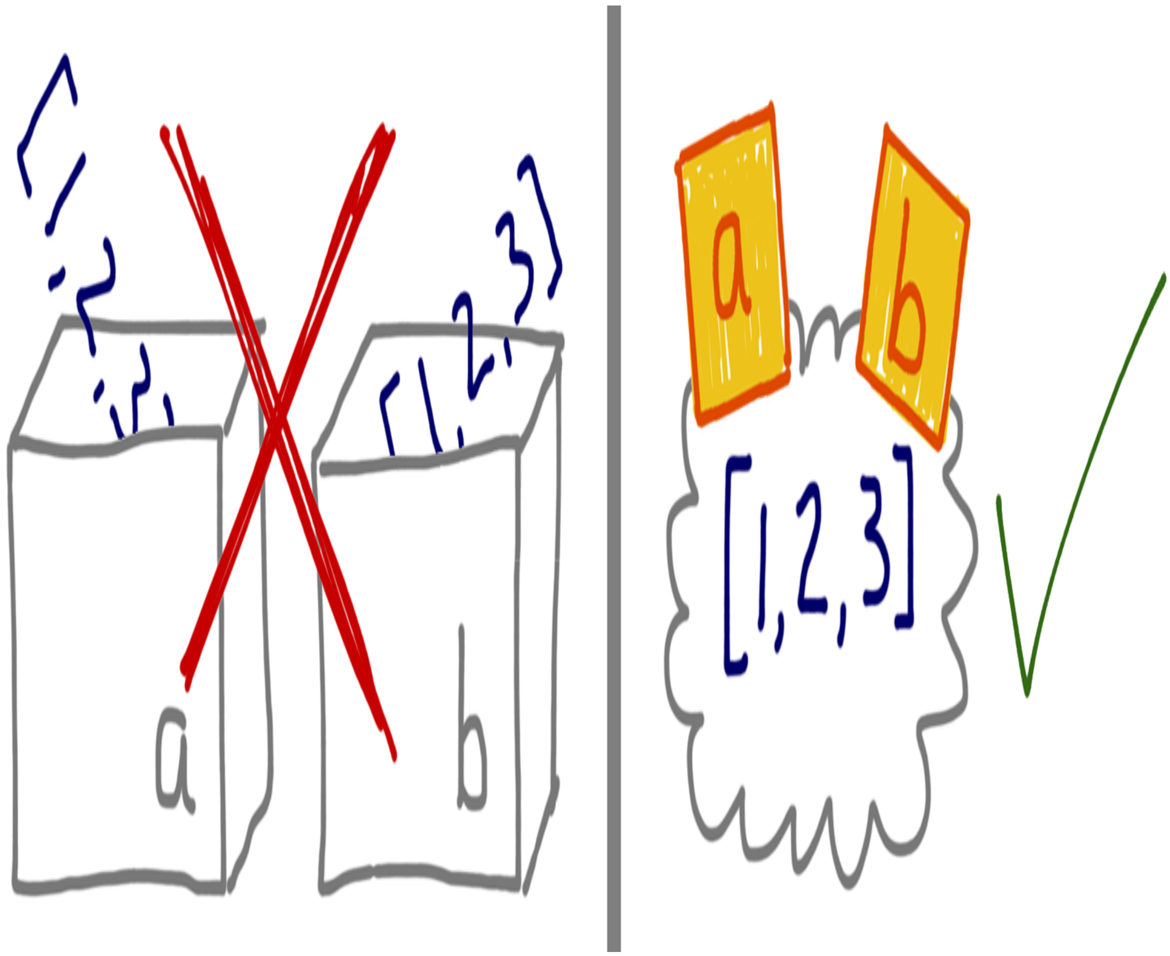


Figure 6-1. If you imagine variables are like boxes, you can't make sense of assignment in Python; instead, think of variables as sticky notes—Example 6-1 then becomes easy to explain

Therefore, the `b = a` statement does not copy the contents of box `a` into box `b`. It attaches the label `b` to the object that already has the label `a`.

Prof. Stein also spoke about assignment in a very deliberate way. For example, when talking about a seesaw object in a simulation, she would say: "Variable *s* is assigned to the seesaw," but never "The seesaw is assigned to variable *s*." With reference variables, it makes much more sense to say that the variable is assigned to an object, and not the other way around. After all, the object is created before the assignment. Example 6-2 proves that the right-hand side of an assignment happens first.

Since the verb "to assign" is used in contradictory ways, a useful alternative is "to bind": Python's assignment statement `x = …` binds the `x` name to the object created or referenced on the right-hand side. And the object must exist before a name can be bound to it, as Example 6-2 proves.

Example 6-2. Variables are bound to objects only after the objects are created.

```
>>> class Gizmo:
...     def __init__(self):
...         print(f'Gizmo id: {id(self)}')
...
>>> x = Gizmo()
Gizmo id: 4301489152  ❶
>>> y = Gizmo() * 10  ❷
Gizmo id: 4301489432  ❸
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unsupported operand type(s) for *: 'Gizmo' and 'int'
>>>
>>> dir()  ❹
['Gizmo', '__builtins__', '__doc__', '__loader__', '__name__',
'__package__', '__spec__', 'x']
```

❶ The output `Gizmo id: ...` is a side effect of creating a `Gizmo` instance.

❷ Multiplying a `Gizmo` instance will raise an exception.

❸ Here is proof that a second `Gizmo` was actually instantiated before the multiplication was attempted.

❹ But variable `y` was never created, because the exception happened while the right-hand side of the assignment was being evaluated.

> **TIP**
>
> To understand an assignment in Python, read the right-hand side first: that's where the object is created or retrieved. After that, the variable on the left is bound to the object, like a label stuck to it. Just forget about the boxes.

Because variables are mere labels, nothing prevents an object from having several labels assigned to it. When that happens, you have *aliasing*, our next topic.

Identity, Equality, and Aliases

Lewis Carroll is the pen name of Prof. Charles Lutwidge Dodgson. Mr. Carroll is not only equal to Prof. Dodgson: they are one and the same. Example 6-3 expresses this idea in Python.

Example 6-3. charles and lewis refer to the same object

```
>>> charles = {'name': 'Charles L. Dodgson', 'born': 1832}
>>> lewis = charles  ❶
>>> lewis is charles
True
>>> id(charles), id(lewis)  ❷
(4300473992, 4300473992)
>>> lewis['balance'] = 950  ❸
>>> charles
{'name': 'Charles L. Dodgson', 'born': 1832, 'balance': 950}
```

❶ `lewis` is an alias for `charles`.

❷ The `is` operator and the `id` function confirm it.

❸ Adding an item to `lewis` is the same as adding an item to `charles`.

However, suppose an impostor—let's call him Dr. Alexander Pedachenko—claims he is Charles L. Dodgson, born in 1832. His credentials may be the same, but Dr. Pedachenko is not Prof. Dodgson. Figure 6-2 illustrates this scenario.

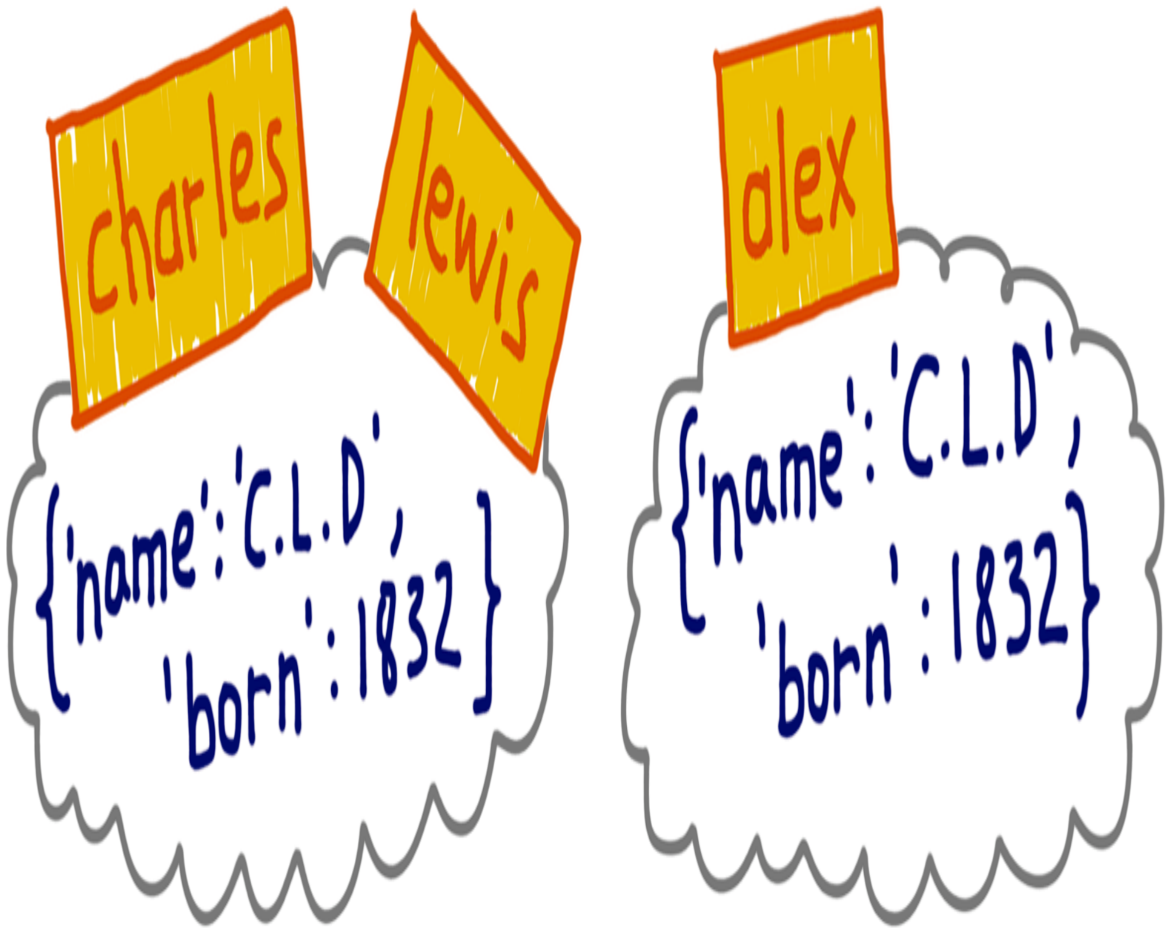


Figure 6-2. charles and lewis are bound to the same object; alex is bound to a separate object of equal value.

Example 6-4 implements and tests the `alex` object depicted in Figure 6-2.

Example 6-4. alex and charles compare equal, but alex is not charles

```
>>> alex = {'name': 'Charles L. Dodgson', 'born': 1832, 'balance':
950}  ❶
>>> alex == charles  ❷
True
>>> alex is not charles  ❸
True
```

❶ `alex` refers to an object that is a replica of the object assigned to `charles`.

❷ The objects compare equal, because of the `__eq__` implementation in the `dict` class.

❸ But they are distinct objects. This is the Pythonic way of writing the negative identity comparison: `a is not b`.

Example 6-3 is an example of *aliasing*. In that code, `lewis` and `charles` are aliases: two variables bound to the same object. On the other hand, `alex` is not an alias for `charles`: these variables are bound to distinct objects. The objects bound to `alex` and `charles` have the same *value*—that's what `==` compares—but they have different identities.

In *The Python Language Reference*, "3.1. Objects, values and types" states:

> *An object's identity never changes once it has been created; you may think of it as the object's address in memory. The `is` operator compares the identity of two objects; the `id()` function returns an integer representing its identity.*

The real meaning of an object's ID is implementation-dependent. In CPython, `id()` returns the memory address of the object, but it may be something else in another Python interpreter. The key point is that the ID is guaranteed to be a unique integer label, and it will never change during the life of the object.

In practice, we rarely use the `id()` function while programming. Identity checks are most often done with the `is` operator, which compares the object IDs, so our code doesn't need to call `id()` explicitly. Next, we'll talk about `is` versus `==`.

TIP

For tech reviewer Leonardo Rochael, the most frequent use for `id()` is while debugging, when the `repr()` of two objects look alike, but you need to understand whether two references are aliases or point to separate objects. If the references are in different contexts—such as different stack frames—using the `is` operator may not be viable.

Choosing Between == and `is`

The `==` operator compares the values of objects (the data they hold), while `is` compares their identities.

While programming, we often care more about values and than object identities, so `==` appears more frequently than `is` in Python code.

However, if you are comparing a variable to a singleton, then it makes sense to use `is`. By far, the most common case is checking whether a variable is bound to `None`. This is the recommended way to do it:

```
x is None
```

And the proper way to write its negation is:

```
x is not None
```

`None` is the most common singleton we test with `is`. Sentinel objects are another example of singletons we test with `is`. Here is one way to create and test a sentinel object:

```
END_OF_DATA = object()
# ... many lines
def traverse(...):
    # ... more lines
    if node is END_OF_DATA:
        return
    # etc.
```

The `is` operator is faster than `==`, because it cannot be overloaded, so Python does not have to find and invoke special methods to evaluate it, and computing is as simple as comparing two integer IDs. In contrast, `a == b` is syntactic sugar for `a.__eq__(b)`. The `__eq__` method inherited from `object` compares object IDs, so it produces the same result as `is`. But most built-in types override `__eq__` with more meaningful implementations that actually take into account the values of the object attributes. Equality may involve a lot of processing—for example, when comparing large collections or deeply nested structures.

> **WARNING**
>
> Usually we are more interested in object equality than identity. Checking for `None` is the **only** common use case for the `is` operator. Most other uses I see while reviewing code are wrong. If you are not sure, use `==`. It's usually what you want, and also works with `None`—albeit not as fast.

To wrap up this discussion of identity versus equality, we'll see that the famously immutable `tuple` is not as unchanging as you may expect.

The Relative Immutability of Tuples

Tuples, like most Python collections—lists, dicts, sets, etc.—are containers: they hold references to objects.[2] If the referenced items are mutable, they may change even if the tuple itself does not. In other words, the immutability of tuples really refers to the physical contents of the `tuple` data structure (i.e., the references it holds), and does not extend to the referenced objects.

Example 6-5 illustrates the situation in which the value of a tuple changes as result of changes to a mutable object referenced in it. What can never change in a tuple is the identity of the items it contains.

Example 6-5. t1 and t2 initially compare equal, but changing a mutable item inside tuple t1 makes it different

```
>>> t1 = (1, 2, [30, 40])  ❶
>>> t2 = (1, 2, [30, 40])  ❷
>>> t1 == t2  ❸
True
>>> id(t1[-1])  ❹
4302515784
>>> t1[-1].append(99)  ❺
>>> t1
(1, 2, [30, 40, 99])
>>> id(t1[-1])  ❻
```

```
4302515784
>>> t1 == t2  ❼
False
```

❶ `t1` is immutable, but `t1[-1]` is mutable.

❷ Build a tuple `t2` whose items are equal to those of `t1`.

❸ Although distinct objects, `t1` and `t2` compare equal, as expected.

❹ Inspect the identity of the list at `t1[-1]`.

❺ Modify the `t1[-1]` list in place.

❻ The identity of `t1[-1]` has not changed, only its value.

❼ `t1` and `t2` are now different.

This relative immutability of tuples is behind the riddle "A += Assignment Puzzler". It's also the reason why some tuples are unhashable, as we've seen in "What is Hashable".

The distinction between equality and identity has further implications when you need to copy an object. A copy is an equal object with a different ID. But if an object contains other objects, should the copy also duplicate the inner objects, or is it OK to share them? There's no single answer. Read on for a discussion.

Copies Are Shallow by Default

The easiest way to copy a list (or most built-in mutable collections) is to use the built-in constructor for the type itself. For example:

```
>>> l1 = [3, [55, 44], (7, 8, 9)]
>>> l2 = list(l1)  ❶
>>> l2
[3, [55, 44], (7, 8, 9)]
```

```
>>> l2 == l1  ❷
True
>>> l2 is l1  ❸
False
```

❶ `list(l1)` creates a copy of `l1`.

❷ The copies are equal.

❸ But refer to two different objects.

For lists and other mutable sequences, the shortcut `l2 = l1[:]` also makes a copy.

However, using the constructor or `[:]` produces a *shallow copy* (i.e., the outermost container is duplicated, but the copy is filled with references to the same items held by the original container). This saves memory and causes no problems if all the items are immutable. But if there are mutable items, this may lead to unpleasant surprises.

In Example 6-6, we create a shallow copy of a list containing another list and a tuple, and then make changes to see how they affect the referenced objects.

> **TIP**
>
> If you have a connected computer on hand, I highly recommend watching the interactive animation for Example 6-6 at the Online Python Tutor. As I write this, direct linking to a prepared example at *pythontutor.com* is not working reliably, but the tool is awesome, so taking the time to copy and paste the code is worthwhile.

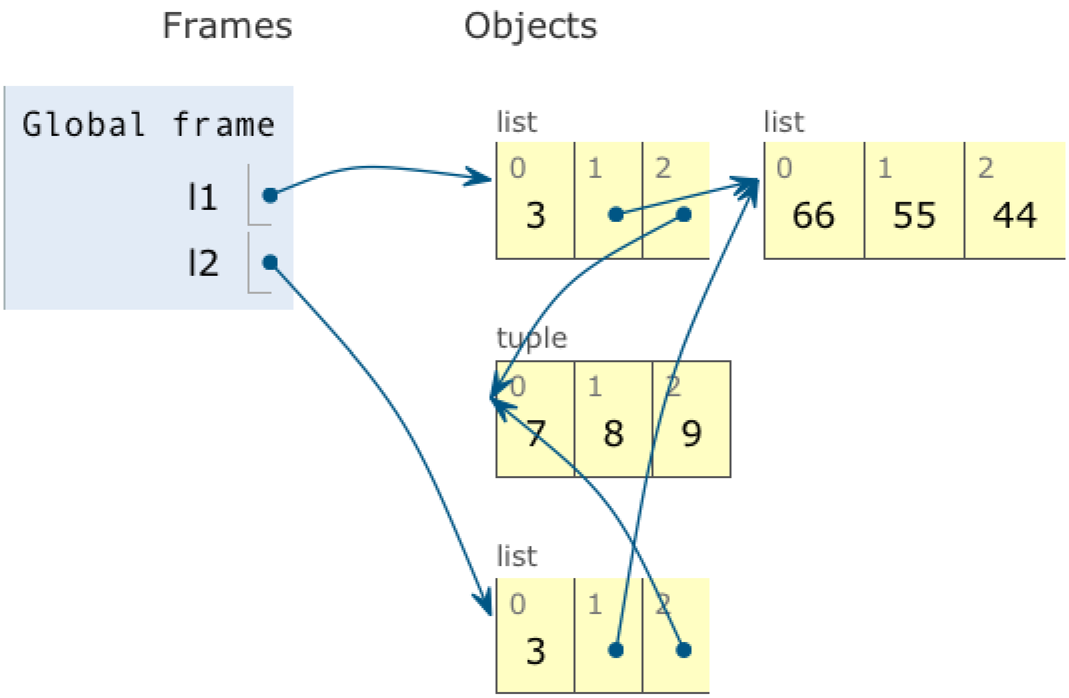


Figure 6-3. Program state immediately after the assignment l2 = list(l1) in Example 6-6. l1 and l2 refer to distinct lists, but the lists share references to the same inner list object [66, 55, 44] and tuple (7, 8, 9). (Diagram generated by the Online Python Tutor.)

Example 6-6. Making a shallow copy of a list containing another list; copy and paste this code to see it animated at the Online Python Tutor

```
l1 = [3, [66, 55, 44], (7, 8, 9)]
l2 = list(l1)      ❶
l1.append(100)     ❷
l1[1].remove(55)   ❸
print('l1:', l1)
print('l2:', l2)
l2[1] += [33, 22]  ❹
l2[2] += (10, 11)  ❺
print('l1:', l1)
print('l2:', l2)
```

❶ `l2` is a shallow copy of `l1`. This state is depicted in Figure 6-3.

❷ Appending `100` to `l1` has no effect on `l2`.

❸ Here we remove `55` from the inner list `l1[1]`. This affects `l2` because `l2[1]` is bound to the same list as `l1[1]`.

❹ For a mutable object like the list referred by `l2[1]`, the operator `+=` changes the list in place. This change is visible at `l1[1]`, which is an alias for `l2[1]`.

❺ `+=` on a tuple creates a new tuple and rebinds the variable `l2[2]` here. This is the same as doing `l2[2] = l2[2] + (10, 11)`. Now the tuples in the last position of `l1` and `l2` are no longer the same object. See Figure 6-4.

The output of Example 6-6 is Example 6-7, and the final state of the objects is depicted in Figure 6-4.

Example 6-7. Output of Example 6-6

```
l1: [3, [66, 44], (7, 8, 9), 100]
l2: [3, [66, 44], (7, 8, 9)]
l1: [3, [66, 44, 33, 22], (7, 8, 9), 100]
l2: [3, [66, 44, 33, 22], (7, 8, 9, 10, 11)]
```

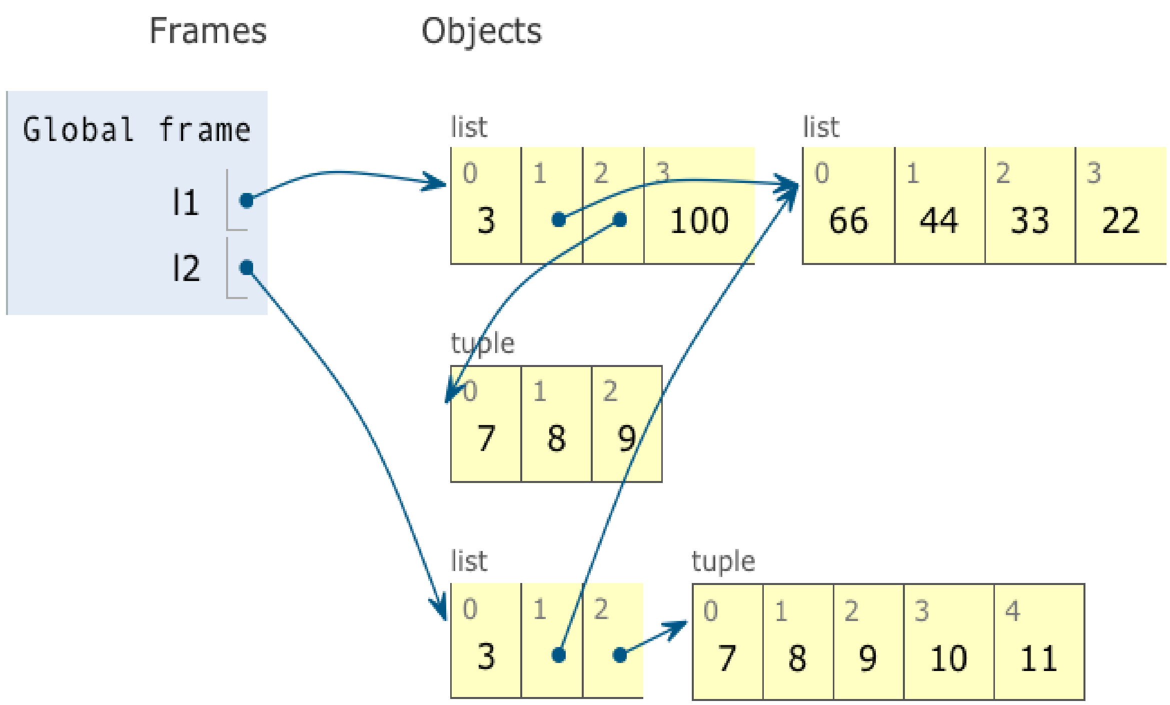


Figure 6-4. Final state of l1 and l2: they still share references to the same list object, now containing [66, 44, 33, 22], but the operation l2[2] += (10, 11) created a new tuple with content (7, 8, 9, 10, 11), unrelated to the tuple (7, 8, 9) referenced by l1[2]. (Diagram generated by the Online Python Tutor.)

It should be clear now that shallow copies are easy to make, but they may or may not be what you want. How to make deep copies is our next topic.

Deep and Shallow Copies of Arbitrary Objects

Working with shallow copies is not always a problem, but sometimes you need to make deep copies (i.e., duplicates that do not share references of embedded objects). The `copy` module provides the `deepcopy` and `copy` functions that return deep and shallow copies of arbitrary objects.

To illustrate the use of `copy()` and `deepcopy()`, Example 6-8 defines a simple class, `Bus`, representing a school bus that is loaded with passengers and then picks up or drops off passengers on its route.

Example 6-8. Bus picks up and drops off passengers

```
class Bus:

    def __init__(self, passengers=None):
        if passengers is None:
            self.passengers = []
        else:
            self.passengers = list(passengers)

    def pick(self, name):
        self.passengers.append(name)

    def drop(self, name):
        self.passengers.remove(name)
```

Now in the interactive Example 6-9 we will create a `bus` object (`bus1`) and two clones—a shallow copy (`bus2`) and a deep copy (`bus3`)—to observe what happens as `bus1` drops off a student.

Example 6-9. Effects of using copy versus deepcopy

```
>>> import copy
>>> bus1 = Bus(['Alice', 'Bill', 'Claire', 'David'])
>>> bus2 = copy.copy(bus1)
>>> bus3 = copy.deepcopy(bus1)
>>> id(bus1), id(bus2), id(bus3)
(4301498296, 4301499416, 4301499752)  ❶
>>> bus1.drop('Bill')
>>> bus2.passengers
```

```
['Alice', 'Claire', 'David']          ❷
>>> id(bus1.passengers), id(bus2.passengers), id(bus3.passengers)
(4302658568, 4302658568, 4302657800)  ❸
>>> bus3.passengers
['Alice', 'Bill', 'Claire', 'David']  ❹
```

❶ Using `copy` and `deepcopy`, we create three distinct `Bus` instances.

❷ After `bus1` drops `'Bill'`, he is also missing from `bus2`.

❸ Inspection of the `passengers` attributes shows that `bus1` and `bus2` share the same list object, because `bus2` is a shallow copy of `bus1`.

❹ `bus3` is a deep copy of `bus1`, so its `passengers` attribute refers to another list.

Note that making deep copies is not a simple matter in the general case. Objects may have cyclic references that would cause a naïve algorithm to enter an infinite loop. The `deepcopy` function remembers the objects already copied to handle cyclic references gracefully. This is demonstrated in Example 6-10.

Example 6-10. Cyclic references: b refers to a, and then is appended to a; deepcopy still manages to copy a

```
>>> a = [10, 20]
>>> b = [a, 30]
>>> a.append(b)
>>> a
[10, 20, [[...], 30]]
>>> from copy import deepcopy
>>> c = deepcopy(a)
>>> c
[10, 20, [[...], 30]]
```

Also, a deep copy may be too deep in some cases. For example, objects may refer to external resources or singletons that should not be copied. You can control the behavior of both `copy` and `deepcopy` by implementing the `__copy__()` and `__deepcopy__()` special methods as described in the `copy` module documentation.

The sharing of objects through aliases also explains how parameter passing works in Python, and the problem of using mutable types as parameter defaults. These issues will be covered next.

Function Parameters as References

The only mode of parameter passing in Python is *call by sharing*. That is the same mode used in most object oriented languages, including JavaScript, Ruby, and Java (this applies to Java reference types; primitive types use call by value). Call by sharing means that each formal parameter of the function gets a copy of each reference in the arguments. In other words, the parameters inside the function become aliases of the actual arguments.

The result of this scheme is that a function may change any mutable object passed as a parameter, but it cannot change the identity of those objects (i.e., it cannot altogether replace an object with another). Example 6-11 shows a simple function using += on one of its parameters. As we pass numbers, lists, and tuples to the function, the actual arguments passed are affected in different ways. The next example demonstrates:

Example 6-11. A function may change any mutable object it receives

```
>>> def f(a, b):
...     a += b
...     return a
...
>>> x = 1
>>> y = 2
>>> f(x, y)
3
>>> x, y  ❶
(1, 2)
>>> a = [1, 2]
>>> b = [3, 4]
>>> f(a, b)
[1, 2, 3, 4]
>>> a, b  ❷
([1, 2, 3, 4], [3, 4])
>>> t = (10, 20)
>>> u = (30, 40)
```

```
>>> f(t, u)  ❸
(10, 20, 30, 40)
>>> t, u
((10, 20), (30, 40))
```

❶ The number `x` is unchanged.

❷ The list `a` is changed.

❸ The tuple `t` is unchanged.

Another issue related to function parameters is the use of mutable values for defaults, as discussed next.

Mutable Types as Parameter Defaults: Bad Idea

Optional parameters with default values are a great feature of Python function definitions, allowing our APIs to evolve while remaining backward-compatible. However, you should avoid mutable objects as default values for parameters.

To illustrate this point, in Example 6-12, we take the `Bus` class from Example 6-8 and change its `__init__` method to create `HauntedBus`. Here we tried to be clever and instead of having a default value of `passengers=None`, we have `passengers=[]`, thus avoiding the `if` in the previous `__init__`. This “cleverness” gets us into trouble.

Example 6-12. A simple class to illustrate the danger of a mutable default

```
class HauntedBus:
    """A bus model haunted by ghost passengers"""

    def __init__(self, passengers=[]):  ❶
        self.passengers = passengers  ❷

    def pick(self, name):
        self.passengers.append(name)  ❸

    def drop(self, name):
        self.passengers.remove(name)
```

❶ When the `passengers` argument is not passed, this parameter is bound to the default list object, which is initially empty.

❷ This assignment makes `self.passengers` an alias for `passengers`, which is itself an alias for the default list, when no `passengers` argument is given.

❸ When the methods `.remove()` and `.append()` are used with `self.passengers` we are actually mutating the default list, which is an attribute of the function object.

Example 6-13 shows the eerie behavior of the `HauntedBus`.

Example 6-13. Buses haunted by ghost passengers

```
>>> bus1 = HauntedBus(['Alice', 'Bill'])  ❶
>>> bus1.passengers
['Alice', 'Bill']
>>> bus1.pick('Charlie')
>>> bus1.drop('Alice')
>>> bus1.passengers  ❷
['Bill', 'Charlie']
>>> bus2 = HauntedBus()  ❸
>>> bus2.pick('Carrie')
>>> bus2.passengers
['Carrie']
>>> bus3 = HauntedBus()  ❹
>>> bus3.passengers  ❺
['Carrie']
>>> bus3.pick('Dave')
>>> bus2.passengers  ❻
['Carrie', 'Dave']
>>> bus2.passengers is bus3.passengers  ❼
True
>>> bus1.passengers  ❽
['Bill', 'Charlie']
```

❶ `bus1` starts with a two-passenger list.

❷ So far, so good: no surprises with `bus1`.

❸ `bus2` starts empty, so the default empty list is assigned to `self.passengers`.

❹ `bus3` also starts empty, again the default list is assigned.

❺ The default is no longer empty!

❻ Now `Dave`, picked by `bus3`, appears in `bus2`.

❼ The problem: `bus2.passengers` and `bus3.passengers` refer to the same list.

❽ But `bus1.passengers` is a distinct list.

The problem is that `HauntedBus` instances that don’t get an initial passenger list end up sharing the same passenger list among themselves.

Such bugs may be subtle. As Example 6-13 demonstrates, when a `HauntedBus` is instantiated with passengers, it works as expected. Strange things happen only when a `HauntedBus` starts empty, because then `self.passengers` becomes an alias for the default value of the `passengers` parameter. The problem is that each default value is evaluated when the function is defined—i.e., usually when the module is loaded—and the default values become attributes of the function object. So if a default value is a mutable object, and you change it, the change will affect every future call of the function.

After running the lines in Example 6-13, you can inspect the `HauntedBus.__init__` object and see the ghost students haunting its `__defaults__` attribute:

```
>>> dir(HauntedBus.__init__)  # doctest: +ELLIPSIS
['__annotations__', '__call__', ..., '__defaults__', ...]
>>> HauntedBus.__init__.__defaults__
(['Carrie', 'Dave'],)
```

Finally, we can verify that `bus2.passengers` is an alias bound to the first element of the `HauntedBus.__init__.__defaults__` attribute:

```
>>> HauntedBus.__init__.__defaults__[0] is bus2.passengers
True
```

The issue with mutable defaults explains why `None` is commonly used as the default value for parameters that may receive mutable values. In Example 6-8, `__init__` checks whether the `passengers` argument is `None`. If it is, `self.passengers` is bound to a new empty list. If `passengers` is not `None`, the correct implementation binds a copy of that argument to `self.passengers`. The next section explains why copying the argument is a good practice.

Defensive Programming with Mutable Parameters

When you are coding a function that receives a mutable parameter, you should carefully consider whether the caller expects the argument passed to be changed.

For example, if your function receives a `dict` and needs to modify it while processing it, should this side effect be visible outside of the function or not? Actually it depends on the context. It's really a matter of aligning the expectation of the coder of the function and that of the caller.

The last bus example in this chapter shows how a `TwilightBus` breaks expectations by sharing its passenger list with its clients. Before studying the implementation, see in Example 6-14 how the `TwilightBus` class works from the perspective of a client of the class.

Example 6-14. Passengers disappear when dropped by a TwilightBus

```
>>> basketball_team = ['Sue', 'Tina', 'Maya', 'Diana', 'Pat']  ❶
>>> bus = TwilightBus(basketball_team)  ❷
>>> bus.drop('Tina')  ❸
>>> bus.drop('Pat')
>>> basketball_team  ❹
['Sue', 'Maya', 'Diana']
```

❶ `basketball_team` holds five student names.

❷ A `TwilightBus` is loaded with the team.

❸ The `bus` drops one student, then another.

❹ The dropped passengers vanished from the basketball team!

`TwilightBus` violates the "Principle of least astonishment," a best practice of interface design.[3] It surely is astonishing that when the bus drops a student, her name is removed from the basketball team roster.

Example 6-15 is the implementation `TwilightBus` and an explanation of the problem.

Example 6-15. A simple class to show the perils of mutating received arguments

```
class TwilightBus:
    """A bus model that makes passengers vanish"""

    def __init__(self, passengers=None):
        if passengers is None:
            self.passengers = []  ❶
        else:
            self.passengers = passengers  ❷

    def pick(self, name):
        self.passengers.append(name)

    def drop(self, name):
        self.passengers.remove(name)  ❸
```

❶ Here we are careful to create a new empty list when `passengers` is `None`.

❷ However, this assignment makes `self.passengers` an alias for `passengers`, which is itself an alias for the actual argument passed to `__init__` (i.e.,`basketball_team` in Example 6-14).

❸ When the methods `.remove()` and `.append()` are used with `self.passengers`, we are actually mutating the original list received as argument to the constructor.

The problem here is that the bus is aliasing the list that is passed to the constructor. Instead, it should keep its own passenger list. The fix is simple: in `__init__`, when the `passengers` parameter is provided, `self.passengers` should be initialized with a copy of it, as we did correctly in Example 6-8:

```
def __init__(self, passengers=None):
    if passengers is None:
        self.passengers = []
    else:
        self.passengers = list(passengers) ❶
```

❶ Make a copy of the `passengers` list, or convert it to a `list` if it's not one.

Now our internal handling of the passenger list will not affect the argument used to initialize the bus. As a bonus, this solution is more flexible: now the argument passed to the `passengers` parameter may be a `tuple` or any other iterable, like a `set` or even database results, because the `list` constructor accepts any iterable. As we create our own list to manage, we ensure that it supports the necessary `.remove()` and `.append()` operations we use in the `.pick()` and `.drop()` methods.

TIP

Unless a method is explicitly intended to mutate an object received as argument, you should think twice before aliasing the argument object by simply assigning it to an instance variable in your class. If in doubt, make a copy. Your clients will be happier. Of course, making a copy is not free: there is a cost in CPU and memory. However, an API that causes subtle bugs is usually a bigger problem than one that is a little slower or uses more resources.

Now let’s talk about one of the most misunderstood of Python’s statements: `del`.

del and Garbage Collection

> *Objects are never explicitly destroyed; however, when they become unreachable they may be garbage-collected.*
>
> —Data Model, chapter of *The Python Language Reference*

The first strange fact about `del` is that it’s not a function: it’s a statement. We write `del x`, and not `del(x)`—although the latter also works, but only because the expressions `x` and `(x)` usually mean the same thing in Python.

The second surprising fact is that `del` deletes references, not objects. Python’s garbage collector may discard an object from memory as an indirect result of `del`, if the deleted variable was the last reference to the object. Rebinding a variable may also cause the number of references to an object to reach zero, causing its destruction.

```
>>> a = [1, 2]  ❶
>>> b = a       ❷
>>> del a       ❸
>>> b           ❹
[1, 2]
>>> b = [3]     ❺
```

❶ Create object `[1, 2]` and bind `a` to it.

❷ Bind `b` to the same `[1, 2]` object.

❸ Delete reference `a`.

❹ `[1, 2]` was not affected, because `b` still points to it.

❺

Rebinding `b` to a different object removes the last remaining reference to `[1, 2]`. Now the garbage collector can discard that object.

> **WARNING**
>
> There is a `__del__` special method, but it does not cause the disposal of the instance, and should not be called by your code. `__del__` is invoked by the Python interpreter when the instance is about to be destroyed to give it a chance to release external resources. You will seldom need to implement `__del__` in your own code, yet some Python programmers spend time coding it for no good reason. The proper use of `__del__` is rather tricky. See the `__del__` special method documentation in the "Data Model" chapter of *The Python Language Reference*.

In CPython, the primary algorithm for garbage collection is reference counting. Essentially, each object keeps count of how many references point to it. As soon as that *refcount* reaches zero, the object is immediately destroyed: CPython calls the `__del__` method on the object (if defined) and then frees the memory allocated to the object. In CPython 2.0, a generational garbage collection algorithm was added to detect groups of objects involved in reference cycles—which may be unreachable even with outstanding references to them, when all the mutual references are contained within the group. Other implementations of Python have more sophisticated garbage collectors that do not rely on reference counting, which means the `__del__` method may not be called immediately when there are no more references to the object. See "PyPy, Garbage Collection, and a Deadlock" by A. Jesse Jiryu Davis for discussion of improper and proper use of `__del__`.

To demonstrate the end of an object's life, Example 6-16 uses `weakref.finalize` to register a callback function to be called when an object is destroyed.

Example 6-16. Watching the end of an object when no more references point to it.

```
>>> import weakref
>>> s1 = {1, 2, 3}
```

```
>>> s2 = s1         ❶
>>> def bye():      ❷
...     print('...like tears in the rain.')
...
>>> ender = weakref.finalize(s1, bye)  ❸
>>> ender.alive  ❹
True
>>> del s1
>>> ender.alive  ❺
True
>>> s2 = 'spam'  ❻
...like tears in the rain.
>>> ender.alive
False
```

❶ `s1` and `s2` are aliases referring to the same set, `{1, 2, 3}`.

❷ This function must not be a bound method of the object about to be destroyed or otherwise hold a reference to it.

❸ Register the `bye` callback on the object referred by `s1`.

❹ The `.alive` attribute is `True` before the `finalize` object is called.

❺ As discussed, `del` did not delete the object, just the `s1` reference to it.

❻ Rebinding the last reference, `s2`, makes `{1, 2, 3}` unreachable. It is destroyed, the `bye` callback is invoked, and `ender.alive` becomes `False`.

The point of Example 6-16 is to make explicit that `del` does not delete objects, but objects may be deleted as a consequence of being unreachable after `del` is used.

You may be wondering why the `{1, 2, 3}` object was destroyed in Example 6-16. After all, the `s1` reference was passed to the `finalize` function, which must have held on to it in order to monitor the object and invoke the callback. This works because `finalize` holds a *weak reference* to `{1, 2, 3}`. Weak references to an object do not increase its reference count. Therefore, a weak reference does not prevent the target object from being garbage collected. Weak references are useful in caching applications because you don't want the cached objects to be kept alive just because they are referenced by the cache.

> **NOTE**
>
> Weak references is a very specialized topic. That's why I chose to skip it in this *Second Edition*. Instead, I published Weak References on *fluentpython.com*.

Tricks Python Plays with Immutables

> **NOTE**
>
> This optional section discusses some Python details that are not really important for *users* of Python, and that may not apply to other Python implementations or even future versions of CPython. Nevertheless, I've seen people stumble upon these corner cases and then start using the `is` operator incorrectly, so I felt they were worth mentioning.

I was surprised to learn that, for a tuple `t`, `t[:]` does not make a copy, but returns a reference to the same object. You also get a reference to the same tuple if you write `tuple(t)`.[4] Example 6-17 proves it.

Example 6-17. A tuple built from another is actually the same exact tuple

```
>>> t1 = (1, 2, 3)
>>> t2 = tuple(t1)
>>> t2 is t1  ❶
True
>>> t3 = t1[:]
>>> t3 is t1  ❷
True
```

❶ `t1` and `t2` are bound to the same object.

❷ And so is `t3`.

The same behavior can be observed with instances of `str`, `bytes`, and `frozenset`. Note that a `frozenset` is not a sequence, so `fs[:]` does not work if `fs` is a `frozenset`. But `fs.copy()` has the same effect: it cheats and returns a reference to the same object, and not a copy at all, as Example 6-18 shows.[5]

Example 6-18. String literals may create shared objects

```
>>> t1 = (1, 2, 3)
>>> t3 = (1, 2, 3)  ❶
>>> t3 is t1  ❷
False
>>> s1 = 'ABC'
>>> s2 = 'ABC'  ❸
>>> s2 is s1 ❹
True
```

❶ Creating a new tuple from scratch.

❷ `t1` and `t3` are equal, but not the same object.

❸ Creating a second `str` from scratch.

❹ Surprise: `a` and `b` refer to the same `str`!

The sharing of string literals is an optimization technique called *interning*. CPython uses a similar technique with small integers to avoid unnecessary duplication of numbers that appear frequently in programs like 0, 1, –1, etc. Note that CPython does not intern all strings or integers, and the criteria it uses to do so is an undocumented implementation detail.

WARNING

Never depend on `str` or `int` interning! Always use `==` instead of `is` to compare strings or integers for equality. Interning is an optimization for internal use of the Python interpreter.

The tricks discussed in this section, including the behavior of `frozenset.copy()`, are harmless “lies” that save memory and make the interpreter faster. Do not worry about them, they should not give you any trouble because they only apply to immutable types. Probably the best use of these bits of trivia is to win bets with fellow Pythonistas.[6]

Chapter Summary

Every Python object has an identity, a type, and a value. Only the value of an object may change over time.[7]

If two variables refer to immutable objects that have equal values (`a == b` is `True`), in practice it rarely matters if they refer to copies or are aliases referring to the same object because the value of an immutable object does not change, with one exception. The exception being immutable collections such as tuples: if an immutable collection holds references to mutable items, then its value may actually change when the value of a mutable item changes. In practice, this scenario is not so common. What never changes in an immutable collection are the identities of the objects within. The `frozenset` class is does not suffer from this problem because it can only hold hashable elements, and the value of hashable objects cannot ever change, by definition.

The fact that variables hold references has many practical consequences in Python programming:

- Simple assignment does not create copies.
- Augmented assignment with `+=` or `*=` creates new objects if the left-hand variable is bound to an immutable object, but may modify a mutable object in place.
- Assigning a new value to an existing variable does not change the object previously bound to it. This is called a rebinding: the variable is now bound to a different object. If that variable was the last reference to the previous object, that object will be garbage collected.
- Function parameters are passed as aliases, which means the function may change any mutable object received as an argument. There is no way to prevent this, except making local copies or using immutable objects (e.g., passing a tuple instead of a list).

- Using mutable objects as default values for function parameters is dangerous because if the parameters are changed in place, then the default is changed, affecting every future call that relies on the default.

In CPython, objects are discarded as soon as the number of references to them reaches zero. They may also be discarded if they form groups with cyclic references but no outside references.

In some situations, it may be useful to hold a reference to an object that will not—by itself—keep an object alive. One example is a class that wants to keep track of all its current instances. This can be done with weak references, a low-level mechanism underlying the more useful collections `WeakValueDictionary`, `WeakKeyDictionary`, `WeakSet`, and the `finalize` function from the `weakref` module. For more on this, please see Weak References at *fluentpython.com*.

Further Reading

The "Data Model" chapter of *The Python Language Reference* starts with a clear explanation of object identities and values.

Wesley Chun, author of the *Core Python* series of books, made a great presentation about many of the topics covered in this chapter during OSCON 2013. You can download the slides from the "Python 103: Memory Model & Best Practices" talk page. There is also a YouTube video of a longer presentation Wesley gave at EuroPython 2011, covering not only the theme of this chapter but also the use of special methods.

Doug Hellmann wrote a long series of excellent blog posts titled Python Module of the Week, which became a book, *The Python Standard Library by Example*. His posts "copy – Duplicate Objects" and "weakref – Garbage-Collectable References to Objects" cover some of the topics we just discussed.

More information on the CPython generational garbage collector can be found in the gc module documentation, which starts with the sentence “This module provides an interface to the optional garbage collector.” The “optional” qualifier here may be surprising, but the “Data Model” chapter also states:

> *An implementation is allowed to postpone garbage collection or omit it altogether—it is a matter of implementation quality how garbage collection is implemented, as long as no objects are collected that are still reachable.*

Pablo Galindo wrote more in-depth treatment of Python’s GC in Design of CPython’s Garbage Collector at the Python Developer’s Guide, aimed at new and experienced contributors to the CPython implementation.

The CPython 3.4 garbage collector improved handling of objects with a `__del__` method, as described in PEP 442 — Safe object finalization.

Wikipedia has an article about string interning, mentioning the use of this technique in several languages, including Python.

SOAPBOX

Equal Treatment to All Objects

I learned Java before I discovered Python. The `==` operator in Java never felt right for me. It is much more common for programmers to care about equality than identity, but for objects (not primitive types) the Java `==` compares references, and not object values. Even for something as basic as comparing strings, Java forces you to use the `.equals` method. Even then, there is another catch: if you write `a.equals(b)` and `a` is `null`, you get a null pointer exception. The Java designers felt the need to overload `+` for strings, so why not go ahead and overload `==` as well?

Python gets this right. The `==` operator compares object values; `is` compares references. And because Python has operator overloading, `==` works sensibly with all objects in the standard library, including `None`, which is a proper object, unlike Java's `null`.

And of course, you can define `__eq__` in your own classes to decide what `==` means for your instances. If you don't override `__eq__`, the method inherited from `object` compares object IDs, so the fallback is that every instance of a user-defined class is considered different.

These are some of the things that made me switch from Java to Python as soon as I finished reading the Python Tutorial one afternoon in September 1998.

Mutability

This chapter would not be necessary if all Python objects were immutable. When you are dealing with unchanging objects, it makes no difference whether variables hold the actual objects or references to shared objects. If `a == b` is true, and neither object can change, they might as well be the same. That's why string interning is safe. Object identity becomes important only when objects are mutable.

In “pure” functional programming, all data is immutable: appending to a collection actually creates a new collection. Elixir is one easy to learn, practical functional language in which all built-in types are immutable, including lists.

Python, however, is not a functional language, much less a pure one. Instances of user-defined classes are mutable by default in Python—as in most object-oriented languages. When creating your own objects, you have to be extra careful to make them immutable, if that is a requirement. Every attribute of the object must also be immutable, otherwise you end up with something like the `tuple`: immutable as far as object IDs go, but the value of a `tuple` may change if it holds a mutable object.

Mutable objects are also the main reason why programming with threads is so hard to get right: threads mutating objects without proper synchronization produce corrupted data. Excessive synchronization, on the other hand, causes deadlocks. The Erlang language and platform—which includes Elixir—was designed to maximize uptime in highly-concurrent, distributed applications such as telecommunications switches. Naturally, they chose immutable data by default.

Object Destruction and Garbage Collection

There is no mechanism in Python to directly destroy an object, and this omission is actually a great feature: if you could destroy an object at any time, what would happen to existing strong references pointing to it?

Garbage collection in CPython is done primarily by reference counting, which is easy to implement, but is prone to memory leaking when there are reference cycles, so with version 2.0 (October 2000) a generational garbage collector was implemented, and it is able to dispose of unreachable objects kept alive by reference cycles.

But the reference counting is still there as a baseline, and it causes the immediate disposal of objects with zero references. This means that, in CPython—at least for now—it’s safe to write this:

```
open('test.txt', 'wt', encoding='utf-8').write('1, 2, 3')
```

That code is safe because the reference count of the file object will be zero after the `write` method returns, and Python will immediately close the file before destroying the object representing it in memory. However, the same line is not safe in Jython or IronPython that use the garbage collector of their host runtimes (the Java VM and the .NET CLR), which are more sophisticated but do not rely on reference counting and may take longer to destroy the object and close the file. In all cases, including CPython, the best practice is to explicitly close the file, and the most reliable way of doing it is using the `with` statement, which guarantees that the file will be closed even if exceptions are raised while it is open. Using `with`, the previous snippet becomes:

```
with open('test.txt', 'wt', encoding='utf-8') as fp:
    fp.write('1, 2, 3')
```

If you are into the subject of garbage collectors, you may want to read Thomas Perl's paper "Python Garbage Collector Implementations: CPython, PyPy and GaS", from which I learned the bit about the safety of the `open().write()` in CPython.

Parameter Passing: Call by Sharing

A popular way of explaining how parameter passing works in Python is the phrase: "Parameters are passed by value, but the values are references." This is not wrong, but causes confusion because the most common parameter passing modes in older languages are *call by value* (the function gets a copy of the argument) and *call by reference* (the function gets a pointer to the argument). In Python, the function gets a copy of the arguments, but the arguments are always references. So the value of the referenced objects may be changed, if they are mutable, but their identity cannot. Also, because the function gets a copy of the reference in an argument, rebinding it in the function body has no effect outside of the function. I adopted the term *call by sharing* after reading up on the subject in *Programming Language Pragmatics, Third Edition* by Michael L. Scott (Morgan Kaufmann), section “8.3.1: Parameter Modes.”

---

1 Lynn Andrea Stein is award-winning computer science educator who currently teaches at Olin College of Engineering

2 In contrast, flat sequences like `str`, `bytes`, and `array.array` don’t contain references but directly hold their contents—characters, bytes, and numbers—in contiguous memory.

3 See *Principle of least astonishment* in the English Wikipedia

4 This is clearly documented. Type `help(tuple)` in the Python console to read: “If the argument is a tuple, the return value is the same object.” I thought I knew everything about tuples before writing this book.

5 The harmless lie of having the `copy` method not copying anything is justified by interface compatibility: it makes `frozenset` more compatible with `set`. Anyway, it makes no difference to the end user whether two identical immutable objects are the same or are copies.

6 A terrible use for this information would be to ask about it when interviewing candidates or authoring questions for “certification” exams. There are countless more important and useful facts to check for Python knowledge.

7 Actually the type of an object may be changed by merely assigning a different class to its `__class__` attribute, but that is pure evil and I regret writing this footnote.

Part III. Functions as Objects

Chapter 7. Functions as First-Class Objects

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 7th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *I have never considered Python to be heavily influenced by functional languages, no matter what people say or think. I was much more familiar with imperative languages such as C and Algol 68 and although I had made functions first-class objects, I didn't view Python as a functional programming language.*[1]
>
> —Guido van Rossum, Python BDFL

Functions in Python are first-class objects. Programming language researchers define a "first-class object" as a program entity that can be:

- created at runtime;
- assigned to a variable or element in a data structure;
- passed as an argument to a function;
- returned as the result of a function.

Integers, strings, and dictionaries are other examples of first-class objects in Python—nothing fancy here. Having functions as first-class objects is an essential feature of functional languages, such as Clojure, Elixir, and Haskell. However, first-class functions are so useful that they've been adopted by popular languages like JavaScript, Go, and Java (since JDK 8), none of which claim to be "functional languages."

This chapter and most of Part III explore the practical applications of treating functions as objects.

> **TIP**
>
> The term "first-class functions" is widely used as shorthand for "functions as first-class objects." It's not ideal because it implies an "elite" among functions. In Python, all functions are first-class.

What's new in this chapter

Section "The Nine Flavors of Callable Objects" was titled "The Seven Flavors of Callable Objects" in the *First Edition*. The new callables are native coroutines and asynchronous generators, introduced in Python 3.5 and 3.6, respectively. Both are covered in Chapter 22, but they are mentioned here along with the other callables for completeness.

"Positional-only parameters" is a new section, covering a feature added in Python 3.8.

I moved coverage of runtime access to function annotations to "Reading Type Hints at Runtime". When I wrote the *First Edition*, PEP 484—Type Hints—was still under consideration, and people used annotations in different ways. Since Python 3.5, annotations should conform to PEP 484. Therefore, the best place to cover them is when discussing type hints.

NOTE

The *First Edition* had sections about the introspection of function objects that were too low-level and distracted from the main subject of this chapter. I merged those sections into a post titled Introspection of Function Parameters at fluentpython.com.

Now let's see why Python functions are full-fledged objects.

Treating a Function Like an Object

The console session in Example 7-1 shows that Python functions are objects. Here we create a function, call it, read its `__doc__` attribute, and check that the function object itself is an instance of the `function` class.

Example 7-1. Create and test a function, then read its __doc__ and check its type

```
>>> def factorial(n):  ❶
...     """returns n!"""
...     return 1 if n < 2 else n * factorial(n - 1)
...
>>> factorial(42)
1405006117752879898543142606244511569936384000000000
>>> factorial.__doc__  ❷
'returns n!'
>>> type(factorial)  ❸
<class 'function'>
```

❶ This is a console session, so we're creating a function at "runtime."

❷ `__doc__` is one of several attributes of function objects.

❸ `factorial` is an instance of the `function` class.

The `__doc__` attribute is used to generate the help text of an object. In the Python console, the command `help(factorial)` will display a screen like Figure 7-1.

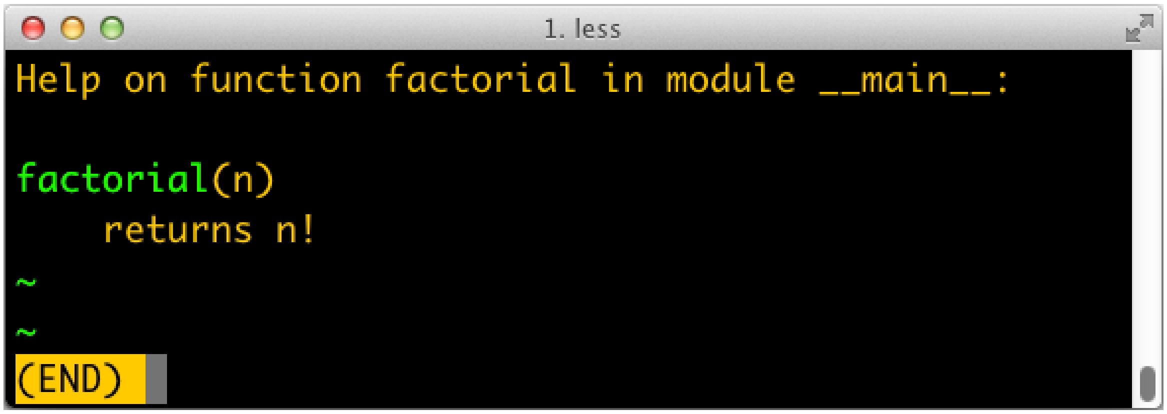


Figure 7-1. Help screen for `factorial`; the text is built from the __doc__ attribute of the function.

Example 7-2 shows the “first class” nature of a function object. We can assign it a variable `fact` and call it through that name. We can also pass `factorial` as an argument to the `map` function. Calling `map(function, iterable)` returns an iterable where each item is the result of calling the first argument (a function) to successive elements of the second argument (an iterable), `range(10)` in this example.

Example 7-2. Use function through a different name, and pass function as argument

```
>>> fact = factorial
>>> fact
<function factorial at 0x...>
>>> fact(5)
120
>>> map(factorial, range(11))
<map object at 0x...>
>>> list(map(factorial, range(11)))
[1, 1, 2, 6, 24, 120, 720, 5040, 40320, 362880, 3628800]
```

Having first-class functions enables programming in a functional style. One of the hallmarks of functional programming is the use of higher-order functions, our next topic.

Higher-Order Functions

A function that takes a function as argument or returns a function as the result is a *higher-order function*. One example is `map`, shown in Example 7-

2. Another is the built-in function `sorted`: the optional `key` argument lets you provide a function to be applied to each item for sorting, as we saw in "list.sort versus the sorted Built-In". For example, to sort a list of words by length, pass the `len` function as the `key`, as in Example 7-3.

Example 7-3. Sorting a list of words by length

```
>>> fruits = ['strawberry', 'fig', 'apple', 'cherry', 'raspberry',
'banana']
>>> sorted(fruits, key=len)
['fig', 'apple', 'cherry', 'banana', 'raspberry', 'strawberry']
>>>
```

Any one-argument function can be used as the key. For example, to create a rhyme dictionary it might be useful to sort each word spelled backward. In Example 7-4, note that the words in the list are not changed at all; only their reversed spelling is used as the sort criterion, so that the berries appear together.

Example 7-4. Sorting a list of words by their reversed spelling

```
>>> def reverse(word):
...     return word[::-1]
>>> reverse('testing')
'gnitset'
>>> sorted(fruits, key=reverse)
['banana', 'apple', 'fig', 'raspberry', 'strawberry', 'cherry']
>>>
```

In the functional programming paradigm, some of the best known higher-order functions are `map`, `filter`, `reduce`, and `apply`. The `apply` function was deprecated in Python 2.3 and removed in Python 3 because it's no longer necessary. If you need to call a function with a dynamic set of arguments, you can write `fn(*args, **kwargs)` instead of `apply(fn, args, kwargs)`.

The `map`, `filter`, and `reduce` higher-order functions are still around, but better alternatives are available for most of their use cases, as the next section shows.

Modern Replacements for map, filter, and reduce

Functional languages commonly offer the `map`, `filter`, and `reduce` higher-order functions (sometimes with different names). The `map` and `filter` functions are still built-ins in Python 3, but since the introduction of list comprehensions and generator expressions, they are not as important. A listcomp or a genexp does the job of `map` and `filter` combined, but is more readable. Consider Example 7-5.

Example 7-5. Lists of factorials produced with map and filter compared to alternatives coded as list comprehensions

```
>>> list(map(factorial, range(6)))  ❶
[1, 1, 2, 6, 24, 120]
>>> [factorial(n) for n in range(6)]  ❷
[1, 1, 2, 6, 24, 120]
>>> list(map(factorial, filter(lambda n: n % 2, range(6))))  ❸
[1, 6, 120]
>>> [factorial(n) for n in range(6) if n % 2]  ❹
[1, 6, 120]
>>>
```

❶ Build a list of factorials from 0! to 5!.

❷ Same operation, with a list comprehension.

❸ List of factorials of odd numbers up to 5!, using both `map` and `filter`.

❹ List comprehension does the same job, replacing `map` and `filter`, and making `lambda` unnecessary.

In Python 3, `map` and `filter` return generators—a form of iterator—so their direct substitute is now a generator expression (in Python 2, these functions returned lists, therefore their closest alternative is a listcomp).

The `reduce` function was demoted from a built-in in Python 2 to the `functools` module in Python 3. Its most common use case, summation, is better served by the `sum` built-in available since Python 2.3 was released in 2003. This is a big win in terms of readability and performance (see Example 7-6).

Example 7-6. Sum of integers up to 99 performed with reduce and sum

```
>>> from functools import reduce  ❶
>>> from operator import add  ❷
>>> reduce(add, range(100))  ❸
4950
>>> sum(range(100))  ❹
4950
>>>
```

❶ Starting with Python 3.0, `reduce` is no longer a built-in.

❷ Import `add` to avoid creating a function just to add two numbers.

❸ Sum integers up to 99.

❹ Same task with `sum`—no need to import and call `reduce` and `add`.

> **NOTE**
>
> The common idea of `sum` and `reduce` is to apply some operation to successive items in a sequence, accumulating previous results, thus reducing a sequence of values to a single value.

Other reducing built-ins are `all` and `any`:

`all(iterable)`

Returns `True` if there are no falsy elements in the iterable; `all([])` returns `True`.

`any(iterable)`

Returns `True` if any element of the `iterable` is truthy; `any([])` returns `False`.

I give a fuller explanation of `reduce` in "Vector Take #4: Hashing and a Faster ==" where an ongoing example provides a meaningful context for the use of this function. The reducing functions are summarized later in the book when iterables are in focus, in "Iterable Reducing Functions".

To use a higher-order function, sometimes it is convenient to create a small, one-off function. That is why anonymous functions exist. We'll cover them next.

Anonymous Functions

The `lambda` keyword creates an anonymous function within a Python expression.

However, the simple syntax of Python limits the body of lambda functions to be pure expressions. In other words, the body cannot contain other Python statements such as `while`, `try`, etc. Assignment with `=` is also a statement, so it cannot occur in a lambda. The new assignment expression syntax using `:=` can be used—but if you need it, your lambda is probably too complicated and hard to read, and it should be refactored into a regular function using `def`.

The best use of anonymous functions is in the context of an argument list for a higher-order function. For example, Example 7-7 is the rhyme index example from Example 7-4 rewritten with `lambda`, without defining a `reverse` function.

Example 7-7. Sorting a list of words by their reversed spelling using lambda

```
>>> fruits = ['strawberry', 'fig', 'apple', 'cherry', 'raspberry',
'banana']
>>> sorted(fruits, key=lambda word: word[::-1])
['banana', 'apple', 'fig', 'raspberry', 'strawberry', 'cherry']
>>>
```

Outside the limited context of arguments to higher-order functions, anonymous functions are rarely useful in Python. The syntactic restrictions tend to make nontrivial lambdas either unreadable or unworkable. If a lambda is hard to read, I strongly advise you follow Fredrik Lundh's refactoring advice.

FREDRIK LUNDH'S LAMBDA REFACTORING RECIPE

If you find a piece of code hard to understand because of a `lambda`, Fredrik Lundh suggests this refactoring procedure:

1. Write a comment explaining what the heck that `lambda` does.
2. Study the comment for a while, and think of a name that captures the essence of the comment.
3. Convert the `lambda` to a `def` statement, using that name.
4. Remove the comment.

These steps are quoted from the Functional Programming HOWTO, a must read.

The `lambda` syntax is just syntactic sugar: a `lambda` expression creates a function object just like the `def` statement. That is just one of several kinds of callable objects in Python. The following section reviews all of them.

The Nine Flavors of Callable Objects

The call operator `()` may be applied to other objects beyond user-defined functions and lambdas. To determine whether an object is callable, use the `callable()` built-in function. As of Python 3.9, the Data Model documentation lists nine callable types:

User-defined functions

Created with `def` statements or `lambda` expressions.

Built-in functions

A function implemented in C (for CPython), like `len` or `time.strftime`.

Built-in methods

Methods implemented in C, like `dict.get`.

Methods

Functions defined in the body of a class.

Classes

When invoked, a class runs its `__new__` method to create an instance, then `__init__` to initialize it, and finally the instance is returned to the caller. Because there is no `new` operator in Python, calling a class is like calling a function.[2]

Class instances

If a class defines a `__call__` method, then its instances may be invoked as functions—that's the subject of the next section.

Generator functions

Functions or methods that use the `yield` keyword in their body. When called, they return a generator object.

Native coroutine functions

Functions or methods defined with `async def`. When called, they return a coroutine object. Added in Python 3.5.

Asynchronous generator functions

Functions or methods defined with `async def` that have `yield` in their body. When called, they return an asynchronous generator for use with `async for`. Added in Python 3.6.

Generators, native coroutines, and asynchronous generator functions are unlike other callables in that their return values are never application data, but objects that require further processing to yield application data or perform useful work. Generator functions return iterators. Both are covered in Chapter 17. Native coroutine functions and asynchronous generator functions return objects that only work with the help of an asynchronous programming framework, such as *asyncio*. They are the subject of Chapter 22.

> **TIP**
>
> Given the variety of existing callable types in Python, the safest way to determine whether an object is callable is to use the `callable()` built-in:
>
> ```
> >>> abs, str, 'Ni!'
> (<built-in function abs>, <class 'str'>, 'Ni!')
> >>> [callable(obj) for obj in (abs, str, 'Ni!')]
> [True, True, False]
> ```

We now move on to building class instances that work as callable objects.

User-Defined Callable Types

Not only are Python functions real objects, but arbitrary Python objects may also be made to behave like functions. Implementing a `__call__` instance method is all it takes.

Example 7-8 implements a `BingoCage` class. An instance is built from any iterable, and stores an internal `list` of items, in random order. Calling the instance pops an item.[3]

Example 7-8. bingocall.py: A BingoCage does one thing: picks items from a shuffled list

```
import random

class BingoCage:

    def __init__(self, items):
        self._items = list(items)  ❶
        random.shuffle(self._items)  ❷
```

```python
    def pick(self):  ❸
        try:
            return self._items.pop()
        except IndexError:
            raise LookupError('pick from empty BingoCage')  ❹

    def __call__(self):  ❺
        return self.pick()
```

❶ `__init__` accepts any iterable; building a local copy prevents unexpected side effects on any `list` passed as an argument.

❷ `shuffle` is guaranteed to work because `self._items` is a `list`.

❸ The main method.

❹ Raise exception with custom message if `self._items` is empty.

❺ Shortcut to `bingo.pick()`: `bingo()`.

Here is a simple demo of Example 7-8. Note how a `bingo` instance can be invoked as a function, and the `callable()` built-in recognizes it as a callable object:

```
>>> bingo = BingoCage(range(3))
>>> bingo.pick()
1
>>> bingo()
0
>>> callable(bingo)
True
```

A class implementing `__call__` is an easy way to create function-like objects that have some internal state that must be kept across invocations, like the remaining items in the `BingoCage`. Another good use case for `__call__` is implementing decorators. Decorators must be callable, and it is sometimes convenient to "remember" something between calls of the decorator (e.g., for memoization—caching the results of expensive computations for later use) or to split a complex implementation into separate methods.

The functional approach to creating functions with internal state is to use closures. Closures, as well as decorators, are the subject of Chapter 9.

Now let's explore the powerful syntax Python offers to declare function parameters and pass arguments into them.

From Positional to Keyword-Only Parameters

One of the best features of Python functions is the extremely flexible parameter handling mechanism. Closely related are the use of `*` and `**` to unpack iterables and mappings into separate arguments when we call a function. To see these features in action, see the code for Example 7-9 and tests showing its use in Example 7-10.

Example 7-9. tag generates HTML elements; a keyword-only argument `class_` is used to pass "class" attributes as a workaround because `class` is a keyword in Python

```
def tag(name, *content, class_=None, **attrs):
    """Generate one or more HTML tags"""
    if class_ is not None:
        attrs['class'] = class_
    attr_pairs = (f' {attr}="{value}"' for attr, value
                    in sorted(attrs.items()))
    attr_str = ''.join(attr_pairs)
    if content:
        elements = (f'<{name}{attr_str}>{c}</{name}>'
                    for c in content)
        return '\n'.join(elements)
    else:
        return f'<{name}{attr_str} />'
```

The `tag` function can be invoked in many ways, as Example 7-10 shows.

Example 7-10. Some of the many ways of calling the tag function from Example 7-9

```
>>> tag('br')  ❶
'<br />'
>>> tag('p', 'hello')  ❷
'<p>hello</p>'
>>> print(tag('p', 'hello', 'world'))
<p>hello</p>
<p>world</p>
>>> tag('p', 'hello', id=33)  ❸
'<p id="33">hello</p>'
>>> print(tag('p', 'hello', 'world', class_='sidebar'))  ❹
<p class="sidebar">hello</p>
<p class="sidebar">world</p>
>>> tag(content='testing', name="img")  ❺
'<img content="testing" />'
>>> my_tag = {'name': 'img', 'title': 'Sunset Boulevard',
...           'src': 'sunset.jpg', 'class': 'framed'}
>>> tag(**my_tag)  ❻
'<img class="framed" src="sunset.jpg" title="Sunset Boulevard" />'
```

❶ A single positional argument produces an empty tag with that name.

❷ Any number of arguments after the first are captured by `*content` as a `tuple`.

❸ Keyword arguments not explicitly named in the `tag` signature are captured by `**attrs` as a `dict`.

❹ The `class_` parameter can only be passed as a keyword argument.

❺ The first positional argument can also be passed as a keyword.

❻ Prefixing the `my_tag` `dict` with `**` passes all its items as separate arguments, which are then bound to the named parameters, with the remaining caught by `**attrs`. In this case we can have a `'class'` key in the arguments `dict`, because it is a string, and does not clash with the `class` reserved word.

Keyword-only arguments are a feature of Python 3. In Example 7-9, the `class_` parameter can only be given as a keyword argument—it will never capture unnamed positional arguments. To specify keyword-only arguments when defining a function, name them after the argument prefixed with `*`. If you don't want to support variable positional arguments but still want keyword-only arguments, put a `*` by itself in the signature, like this:

```
>>> def f(a, *, b):
...     return a, b
...
>>> f(1, b=2)
(1, 2)
>>> f(1, 2)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: f() takes 1 positional argument but 2 were given
```

Note that keyword-only arguments do not need to have a default value: they can be mandatory, like `b` in the preceding example.

Positional-only parameters

Since Python 3.8, user-defined function signatures may specify positional-only parameters. This feature always existed for built-in functions, such as `divmod(a, b)`, which can only be called with positional parameters, and not as `divmod(a=10, b=4)`.

To define a function requiring positional-only parameters, use `/` in the parameter list.

This example from What's New In Python 3.8 shows how to emulate the `divmod` built-in function:

```
def divmod(a, b, /):
    return (a // b, a % b)
```

All arguments to the left of the `/` are positional-only. After the `/`, you may specify other arguments, which work as usual.

> **WARNING**
>
> The `/` in the parameter list is a syntax error in Python 3.7 or earlier.

For example, consider the `tag` function from Example 7-9. If we want the `name` parameter to be positional only, we can add a `/` after it in the function signature, like this:

```
def tag(name, /, *content, class_=None, **attrs):
    ...
```

You can find other examples of positional-only parameters in What's New In Python 3.8 and in PEP 570.

After diving into Python's flexible argument declaration features, the remainder of this chapter covers the most useful packages in the standard library for programming in a functional style.

Packages for Functional Programming

Although Guido makes it clear that he did not design Python to be a functional programming language, a functional coding style can be used to good extent, thanks to first-class functions, pattern matching, and the support of packages like `operator` and `functools`, which we cover in the next two sections.

The operator Module

Often in functional programming it is convenient to use an arithmetic operator as a function. For example, suppose you want to multiply a sequence of numbers to calculate factorials without using recursion. To perform summation, you can use `sum`, but there is no equivalent function for multiplication. You could use `reduce`—as we saw in "Modern Replacements for map, filter, and reduce"—but this requires a function to multiply two items of the sequence. Example 7-11 shows how to solve this using `lambda`.

Example 7-11. Factorial implemented with reduce and an anonymous function

```
from functools import reduce

def factorial(n):
    return reduce(lambda a, b: a*b, range(1, n+1))
```

The `operator` module provides function equivalents for dozens of operators so you don't have to code trivial functions like `lambda a, b: a*b`. With it, we can rewrite Example 7-11 as Example 7-12.

Example 7-12. Factorial implemented with reduce and operator.mul

```
from functools import reduce
from operator import mul

def factorial(n):
    return reduce(mul, range(1, n+1))
```

Another group of one-trick lambdas that `operator` replaces are functions to pick items from sequences or read attributes from objects: `itemgetter` and `attrgetter` are factories that build custom functions to do that.

Example 7-13 shows a common use of `itemgetter`: sorting a list of tuples by the value of one field. In the example, the cities are printed sorted by country code (field 1). Essentially, `itemgetter(1)` creates a function that, given a collection, returns the item at index 1. That's easier to write and read than `lambda fields: fields[1]`, which does the same:

Example 7-13. Demo of itemgetter to sort a list of tuples (data from Example 2-8)

```
>>> metro_data = [
...     ('Tokyo', 'JP', 36.933, (35.689722, 139.691667)),
...     ('Delhi NCR', 'IN', 21.935, (28.613889, 77.208889)),
...     ('Mexico City', 'MX', 20.142, (19.433333, -99.133333)),
...     ('New York-Newark', 'US', 20.104, (40.808611, -74.020386)),
...     ('São Paulo', 'BR', 19.649, (-23.547778, -46.635833)),
... ]
>>>
```

```
>>> from operator import itemgetter
>>> for city in sorted(metro_data, key=itemgetter(1)):
...     print(city)
...
('São Paulo', 'BR', 19.649, (-23.547778, -46.635833))
('Delhi NCR', 'IN', 21.935, (28.613889, 77.208889))
('Tokyo', 'JP', 36.933, (35.689722, 139.691667))
('Mexico City', 'MX', 20.142, (19.433333, -99.133333))
('New York-Newark', 'US', 20.104, (40.808611, -74.020386))
```

If you pass multiple index arguments to `itemgetter`, the function it builds will return tuples with the extracted values, which is useful for sorting on multiple keys:

```
>>> cc_name = itemgetter(1, 0)
>>> for city in metro_data:
...     print(cc_name(city))
...
('JP', 'Tokyo')
('IN', 'Delhi NCR')
('MX', 'Mexico City')
('US', 'New York-Newark')
('BR', 'São Paulo')
>>>
```

Because `itemgetter` uses the `[]` operator, it supports not only sequences but also mappings and any class that implements `__getitem__`.

A sibling of `itemgetter` is `attrgetter`, which creates functions to extract object attributes by name. If you pass `attrgetter` several attribute names as arguments, it also returns a tuple of values. In addition, if any argument name contains a `.` (dot), `attrgetter` navigates through nested objects to retrieve the attribute. These behaviors are shown in Example 7-14. This is not the shortest console session because we need to build a nested structure to showcase the handling of dotted attributes by `attrgetter`.

Example 7-14. Demo of attrgetter to process a previously defined list of namedtuple called metro_data (the same list that appears in Example 7-13)

```
>>> from collections import namedtuple
>>> LatLon = namedtuple('LatLon', 'lat lon')  ❶
>>> Metropolis = namedtuple('Metropolis', 'name cc pop coord')  ❷
>>> metro_areas = [Metropolis(name, cc, pop, LatLon(lat, lon))  ❸
...     for name, cc, pop, (lat, lon) in metro_data]
>>> metro_areas[0]
Metropolis(name='Tokyo', cc='JP', pop=36.933,
coord=LatLon(lat=35.689722,
lon=139.691667))
>>> metro_areas[0].coord.lat  ❹
35.689722
>>> from operator import attrgetter
>>> name_lat = attrgetter('name', 'coord.lat')  ❺
>>>
>>> for city in sorted(metro_areas, key=attrgetter('coord.lat')):
❻
...     print(name_lat(city))  ❼
...
('São Paulo', -23.547778)
('Mexico City', 19.433333)
('Delhi NCR', 28.613889)
('Tokyo', 35.689722)
('New York-Newark', 40.808611)
```

❶ Use `namedtuple` to define `LatLon`.

❷ Also define `Metropolis`.

❸ Build `metro_areas` list with `Metropolis` instances; note the nested tuple unpacking to extract `(lat, lon)` and use them to build the `LatLon` for the `coord` attribute of `Metropolis`.

❹ Reach into element `metro_areas[0]` to get its latitude.

❺ Define an `attrgetter` to retrieve the `name` and the `coord.lat` nested attribute.

❻ Use `attrgetter` again to sort list of cities by latitude.

❼ Use the `attrgetter` defined in ❺ to show only city name and latitude.

Here is a partial list of functions defined in `operator` (names starting with _ are omitted, because they are mostly implementation details):

```
>>> [name for name in dir(operator) if not name.startswith('_')]
['abs', 'add', 'and_', 'attrgetter', 'concat', 'contains',
'countOf', 'delitem', 'eq', 'floordiv', 'ge', 'getitem', 'gt',
'iadd', 'iand', 'iconcat', 'ifloordiv', 'ilshift', 'imatmul',
'imod', 'imul', 'index', 'indexOf', 'inv', 'invert', 'ior',
'ipow', 'irshift', 'is_', 'is_not', 'isub', 'itemgetter',
'itruediv', 'ixor', 'le', 'length_hint', 'lshift', 'lt',
'matmul',
'methodcaller', 'mod', 'mul', 'ne', 'neg', 'not_', 'or_', 'pos',
'pow', 'rshift', 'setitem', 'sub', 'truediv', 'truth', 'xor']
```

Most of the 54 names listed are self-evident. The group of names prefixed with `i` and the name of another operator—e.g., `iadd`, `iand`, etc.—correspond to the augmented assignment operators—e.g., `+=`, `&=`, etc. These change their first argument in place, if it is mutable; if not, the function works like the one without the `i` prefix: it simply returns the result of the operation.

Of the remaining `operator` functions, `methodcaller` is the last we will cover. It is somewhat similar to `attrgetter` and `itemgetter` in that it creates a function on the fly. The function it creates calls a method by name on the object given as argument, as shown in Example 7-15.

Example 7-15. Demo of methodcaller: second test shows the binding of extra arguments

```
>>> from operator import methodcaller
>>> s = 'The time has come'
>>> upcase = methodcaller('upper')
>>> upcase(s)
'THE TIME HAS COME'
>>> hyphenate = methodcaller('replace', ' ', '-')
>>> hyphenate(s)
'The-time-has-come'
```

The first test in Example 7-15 is there just to show `methodcaller` at work, but if you need to use the `str.upper` as a function, you can just call it on the `str` class and pass a string as argument, like this:

```
>>> str.upper(s)
'THE TIME HAS COME'
```

The second test in Example 7-15 shows that `methodcaller` can also do a partial application to freeze some arguments, like the `functools.partial` function does. That is our next subject.

Freezing Arguments with functools.partial

The `functools` module provides several higher-order functions. We saw `reduce` in "Modern Replacements for map, filter, and reduce". Another is `partial`: given a callable, it produces a new callable with some of the arguments of the original callable bound to pre-determined values. This is useful to adapt a function that takes one or more arguments to an API that requires a callback with fewer arguments. Example 7-16 is a trivial demonstration.

Example 7-16. Using partial to use a two-argument function where a one-argument callable is required

```
>>> from operator import mul
>>> from functools import partial
>>> triple = partial(mul, 3)  ❶
>>> triple(7)  ❷
21
>>> list(map(triple, range(1, 10)))  ❸
[3, 6, 9, 12, 15, 18, 21, 24, 27]
```

❶ Create new `triple` function from `mul`, binding first positional argument to `3`.

❷ Test it.

❸ Use `triple` with `map`; `mul` would not work with `map` in this example.

A more useful example involves the `unicode.normalize` function that we saw in "Normalizing Unicode for Reliable Comparisons". If you work with text from many languages, you may want to apply `unicode.normalize('NFC', s)` to any string `s` before comparing or storing it. If you do that often, it's handy to have an `nfc` function to do so, as in Example 7-17.

Example 7-17. Building a convenient Unicode normalizing function with `partial`

```
>>> import unicodedata, functools
>>> nfc = functools.partial(unicodedata.normalize, 'NFC')
>>> s1 = 'café'
>>> s2 = 'cafe\u0301'
>>> s1, s2
('café', 'café')
>>> s1 == s2
False
>>> nfc(s1) == nfc(s2)
True
```

`partial` takes a callable as first argument, followed by an arbitrary number of positional and keyword arguments to bind.

Example 7-18 shows the use of `partial` with the `tag` function from Example 7-9, to freeze one positional argument and one keyword argument.

Example 7-18. Demo of `partial` applied to the function tag from Example 7-9

```
>>> from tagger import tag
>>> tag
<function tag at 0x10206d1e0>  ❶
>>> from functools import partial
>>> picture = partial(tag, 'img', class_='pic-frame')  ❷
>>> picture(src='wumpus.jpeg')
'<img class="pic-frame" src="wumpus.jpeg" />'  ❸
>>> picture
functools.partial(<function tag at 0x10206d1e0>, 'img',
class_='pic-frame')  ❹
>>> picture.func  ❺
<function tag at 0x10206d1e0>
>>> picture.args
('img',)
>>> picture.keywords
{'class_': 'pic-frame'}
```

❶ Import `tag` from Example 7-9 and show its ID.

❷ Create `picture` function from `tag` by fixing the first positional argument with `'img'` and the `class_` keyword argument with `'pic-frame'`.

❸ `picture` works as expected.

❹ `partial()` returns a `functools.partial` object.[4]

❺ A `functools.partial` object has attributes providing access to the original function and the fixed arguments.

The `functools.partialmethod` function does the same job as `partial`, but is designed to work with methods.

The `functools` module also include higher-order functions designed to be used as function decorators, such as `cache` and `singledispatch`, among others. Those functions are the covered in Chapter 9, which also explains how to implement custom decorators.

Chapter Summary

The goal of this chapter was to explore the first-class nature of functions in Python. The main ideas are that you can assign functions to variables, pass them to other functions, store them in data structures, and access function attributes, allowing frameworks and tools to act on that information.

Higher-order functions, a staple of functional programming, are common in Python. The `sorted`, `min`, and `max` built-ins, and `functools.partial` are examples of commonly used higher-order functions in the language. Using `map`, `filter`, and `reduce` is not as common as it used to be—thanks to list comprehensions (and similar constructs like generator expressions) and the addition of reducing built-ins like `sum`, `all`, and `any`.

Callables come in nine different flavors since Python 3.6, from the simple functions created with `lambda` to instances of classes implementing `__call__`. Generators and coroutines are also callable, although their behavior is very different from other callables. All callables can be detected by the `callable()` built-in. Callables offer rich syntax for declaring formal parameters, including keyword-only parameters, positional-only paramenters, and annotations.

Lastly, we covered some functions from the `operator` module and `functools.partial`, which facilitate functional programming by minimizing the need for the functionally challenged `lambda` syntax.

Further Reading

The next chapters continue our exploration of programming with function objects. Chapter 8 is devoted to type hints in function parameters and return values. Chapter 9 dives into function decorators—a special kind of higher-order function—and the closure mechanism that makes them work. Chapter 10 shows how first-class functions can simplify some classic object-oriented design patterns.

In *The Python Language Reference*, "3.2. The standard type hierarchy" presents the nine callable types, along with all the other built-in types.

Chapter 7 of the *Python Cookbook, Third Edition* (O'Reilly), by David Beazley and Brian K. Jones, is an excellent complement to the current chapter as well as Chapter 9 of this book, covering mostly the same concepts with a different approach.

See PEP 3102 — Keyword-Only Arguments if you are interested in the rationale and use cases for that feature.

A great introduction to functional programming in Python is A. M. Kuchling's Python Functional Programming HOWTO. The main focus of that text, however, is the use of iterators and generators, which are the subject of Chapter 17.

The StackOverflow question "Python: Why is functools.partial necessary?" has a highly informative (and funny) reply by Alex Martelli, co-author of the classic *Python in a Nutshell*.

Reflecting on the question "Is Python a functional language?", I created one of my favorite talks: *Beyond Paradigms*, which I presented at PyCaribbean, PyBay and PyConDE. See the slides and video from the Berlin presentation—where I met Miroslav Šedivý and Jürgen Gmach, two of the technical reviewers of this book.

SOAPBOX

Is Python a Functional Language?

Sometime in the year 2000 I attended a Zope workshop at Zope Corporation in the United States when Guido van Rossum dropped by the classroom (he was not the instructor). In the Q&A that followed, somebody asked him which features of Python were borrowed from other languages. Guido's answer: "Everything that is good in Python was stolen from other languages."

Shriram Krishnamurthi, professor of Computer Science at Brown University, starts his "Teaching Programming Languages in a Post-Linnaean Age" paper with this:

> *Programming language "paradigms" are a moribund and tedious legacy of a bygone age. Modern language designers pay them no respect, so why do our courses slavishly adhere to them?*

In that paper, Python is mentioned by name in this passage:

> *What else to make of a language like Python, Ruby, or Perl? Their designers have no patience for the niceties of these Linnaean hierarchies; they borrow features as they wish, creating melanges that utterly defy characterization.*

Krishnamurthi argues that instead of trying to classify languages in some taxonomy, it's more useful to consider them as aggregations of features. His ideas inspired my talk *Beyond Paradigms*, mentioned at the end of "Further Reading".

Even if it was not Guido's goal, endowing Python with first-class functions opened the door to functional programming. In his post "Origins of Python's *Functional* Features", he says that `map`, `filter`, and `reduce` were the motivation for adding `lambda` to Python in the first place. All of these features were contributed together by Amrit Prem for Python 1.0 in 1994 (according to Misc/HISTORY in the CPython source code).

Functions like `map`, `filter`, and `reduce` first appeared in Lisp, the original functional language. However, Lisp does not limit what can be done inside a `lambda`, because everything in Lisp is an expression. Python uses a statement-oriented syntax in which expressions cannot contain statements, and many language constructs are statements—including `try/catch`, which is what I miss most often when writing `lambdas`. This is the price to pay for Python's highly readable syntax.[5] Lisp has many strengths, but readability is not one of them.

Ironically, stealing the list comprehension syntax from another functional language—Haskell—significantly diminished the need for `map` and `filter`, and also for `lambda`.

Besides the limited anonymous function syntax, the biggest obstacle to wider adoption of functional programming idioms in Python is the lack of tail-call elimination, an optimization that allows memory-efficient computation of a function that makes a recursive call at the "tail" of its body. In another blog post, "Tail Recursion Elimination", Guido gives several reasons why such optimization is not a good fit for Python. That post is a great read for the technical arguments, but even more so because the first three and most important reasons given are usability issues. It is no accident that Python is a pleasure to use, learn, and teach. Guido made it so.

So there you have it: Python is not, by design, a functional language—whatever that means. Python just borrows a few good ideas from functional languages.

The Problem with Anonymous Functions

Beyond the Python-specific syntax constraints, anonymous functions have a serious drawback in any language: they have no name.

I am only half joking here. Stack traces are easier to read when functions have names. Anonymous functions are a handy shortcut, people have fun coding with them, but sometimes they get carried away—especially if the language and environment encourage deep nesting of anonymous functions, like JavaScript on Node.js do. Lots of nested anonymous functions make debugging and error handling hard. Asynchronous programming in Python is more structured, perhaps because the limited `lambda` syntax prevents its abuse and forces a more explicit approach. Promises, futures, and deferreds are concepts used in modern asynchronous APIs. Along with coroutines, they provide an escape from the so-called "callback hell." I promise to write more about asynchronous programming in the future, but this subject must be deferred to Chapter 22.

---

1 "Origins of Python's *Functional* Features", from Guido's The History of Python blog.

2 Calling a class usually creates an instance of that same class, but other behaviors are possible by overriding `__new__`. We'll see an example of this in "Flexible Object Creation with __new__".

3 Why build a `BingoCage` when we already have `random.choice`? The `choice` function may return the same item multiple times, because the picked item is not removed from the collection given. Calling `BingoCage` never returns duplicate results—as long as the instance is filled with unique values.

4 The source code for `functools.py` reveals that the `functools.partial` class is implemented in C and is used by default. If that is not available, a pure-Python implementation of `partial` is available since Python 3.4.

5 There is also the problem of lost indentation when pasting code to Web forums, but I digress.

Chapter 8. Type Hints in Functions

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 8th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *It should also be emphasized that* ***Python will remain a dynamically typed language, and the authors have no desire to ever make type hints mandatory, even by convention***.[1]
>
> —Guido van Rossum, Jukka Lehtosalo, and Łukasz Langa, PEP 484—Type Hints

Type hints are the biggest change in the history of Python since the unification of types and classes in Python 2.2, released in 2001. However, type hints do not benefit all Python users equally. That's why they should always be optional.

PEP 484—Type Hints introduced syntax and semantics for explicit type declarations in function arguments, return values, and variables. The goal is to help developer tools find bugs in Python codebases via static analysis, i.e. without actually running the code through tests.

The main beneficiaries are professional software engineers using IDEs (Integrated Development Environments) and CI (Continuous Integration). The cost-benefit analysis that makes type hints attractive to that group does not apply to all users of Python.

Python’s user base is much wider than that. It includes scientists, traders, journalists, artists, makers, analysts and students in many fields—among others. For most of them, the cost of learning type hints is higher—unless they already know a language with static types, subtyping, and generics. The cost is likely to be higher and the benefits will be lower for many of those users, given how they interact with Python, and the smaller size of their code bases and teams—often, “teams” of one. Python’s default dynamic typing is simpler and more expressive when writing code for exploring data and ideas, as in data science, creative computing, and learning,

This chapter focuses on Python’s type hints in function signatures. Chapter 15 explores type hints in the context of classes, and other `typing` module features.

The major topics in this chapter are:

- A hands-on introduction to gradual typing with Mypy.
- The complementary perspectives of duck typing and nominal typing.
- Overview of the main categories of types that can appear in annotations—this is about 60% of the chapter.
- Type hinting variadic parameters (`*args`, `**kwargs`).
- Limitations and downsides of type hints and static typing.

What’s new in this chapter

This chapter is completely new. Type hints appeared in Python 3.5 after I wrapped up the first edition of *Fluent Python*.

Given the limitations of a static type system, the best idea of PEP 484 was to propose a *gratual type system*. Let's begin by defining what that means.

About gradual typing

PEP 484 introduced a *gradual type system* to Python. Other languages with gradual type systems are Microsoft's TypeScript, Dart (the language of the Flutter SDK, created by Google), and Hack (a dialect of PHP supported by Facebook's HHVM virtual machine). The Mypy type checker itself started as a language: a gradually typed dialect of Python with its own interpreter. Guido van Rossum convinced the creator of Mypy, Jukka Lehtosalo, to make it a tool for checking annotated Python code.

A gradual type system:

Is optional.

> By default, the type checker should not emit warnings for code that has no type hints. Instead, the type checker assumes the `Any` type when it cannot determine the type of an object. The `Any` type is considered compatible with all other types.

Does not catch type errors at runtime.

> Type hints are used by static type checkers, linters, and IDEs to raise warnings. They do not prevent inconsistent values to be passed to functions or assigned to variables at runtime.

Does not enhance performance.

> Type annotations provide data that could, in theory, allow optimizations in the generated byte code, but such optimizations are not implemented in any Python runtime that I am aware in July 2021.[2]

The best usability feature of gradual typing is that annotations are always optional.

With static type systems, most type constraints are easy to express, many are cumbersome, some are hard, and a few are impossible.[3] You may very well write an excellent piece of Python code, with good test coverage and passing tests, but still be unable to add type hints that satisfy a type checker. That's ok, just leave out the problematic type hints and ship it!

Type hints are optional at all levels: you can have entire packages with no type hints, you can silence the type checker when you import one of those packages into a module where you use type hints, and you can add special comments to make the type checker ignore specific lines in your code.

> **TIP**
>
> Seeking 100% coverage of type hints is likely to stimulate type hinting without proper thought, only to satisfy the metric. It will also prevent teams from making the most of the power and flexibility of Python. Code without type hints should naturally be accepted when annotations would make an API less user-friendly, or unduly complicate its implementation.

Gradual typing in practice

Let's see how gradual typing works in practice, starting with a simple function and gradually adding type hints to it, guided by Mypy.

> **NOTE**
>
> There are several Python type checkers compatible with PEP 484, including Google's pytype, Microsoft's Pyright, Facebook's Pyre—in addition to type checkers embedded in IDEs such as PyCharm. I picked Mypy for the examples because it's the best known. However, one of the others may be a better fit for some projects or teams. Pytype, for example, is designed to handle codebases with no type hints and still provide useful advice. It is more lenient than Mypy, and can also generate annotations for your code.

We will annotate a `show_count` function that returns a string with a count and a singular or plural word, depending on the count:

```
>>> show_count(99, 'bird')
'99 birds'
>>> show_count(1, 'bird')
'1 bird'
>>> show_count(0, 'bird')
'no birds'
```

Example 8-1 shows the source code of `show_count`, without annotations.

Example 8-1. `show_count` from `messages.py` without type hints.

```
def show_count(count, word):
    if count == 1:
        return f'1 {word}'
    count_str = str(count) if count else 'no'
    return f'{count_str} {word}s'
```

Starting with Mypy

To begin type checking, I run the `mypy` command on the `messages.py` module:

```
…/no_hints/ $ pip install mypy
[lots of messages omitted...]
…/no_hints/ $ mypy messages.py
Success: no issues found in 1 source file
```

Mypy with default settings finds no problem with Example 8-2:

> **WARNING**
>
> I am using Mypy 0.910, the most recent release as I review this in July 2021. The Mypy Introduction warns it "is officially beta software. There will be occasional changes that break backward compatibility." Mypy is giving me at least one report that is not the same I got when I wrote this chapter in April 2020. By the time you read this, you may get different results than shown here.

If a function signature has no annotations, Mypy ignores it by default. That's the spirit of gradual typing.

For this example, I also have `pytest` unit tests. This is the code in `messages_test.py`.

Example 8-2. `messages_test.py` without type hints.

```
from pytest import mark

from messages import show_count

@mark.parametrize('qty, expected', [
    (1, '1 part'),
    (2, '2 parts'),
])
def test_show_count(qty, expected):
    got = show_count(qty, 'part')
    assert got == expected

def test_show_count_zero():
    got = show_count(0, 'part')
    assert got == 'no parts'
```

Now let’s add type hints, guided by Mypy.

Making Mypy More Strict

The command-line option `--disallow-untyped-defs` makes Mypy flag any function definition that does not have type hints for all its parameters and for its return value.

Using `--disallow-untyped-defs` on the test file produces three errors and a note:

```
…/no_hints/ $ mypy --disallow-untyped-defs messages_test.py
messages.py:14: error: Function is missing a type annotation
messages_test.py:10: error: Function is missing a type annotation
messages_test.py:15: error: Function is missing a return type
annotation
messages_test.py:15: note: Use "-> None" if function does not
return a value
Found 3 errors in 2 files (checked 1 source file)
```

For the first steps with gradual typing, I prefer to use another option: `--disallow-incomplete-defs`. Initially, it tells me nothing:

```
…/no_hints/ $ mypy --disallow-incomplete-defs messages_test.py
Success: no issues found in 1 source file
```

Now I can add just the return type to `show_count` in `messages.py`:

```
def show_count(count, word) -> str:
```

This is enough to make Mypy look at it. Using the same command line as before to check `messages_test.py`, will lead Mypy to look at `messages.py` again:

```
…/no_hints/ $ mypy --disallow-incomplete-defs messages_test.py
messages.py:14: error: Function is missing a type annotation for
one or more arguments
Found 1 error in 1 file (checked 1 source file)
```

Now I can gradually add type hints function by function, without getting warnings about functions that I haven't annotated. This is a fully annotated signature that satisfies Mypy:

```
def show_count(count: int, word: str) -> str:
```

> **TIP**
>
> Instead of typing command line options like `--disallow-incomplete-defs`, you can save your favorite as described in the Mypy configuration file documentation. You can have global settings and per-module settings. Here is a simple `mypy.ini` to get started:
>
> ```
> [mypy]
> python_version = 3.9
> warn_unused_configs = True
> disallow_incomplete_defs = True
> ```

A Default Parameter Value

The `show_count` function in Example 8-2 only works with regular nouns. If the plural can't be spelled by appending an `'s'`, we should let the user provide the plural form, like this:

```
>>> show_count(3, 'mouse', 'mice')
'3 mice'
```

Let's do a little "type driven development." First we add a test that uses that third argument. Don't forget to add the return type hint to the test function, otherwise Mypy will not check it.

```
def test_irregular() -> None:
    got = show_count(2, 'child', 'children')
    assert got == '2 children'
```

Mypy detects the error:

```
…/hints_2/ $ mypy messages_test.py
messages_test.py:22: error: Too many arguments for "show_count"
Found 1 error in 1 file (checked 1 source file)
```

Now I edit `show_count`, adding the optional `plural` parameter:

Example 8-3. `showcount` from `hints_2/messages.py` with an optional parameter.

```
def show_count(count: int, singular: str, plural: str = '') -> str:
    if count == 1:
        return f'1 {singular}'
    count_str = str(count) if count else 'no'
    if not plural:
        plural = singular + 's'
    return f'{count_str} {plural}'
```

Now Mypy reports "Success."

WARNING

Here is one typing mistake that Python does not catch. Can you spot it?

```
def hex2rgb(color=str) -> tuple[int, int, int]:
```

Mypy's error report is not very helpful:

```
colors.py:24: error: Function is missing a type
    annotation for one or more arguments
```

The type hint for the `color` argument should be `color: str`. I wrote `color=str`, which is not an annotation: it sets the default value of `color` to `str`.

In my experience, it's a common mistake and easy to overlook, especially in complicated type hints.

The following details are considered good style for type hints:

- There should be no space between the parameter name and the `:`, and one space after the `:`.
- There should be spaces on both sides of the `=` that precedes a default parameter value.

On the other hand, PEP 8 says there should be no spaces around the `=` if there is no type hint for that particular parameter.

CODE STYLE: USE FLAKE8 AND BLUE

Instead of memorizing such silly rules, use tools like *flake8* and *blue*. *flake8* reports on code styling, among many other issues, and *blue* rewrites source code according to (most) rules embeded in the *black* code formatting tool.

Given the goal of enforcing a "standard" coding style, *blue* is better than *black* because it follows Python's own style of using single quotes by default, double quotes as an alternative:

```
>>> "I prefer single quotes"
'I prefer single quotes'
```

The preference for single quotes is embedded in `repr()`, among other places in CPython. The *doctest* module depends on `repr()` using single quotes by default.

If you you must use *black*, use the `black -S` option. Then it will leave your quotes as they are.

> **NOTE**
>
> One of the authors of *blue* is Barry Warsaw, co-author of PEP 8, Python core developer since 1994, and member of Python's Steering Council from 2019 to present (July, 2021). We are in very good company when we choose single quotes by default.

Using None as a default

In Example 8-3 the parameter `plural` is annotated as `str`, and the default value is `''`, so there is no type conflict.

I like that solution, but in other contexts `None` is a better default. If the optional parameter expects a mutable type, then `None` is the only sensible default—as we saw in "Mutable Types as Parameter Defaults: Bad Idea".

To have `None` as the default for the `plural` parameter, here is how the signature would look like:

```
from typing import Optional

def show_count(count: int, singular: str, plural: Optional[str] =
None) -> str:
```

Let’s unpack that:

- `Optional[str]` means `plural` may be a `str` or `None`.
- You must explicitly provide the default value `= None`.

If you don’t assign a default value to `plural`, the Python runtime will treat it as a required parameter. Remember: at runtime, type hints are ignored.

Note that we need to import `Optional` from the `typing` module. When importing types, it’s good practice to use the syntax `from typing import X`, to reduce the length of the function signatures.

> **WARNING**
>
> `Optional` is not a great name, because that annotation does not make the parameter optional. What makes it optional is assigning a default value to the parameter. `Optional[str]` just means: the type of this parameter may be `str` or `NoneType`. In the Haskell and Elm languages, a similar type is named `Maybe`.

Now that we’ve had a first practical view of gradual typing, let’s consider what the concept of *type* means in practice.

Types are defined by supported operations

> *There are many definitions of the concept of type in the literature. Here we assume that type is a set of values and a set of functions that one can apply to these values.*
>
> —PEP 483: The Theory of Type Hints

In practice, it's more useful to consider the set of supported operations as the defining characteristic of a type.[4]

For example, from the point of view of applicable operations, what are the valid types for `x` in the following function?

```
def double(x):
    return x * 2
```

The `x` parameter type may be numeric (`int`, `complex`, `Fraction`, `numpy.uint32` etc.) but it may also be a sequence (`str`, `tuple`, `list`, `array`), an N-dimensional `numpy.array` or any other type that implements or inherits a `__mul__` method that accepts an `int` argument.

However, consider this annotated `double`. Please ignore the missing return type for now, let's focus on the parameter type:

```
from collections import abc

def double(x: abc.Sequence):
    return x * 2
```

A type checker will reject that code. If you tell Mypy that `x` is of type `abc.Sequence`, it will flag `x * 2` as an error because the `Sequence` ABC does not implement or inherit the `__mul__` method. At runtime, that code will work with concrete sequences such as `str`, `tuple`, `list`, `array` etc.—as well as numbers, because at runtime the type hints are ignored. But the type checker only cares about what is explicitly declared, and `abc.Sequence` has no `__mul__`.

That's why the title of this section is "Types are defined by supported operations". The Python runtime accepts any object as the `x` argument for both versions of the `double` function. The computation `x * 2` may work, or it may raise `TypeError` if the operation is not supported by `x`. In contrast, Mypy will declare `x * 2` as wrong while analyzing the annotated `double` source code, because it's an unsupported operation for the declared type: `x: abc.Sequence`.

In a gradual type system, we have the interplay of two different views of types:

Duck typing

The view adopted by Smalltalk—the pioneering OO language—as well as Python, JavaScript, and Ruby. Objects have types, but variables (including parameters) are untyped. In practice, it doesn't matter what is the declared type of the object, only what operations it actually supports. If I can invoke `birdie.quack()`, then `birdie` is a duck in this context. By definition, duck typing is only enforced at runtime, when operations on objects are attempted. This is more flexible than *nominal typing*, at the cost of allowing more errors at runtime.[5]

Nominal typing

The view adopted by C++, Java, and C#, supported by annotated Python. Objects and variables have types. But objects only exist at runtime, and the type checker only cares about the source code where variables (including parameters) are annotated with type hints. If `Duck` is a subclass of `Bird`, you can assign a `Duck` instance to a parameter annotated as `birdie: Bird`. But in the body of the function, the type checker considers the call `birdie.quack()` illegal, because `birdie` is nominally a `Bird`, and that class does not provide the `.quack()` method. It doesn't matter if the actual argument at runtime is a `Duck`, because nominal typing is enforced statically. The type checker doesn't run any part of the program, it only reads the source code. This is more rigid than *duck typing*, with the advantage of catching some bugs earlier in a build pipeline, or even as the code is typed in an IDE.

Here is a silly example that contrasts duck typing and nominal typing, as well as static type checking and runtime behavior[6]:

Example 8-4. `birds.py`

```
class Bird:
    pass

class Duck(Bird):  ❶
    def quack(self):
        print('Quack!')

def alert(birdie):  ❷
    birdie.quack()

def alert_duck(birdie: Duck) -> None:  ❸
    birdie.quack()

def alert_bird(birdie: Bird) -> None:  ❹
    birdie.quack()
```

❶ `Duck` is a subclass of `Bird`.

❷ `alert` has no type hints, so the type checker ignores it.

❸ `alert_duck` takes one argument of type `Duck`.

❹ `alert_bird` takes one argument of type `Bird`.

Type checking `birds.py` with Mypy, we see a problem:

```
…/birds/ $ mypy birds.py
birds.py:16: error: "Bird" has no attribute "quack"
Found 1 error in 1 file (checked 1 source file)
```

Just by analyzing the source code, Mypy sees that `alert_bird` is problematic: the type hint declares the `birdie` parameter with type `Bird`, but the body of the function calls `birdie.quack()`—and the `Bird` class has no such method.

Now let's try to use the `birds` module in `daffy.py`:

Example 8-5. `daffy.py`

```
from birds import *

daffy = Duck()
alert(daffy)       ❶
alert_duck(daffy)  ❷
alert_bird(daffy)  ❸
```

❶ Valid call, because `alert` has no type hints.

❷ Valid call, because `alert_duck` takes a `Duck` argument, and `daffy` is a `Duck`.

❸ Valid call, because `alert_bird` takes a `Bird` argument, and `daffy` is a also a `Bird`—the superclass of `Duck`.

Running Mypy on `daffy.py` raises the same error about the `quack` call in the `alert_bird` function defined in `birds.py`:

```
…/birds/ $ mypy daffy.py
birds.py:16: error: "Bird" has no attribute "quack"
Found 1 error in 1 file (checked 1 source file)
```

But Mypy sees no problem with `daffy.py` itself: the three function calls are OK.

Now, if you run `daffy.py`, this is what you get:

```
…/birds/ $ python3 daffy.py
Quack!
Quack!
Quack!
```

Everything works! Duck typing FTW!

At runtime, Python doesn't care about declared types. It uses duck typing only. Mypy flagged an error in `alert_bird`, but calling it with `daffy` works fine at runtime. This may surprise many Pythonistas at first: a static type checker will sometimes find errors in programs that we know will execute.

However, if months from now you are tasked with extending the silly bird example, you may be grateful for Mypy. Consider this `woody.py` module which also uses `birds`:

Example 8-6. `woody.py`

```
from birds import *

woody = Bird()
alert(woody)
alert_duck(woody)
alert_bird(woody)
```

Mypy finds two errors while checking `woody.py`:

```
…/birds/ $ mypy woody.py
birds.py:16: error: "Bird" has no attribute "quack"
woody.py:5: error: Argument 1 to "alert_duck" has incompatible
type "Bird"; expected "Duck"
Found 2 errors in 2 files (checked 1 source file)
```

The first error is in `birds.py`: the `birdie.quack()` call in `alert_bird`, which we've seen before. The second error is in `woody.py`: `woody` is an instance of `Bird`, so the call `alert_duck(woody)` is invalid because that function requires a `Duck`. Every `Duck` is a `Bird`, but not every `Bird` is a `Duck`.

At runtime, none of the calls in `woody.py` succeed. The succession of failures is best illustrated in a console session with callouts:

Example 8-7. Runtime errors and how Mypy could have helped.

```
>>> from birds import *
>>> woody = Bird()
>>> alert(woody)  ❶
Traceback (most recent call last):
  ...
AttributeError: 'Bird' object has no attribute 'quack'
>>>
>>> alert_duck(woody) ❷
Traceback (most recent call last):
```

```
  ...
AttributeError: 'Bird' object has no attribute 'quack'
>>>
>>> alert_bird(woody)  ❸
Traceback (most recent call last):
  ...
AttributeError: 'Bird' object has no attribute 'quack'
```

❶ Mypy could not detect this error because there are no type hints in `alert`.

❷ Mypy reported the problem: `Argument 1 to "alert_duck" has incompatible type "Bird"; expected "Duck"`.

❸ Mypy has been telling us since Example 8-4 that the body of the `alert_bird` function is wrong: `"Bird" has no attribute "quack"`.

This little experiment shows that duck typing is easier to get started and is more flexible, but allows unsupported operations to cause errors at runtime. Nominal typing detects errors before runtime, but sometimes can reject code that actually runs—such as the call `alert_bird(daffy)` in Example 8-5. Even if it sometimes works, the `alert_bird` function is misnamed: its body does require an object that supports the `.quack()` method, which `Bird` doesn't have.

In this silly example, the functions are one-liners. But in real code they could be longer, they could pass the `birdie` argument to more functions, and the origin of the `birdie` argument could be many function calls away, making it hard to pinpoint the cause of a runtime error. The type checker prevents many such errors from ever happening at runtime.

> **NOTE**
>
> The value of type hints is questionable in the tiny examples that fit in a book. The benefits grow with the size of the codebase. That's why companies with millions of lines of Python code—like Dropbox, Google, and Facebook—invested in teams and tools to support the company-wide adoption of type hints, and have significant and increasing portions of their Python codebases type checked in their CI pipelines.

In this section we explored the relationship of types and operations in duck typing and nominal typing, starting with the simple `double()` function—which we left without proper type hints. Now we will tour the most important types used for annotating functions. We'll see a good way to add type hints to `double()` when we reach "Static Protocols". But before we get to that, there are more fundamental types to know.

Types usable in annotations

Pretty much any Python type can be used in type hints, but there are restrictions and recommendations. In addition, the `typing` module introduced special constructs with semantics that are sometimes surprising.

This section covers all the major types you can use with annotations:

- `typing.Any`;
- Simple types and classes;
- `typing.Optional` and `typing.Union`;
- Generic collections, including tuples and mappings;
- Abstract Base Classes;
- Generic iterables;
- Parameterized generics and `TypeVar`;
- `typing.Protocols`—the key to *static duck typing*;

- `typing.Callable`;
- `typing.NoReturn`—a good way to end this list.

We’ll cover each of these in turn, starting with a type that is strange, apparently useless, but crucially important.

The Any type

The keystone of any gradual type system is the `Any` type, also known as the *dynamic type*. When a type checker sees an untyped function like this:

```
def double(x):
    return x * 2
```

It assumes this:

```
def double(x: Any) -> Any:
    return x * 2
```

That means the `x` argument and the return value can be of any type, including different types. `Any` is assumed to support every possible operation.

Contrast `Any` with `object`. Consider this signature:

```
def double(x: object) -> object:
```

This function also accepts arguments of every type, because every type is a *subtype-of* `object`.

However, a type checker will reject this function:

```
def double(x: object) -> object:
    return x * 2
```

The problem is that `object` does not support the `__mul__` operation. This is what Mypy reports:

```
…/birds/ $ mypy double_object.py
double_object.py:2: error: Unsupported operand types for *
("object" and "int")
Found 1 error in 1 file (checked 1 source file)
```

More general types have narrower interfaces, i.e. they support less operations. The `object` class implements fewer operations than `abc.Sequence`, which implements fewer operations than `abc.MutableSequence`, which implements fewer operations than `list`.

But `Any` is a magic type that sits at the top and the bottom of the type hierarchy. It's simultaneously the most general type—so that an argument `n: Any` accepts values of every type—and the most specialized type, supporting every possible operation. At least, that's how the type checker understands `Any`.

Of course, no type can support every possible operation, so using `Any` prevents the type checker from fulfilling its core mission: detecting potentially illegal operations before your program crashes with a runtime exception.

Subtype-of versus Consistent-with

Traditional object-oriented nominal type systems rely on the is *subtype-of* relationship. Given a class `T1` and a subclass `T2`, then `T2` is *subtype-of* `T1`.

Consider this code:

```python
class T1:
    ...

class T2(T1):
    ...

def f1(p: T1) -> None:
    ...

o2 = T2()

f1(o2)  # OK
```

The call `f1(o2)` is an application of the Liskov Substitution Principle—LSP. Barbara Liskov[7] actually defined *is-sub-type-of* in terms of supported operations: if an object of type `T2` substitutes an object of type `T1` and the program still behaves correctly, then `T2` is *subtype-of* `T1`.

Continuing from the previous code, this shows a violation of the LSP:

```
def f2(p: T2) -> None:
    ...

o1 = T1()

f2(o1)  # type error
```

From the point of view of supported operations, this makes perfect sense: as a subclass, `T2` inherits and must support all operations that `T1` does. So an instance of `T2` can be used anywhere a instance of `T1` is expected. But the reverse is not necessarily true: `T2` may implement additional methods, so an instance of `T1` may not be used everywhere an instance of `T2` is expected. This focus on supported operations is reflected in the name *behavioral subtyping*, also used to refer to the LSP.

In a gradual type system, there is another relationship: *consistent-with*, which applies wherever *subtype-of* applies, with special provisions for type `Any`.

The rules for *consistent-with* are:

1. Given `T1` and a subtype `T2`, then `T2` is *consistent-with* `T1` (Liskov substitution).

2. Every type is *consistent-with* `Any`: you can pass objects of every type to an argument declared of type `Any`.

3. `Any` is *consistent-with* every type: you can always pass an object of type `Any` where an argument of another type is expected.

Considering the previous definitions of the objects `o1` and `o2`, here are examples of valid code, illustrating rules #2 and #3:

```python
def f3(p: Any) -> None:
    ...

o0 = object()
o1 = T1()
o2 = T2()

f3(o0)  #
f3(o1)  #  all OK: rule #2
f3(o2)  #

def f4():  # implicit return type: `Any`
    ...

o4 = f4()  # inferred type: `Any`

f1(o4)  #
f2(o4)  #  all OK: rule #3
f3(o4)  #
```

Every gradual type system needs a wildcard type like `Any`.

> **TIP**
>
> The verb "to infer" is a fancy synomym for "to guess", used in the context of type analysis. Modern type checkers in Python and other languages don't require type annotations everywhere because they can infer the type of many expressions. For example, if I write `x = len(s) * 10`, the type checker doesn't need an explicit local declaration to know that `x` is an `int`, as long as it can find type hints for the `len` built-in.

Now we can explore the rest of the types used in annotations.

Simple types and classes

Simple types like `int`, `float`, `str`, `bytes` may be used directly in type hints. Concrete classes from the standard library, external packages, or user defined—`FrenchDeck`, `Vector2d`, and `Duck`—may also be used in type hints.

Abstract Base Classes are also useful in type hints. We'll get back to them as we study collection types, and in "Abstract Base Classes".

Among classes, is *consistent-with* is defined like is *subtype-of*: a subclass is *consistent-with* all its superclasses.

However, "practicality beats purity" so there is an important exception:

> **INT IS *CONSISTENT-WITH* COMPLEX**
>
> There is no nominal subtype relationship between the built-in types `int`, `float` and `complex`: they are direct subclasses of `object`. But PEP 484 declares that `int` is *consistent-with* `float`, and `float` is *consistent-with* `complex`. It makes sense in practice: `int` implements all operations that `float` does, and `int` implements additional ones as well—bitwise operations like `&`, `|`, `<<` etc. The end result is: `int` is *consistent-with* `complex`. For `i = 3`, `i.real` is `3`, and `i.imag` is `0`.

`Optional` and `Union` types

We saw the `Optional` special type in "Using `None` as a default". It solves the problem of having `None` as a default, as in this example from that section:

```
from typing import Optional

def show_count(count: int, singular: str, plural: Optional[str] =
None) -> str:
```

The construct `Optional[str]` is actually a shortcut for `Union[str, None]` which means the type of `plural` may be `str` or `None`.

The `ord` built-in function's signature is a simple example of `Union`—it accepts `str` or `bytes`, and returns an `int`:[8]

```
def ord(c: Union[str, bytes]) -> int: ...
```

> **TIP**
>
> In "Dual-Mode str and bytes APIs" we saw functions that accept either `str` or `bytes` arguments but return `str` if the argument was `str` or `bytes` if the arguments was `bytes`. In those cases, the return type is determined by the input type, so `Union` is not an accurate solution. To properly annotate such functions, we need a type variable—presented in "Parameterized generics and `TypeVar`"—or overloading, which we'll see in "Overloaded signatures".

Here is an example of a function that takes a `str`, but may return a `str` or a `float`:

```
from typing import Union

def parse_token(token: str) -> Union[str, float]:
    try:
        return float(token)
    except ValueError:
        return token
```

If possible, avoid creating functions that return `Union` types, as they put an extra burden on the user—forcing them to check the type of the returned value at runtime to know what to do with it. But the `parse_token` above is a reasonable use case in the context of a simple expression evaluator.

`Union[]` requires at least two types. Nested `Union` types have the same effect as a flattened `Union`. So this type hint:

```
Union[A, B, Union[C, D, E]]
```

is the same as:

```
Union[A, B, C, D, E]
```

`Union` is more useful with types that are not consistent among themselves. For example: `Union[int, float]` is redundant because `int` is *consistent-with* `float`. If you just use `float` to annotate the parameter, it will accept `int` values as well.

> **BETTER SYNTAX FOR UNION IN PYTHON 3.10**
>
> In Python 3.10 we can write `str | float` instead of `Union[str, float]`. It's shorter, more readable, and doesn't require importing `typing.Union`. For more, see PEP 604—Complementary syntax for Union[].

Generic collections

Most Python collections are heterogeneous. For example, you can put any mixture of different types in a `list`. However, in practice that's not very useful: if you put objects in a collection, you are likely to want to operate on them later, and usually this means they must share at least one common method.[9]

Generic types can be declared with type parameters to specify the type of the items they can handle.

For example, a `list` can be parameterized to constrain the type of the elements in it:

Example 8-8. `tokenize` with type hints for Python ≥ 3.9

```
def tokenize(text: str) -> list[str]:
    return text.upper().split()
```

In Python ≥ 3.9, that means `tokenize` returns a `list` where every item is of type `str`.

The annotations `stuff: list` and `stuff: list[Any]` mean the same thing: `stuff` is a list of objects of any type.

> **TIP**
>
> If you are using Python 3.8 or earlier the concept is the same, but you need more code to make it work—as explained the optional box “Legacy Support and Deprecated Collection Types”.

PEP 585—Type Hinting Generics In Standard Collections lists collections from the standard library accepting generic type hints. The following list shows only those collections that use the simplest form of generic type hint: `container[item]`.

```
list         collections.deque        abc.Sequence
abc.MutableSequence
set          abc.Container            abc.Set
abc.MutableSet
frozenset    abc.Collection
```

The `tuple` and mapping types support more complex type hints, as we’ll see in their respective sections.

As of Python 3.10, there is no good way to annotate `array.array` taking into account the `typecode` constructor argument which determines whether integers or floats are stored in the array. An even harder problem is how to typecheck integer ranges to prevent `OverflowError` at runtime when adding elements to arrays. For example, an `array` with `typecode='B'` can only hold `int` values from 0 to 255. Currently, Python’s static type system is not up to this challenge.

LEGACY SUPPORT AND DEPRECATED COLLECTION TYPES

(You may skip this box if you only use Python 3.9 or later.)

For Python 3.7 and 3.8, you need a `__future__` import to make the `[]` notation work with built-in collections such as `list`:

Example 8-9. `tokenize` with type hints for Python ≥ 3.7

```
from __future__ import annotations

def tokenize(text: str) -> list[str]:
    return text.upper().split()
```

That `__future__` import does not work with Python 3.6 or earlier. This is how to annotate `tokenize` in a way that works with Python ≥ 3.5:

Example 8-10. `tokenize` with type hints for Python ≥ 3.5

```
from typing import List

def tokenize(text: str) -> List[str]:
    return text.upper().split()
```

To provide the initial support for generic type hints, the authors of PEP 484 created dozens of generic types in the `typing` module. Table 8-1 shows some of them. For the full list, visit the *typing* documentation.

Table 8-1. Some collection types and the *irtypehintequivalents*

collection	type hint equivalent
`list`	`typing.List`
`set`	`typing.Set`
`frozenset`	`typing.FrozenSet`
`collections.deque`	`typing.Deque`
`collections.abc.MutableSequence`	`typing.MutableSequence`
`collections.abc.Sequence`	`typing.Sequence`
`collections.abc.Set`	`typing.AbstractSet`

`collections.abc.MutableSet`	`typing.MutableSet`

PEP 585—Type Hinting Generics In Standard Collections started a multi-year process to improve the usability of generic type hits. We can summarize that process in 4 steps:

1. Introduce `from __future__ import annotations` in Python 3.7 to enable the use of standard library classes as generics with `list[str]` notation.
2. Make that behavior the default in Python 3.9: `list[str]` now works without the `future` import.
3. Deprecate all the redundant generic types from the `typing` module.[10] Deprecation warnings will not be issued by the Python interpreter because type checkers should flag the deprecated types when the checked program targets Python 3.9 or newer.
4. Remove those redundant generic types in the first version of Python released 5 years after Python 3.9. At the current cadence, that could be Python 3.14, a.k.a as Python Pi.

Now let's see how to annotate generic tuples.

Tuple types

There are three ways to annotate tuple types:

1. tuples as records;
2. tuples as records with named fields;
3. tuples as immutable sequences.

Tuples as records

If you’re using a `tuple` as a record, use the `tuple` built-in and declare the types of the fields within `[]`.

For example, the type hint would be `tuple[str, float, str]` to accept a tuple with city name, population and country: `('Shanghai', 24.28, 'China')`.

Consider a function that takes a pair of geographic coordinates and returns a Geohash, used like this:

```
>>> shanghai = 31.2304, 121.4737
>>> geohash(shanghai)
'wtw3sjq6q'
```

This is how `geohash` is defined, using the `geolib` package from PyPI:

Example 8-11. `coordinates.py` with the `geohash` function.

```
from geolib import geohash as gh  # type: ignore  ❶

PRECISION = 9

def geohash(lat_lon: tuple[float, float]) -> str:  ❷
    return gh.encode(*lat_lon, PRECISION)
```

❶ This comment stops Mypy from reporting that the `geolib` package doesn’t have type hints.

❷ `lat_lon` parameter annotated as a `tuple` with two `float` fields.

> **TIP**
>
> For Python < 3.9, import and use `typing.Tuple` in type hints. It is deprecated but will remain in the standard library at least until 2024.

Tuples as records with named fields

To annotate a tuple with many fields, or specific types of tuple your code uses in many places, I highly recommend using `typing.NamedTuple`—as seen in Chapter 5. Here is a variation of Example 8-11 with `NamedTuple`:

Example 8-12. `coordinates_named.py` with the `NamedTuple` `Coordinates` and the `geohash` function.

```
from typing import NamedTuple

from geolib import geohash as gh  # type: ignore

PRECISION = 9

class Coordinate(NamedTuple):
    lat: float
    lon: float

def geohash(lat_lon: Coordinate) -> str:
    return gh.encode(*lat_lon, PRECISION)
```

As explained in "Overview of data class builders", `typing.NamedTuple` is a factory for `tuple` subclasses, so `Coordinate` is *consistent-with* `tuple[float, float]` but the reverse is not true—after all, `Coordinate` has extra methods added by `NamedTuple`, like `._asdict()`, and could also have user-defined methods.

In practice, this means that it is typesafe to pass a `Coordinate` instance to the `display` function defined below.

```
def display(lat_lon: tuple[float, float]) -> str:
    lat, lon = lat_lon
    ns = 'N' if lat >= 0 else 'S'
    ew = 'E' if lon >= 0 else 'W'
    return f'{abs(lat):0.1f}°{ns}, {abs(lon):0.1f}°{ew}'
```

Tuples as immutable sequences

To annotate tuples of unspecified length that are used as immutable lists you must specify a single type, followed by a comma and `...` (that's Python's ellipsis token, made of three periods, not Unicode `U+2026`—`HORIZONTAL ELLIPSIS`).

For example, `tuple[int, ...]` is a tuple with `int` items.

The ellipsis indicates that any number of elements >= 1 is acceptable. There is no way to specify fields of different types for tuples of arbitrary length.

The annotations `stuff: tuple[Any, ...]` and `stuff: tuple` mean the same thing: `stuff` is a tuple of unspecified length with objects of any type.

Here is a `columnize` function that transforms a sequence into a table of rows and cells in the form of list of tuples with unspecified lengths. This is useful to display items in columns, like this:

```
>>> animals = 'drake fawn heron ibex koala lynx tahr xerus yak
zapus'.split()
>>> table = columnize(animals)
>>> table
[('drake', 'koala', 'yak'), ('fawn', 'lynx', 'zapus'), ('heron',
'tahr'),
 ('ibex', 'xerus')]
>>> for row in table:
...     print(''.join(f'{word:10}' for word in row))
...
drake     koala     yak
fawn      lynx      zapus
heron     tahr
ibex      xerus
```

Example 8-13 shows the implementation of `columnize`. Note the return type:

```
`list[tuple[str, ...]]`.
```

Example 8-13. `columnize.py` returns a list of tuples of strings.

```
from collections.abc import Sequence

def columnize(sequence: Sequence[str], num_columns: int = 0) ->
list[tuple[str, ...]]:
    if num_columns == 0:
```

```
        num_columns = round(len(sequence) ** .5)
    num_rows, reminder = divmod(len(sequence), num_columns)
    num_rows += bool(reminder)
    return [tuple(sequence[i::num_rows]) for i in range(num_rows)]
```

Generic mappings

Generic mapping types are annotated as `MappingType[KeyType, ValueType]`. The built-in `dict` and the mapping types in `collections` and `collections.abc` accept that notation in Python ≥ 3.9. For earlier versions, you must use `typing.Dict` and other mapping types from the `typing` module, as described in "Legacy Support and Deprecated Collection Types".

Example 8-14 shows a practical use of a function returning an inverted index to search Unicode characters by name—a variation of Example 4-21 more suitable for server-side code that we'll study in Chapter 22.

Given starting and ending Unicode character codes, `name_index` returns a `dict[str, set[str]]` which is an inverted index mapping each word to a set of characters that have that word in their names. For example, after indexing ASCII characters from 32 to 64, here are the sets of characters mapped to the words `'SIGN'` and `'DIGIT'`, and how to find the character named `'DIGIT EIGHT'`:

```
>>> index = name_index(32, 65)
>>> index['SIGN']
{'$', '>', '=', '+', '<', '%', '#'}
>>> index['DIGIT']
{'8', '5', '6', '2', '3', '0', '1', '4', '7', '9'}
>>> index['DIGIT'] & index['EIGHT']
{'8'}
```

Below is the source code for `charindex.py` with the `name_index` function. Besides a `dict[]` type hint, this example has three features appearing for the first time in the book.

Example 8-14. `charindex.py`

```
import sys
import re
import unicodedata
from collections.abc import Iterator

RE_WORD = re.compile(r'\w+')
STOP_CODE = sys.maxunicode + 1

def tokenize(text: str) -> Iterator[str]:  ❶
    """return iterable of uppercased words"""
    for match in RE_WORD.finditer(text):
        yield match.group().upper()

def name_index(start: int = 32, end: int = STOP_CODE) -> dict[str,
set[str]]:
    index: dict[str, set[str]] = {}  ❷
    for char in (chr(i) for i in range(start, end)):
        if name := unicodedata.name(char, ''):  ❸
            for word in tokenize(name):
                index.setdefault(word, set()).add(char)
    return index
```

❶ `tokenize` is a generator function. Chapter 17 is about generators.

❷ The local variable `index` is annotated. Without the hint, Mypy says: `Need type annotation for 'index' (hint: "index: dict[<type>, <type>] = ...")`.

❸ I used the walrus operator `:=` in the `if` condition. It assigns the result of the `unicodedata.name()` call to `name`, and the whole expression evaluates to that result. When the result is `''`, that's falsy and the `index` is not updated.[11]

> **NOTE**
>
> When using a `dict` as a record, it is common to have all keys of the `str` type, with values of different types depending on the keys. That is covered in "TypedDict", Chapter 15.

Abstract Base Classes

> *Be conservative in what you send, be liberal in what you accept.*
>
> —Postel’s law, a.k.a. the Robustness Principle

Table 8-1 list several abstract classes from `collections.abc`. Ideally, a function should accept arguments of those abstract types—or their `typing` equivalents before Python 3.9—and not concrete types. This gives more flexibility to the caller.

Consider this function signature:

```
from collections.abc import Mapping

def name2hex(name: str, color_map: Mapping[str, int]) -> str:
```

Using `abc.Mapping` allows the caller to provide an instance of `dict`, `defaultdict`, `ChainMap`, a `UserDict` subclass or any other type that is a *subtype-of* `Mapping`.

In contrast, consider this signature:

```
def name2hex(name: str, color_map: dict[str, int]) -> str:
```

Now `color_map` must be a `dict` or one of its subtypes such as `defaultDict` or `OrderedDict`. In particular, a subclass of `collections.UserDict` would not pass the type check for `color_map`, despite being the recommended way to create user-defined mappings, as we saw in “Subclassing `UserDict` Instead of `dict`”. Mypy would reject a `UserDict` or an instance of a class derived from it, because `UserDict` is not a subclass of `dict`; they are siblings. Both are subclasses of `abc.MutableMapping`.[12]

Therefore, in general it’s better to use `abc.Mapping` or `abc.MutableMapping` in parameter type hints, instead of `dict` (or `typing.Dict` in legacy code). If the `name2hex` function doesn’t need to mutate the given `color_map`, the most accurate type hint for `color_map` is `abc.Mapping`. That way, the caller doesn’t need to provide an object that implements methods like `setdefault`, `pop` and `update` which are part of the `MutableMapping` interface, but not of `Mapping`. This has to do with the second part of Postel's law: "be liberal in what you accept."

Postel's law also tells us to be conservative in what we send. The return value of a function is always a concrete object, so the return type hint should be a concrete type, as in the example from "Generic collections"—which uses `list[str]`.

```
def tokenize(text: str) -> list[str]:
    return text.upper().split()
```

Under the entry of `typing.List`, the Python documentation says:

> *Generic version of `list`. Useful for annotating return types. To annotate arguments it is preferred to use an abstract collection type such as `Sequence` or `Iterable`.*

A similar comment appears in the entries for `typing.Dict` and `typing.Set`.

Remember that most ABCs from `collections.abc` and other concrete classes from `collections`, as well as built-in collections, support generic type hint notation like `collections.deque[str]` starting with Python 3.9. The corresponding `typing` collections are only needed to support code written in Python 3.8 or earlier. The full list of classes that became generic appears in section Implementation of PEP 585—Type Hinting Generics In Standard Collections.

To wrap up our discussion of ABCs in type hints, we need to talk about the `numbers` ABCs.

The Fall of the Numeric Tower

Since Python 2.6, the `numbers` module defines a hierarchy of ABCs with `Number` at the top, then `Complex`, `Real`, `Rational`, and `Integral`. Those ABCs allow `isinstance` checks independent of concrete numeric types. For example, `isinstance(x, numbers.Real)` is `True` for `x` of type `float`, but also for NumPy types like `float32`, `longdouble` etc.

Those ABCs work perfectly well for runtime type checking, but not for static type checking, for one main reason: the `Number` ABC defines no method, therefore a typechecker would not let your code do anything with a value declared or inferred to be of the `Number` type, which makes it useless. As of July 2021, Mypy does not support the use of the `numbers` ABCs in type hints. See Mypy issue *int is not a Number?*.

Section The Numeric Tower of PEP 484 rejects the `numbers` ABCs and dictates that the built-in types `complex`, `float`, and `int` should be treated as special cases, as explained in "int is consistent-with complex".

> **TIP**
>
> To annotate numeric parameters without hard coding concrete types, use numeric protocol types, covered in "Runtime checkable static protocols". "Static Protocols" is a pre-requisite for that section.

Iterable

The `typing.List` documentation I just quoted recommends `Sequence` and `Iterable` for function parameter type hints.

One example of `Iterable` argument appears the `math.fsum` function from the standard library:

```
def fsum(__seq: Iterable[float]) -> float:
```

STUB FILES AND THE TYPESHED PROJECT.

As of Python 3.10, the standard library has no annotations but Mypy, PyCharm etc. can find the necessary type hints in the Typeshed project, in the form of *stub files*: special source files with a `.pyi` extension that have annotated function and method signatures, without the implementation—much like header files in C.

The signature for `math.fsum` is in `/stdlib/2and3/math.pyi`. The leading underscores in `__seq` are a PEP 484 convention for positional-only parameters, explained in "Annotating positional-only and variadic parameters".

Example 8-15 is another example using an `Iterable` parameter that produces items that are `tuple[str, str]`. Here is how the function is used:

```
>>> l33t = [('a', '4'), ('e', '3'), ('i', '1'), ('o', '0')]
>>> text = 'mad skilled noob powned leet'
>>> from replacer import zip_replace
>>> zip_replace(text, l33t)
'm4d sk1ll3d n00b p0wn3d l33t'
```

And here is how it's implemented:

Example 8-15. `replacer.py`

```
from collections.abc import Iterable

FromTo = tuple[str, str]  ❶

def zip_replace(text: str, changes: Iterable[FromTo]) -> str:  ❷
    for from_, to in changes:
        text = text.replace(from_, to)
    return text
```

❶ `FromTo` is a *type alias*: I assigned `tuple[str, str]` to `FromTo`, to make the signature of `zip_replace` more readable.

❷ `changes` needs to be an `Iterable[FromTo]`; that's the same as `Iterable[tuple[str, str]]`, but shorter and easier to read.

EXPLICIT TYPEALIAS IN PYTHON 3.10

PEP 613—Explicit Type Aliases introduced a special type, `TypeAlias`, to make the assignments that create type aliases more visible and easier to typecheck. Starting with Python 3.10, this is the preferred way to create type aliases:

```
from typing import TypeAlias

FromTo: TypeAlias = tuple[str, str]
```

`abc.Iterable` versus `abc.Sequence`

Both `math.fsum` and `replacer.zip_replace` must iterate over the entire `Iterable` arguments to return a result. Given an endless iterable such as the `itertools.cycle` generator as input, these functions would consume all memory and crash the Python process. Despite this potential danger, it is fairly common in modern Python to offer functions that accept an `Iterable` input even if they must process it completely to return a result. That gives the caller the option of providing input data as a generator instead of a pre-built sequence, potentially saving a lot of memory if the number of input items is large.

On the other hand, the `columnize` function from Example 8-13 needs a `Sequence` parameter, and not an `Iterable`, because it must get the `len()` of the input to compute the number of rows up front.

Like `Sequence`, `Iterable` is best used as a parameter type. It’s too vague as a return type. A function should be more precise about the concrete type it returns.

Closely related to `Iterable` is the `Iterator` type, used as a return type in Example 8-14. We’ll get back to it in Chapter 17 which is about generators and classic iterators.

Parameterized generics and `TypeVar`

A parameterized generic is a generic type, written as `list[T]` where `T` is a type variable that will be bound to a specific type with each usage. This allows a parameter type to be reflected on the result type.

Example 8-16 defines `sample`, a function that takes two arguments: a `Sequence` of elements of type `T`, and an `int`. It returns a `list` of elements of the same type `T`, picked at random from the first argument.

This is the implementation:

Example 8-16. `sample.py`

```
from collections.abc import Sequence
from random import shuffle
from typing import TypeVar

T = TypeVar('T')

def sample(population: Sequence[T], size: int) -> list[T]:
    if size < 1:
        raise ValueError('size must be >= 1')
    result = list(population)
    shuffle(result)
    return result[:size]
```

Here are two examples why I used a type variable in `sample`:

1. If called with a tuple of type `tuple[int, ...]`—which is *consistent-with* `Sequence[int]`—then the type parameter is `int`, so the return type is `list[int]`;
2. If called with a `str`—which is *consistent-with* `Sequence[str]`—then the type parameter is `str`, so the return type is `list[str]`.

> **WHY IS TYPEVAR NEEDED?**
>
> The authors of PEP 484 wanted to introduce type hints by adding the `typing` module and not changing anything else in the language. With clever metaprogramming they could make the `[]` operator work on classes like `Sequence[T]`. But the name of the `T` variable inside the brackets must be defined somewhere—otherwise the Python interpreter would need deep changes to support generic type notation as special use of `[]`. That's why the `typing.TypeVar` constructor is needed: to introduce the variable name in the current namespace. Languages such as Java, C#, and TypeScript don't require the name of type variable to be declared beforehand, so they have no equivalent of Python's `TypeVar` class.

Another example is the `statistics.mode` function from the standard library, which returns the most common data point from a series.

Here is one usage example from the documentation:

```
>>> mode([1, 1, 2, 3, 3, 3, 3, 4])
3
```

Without using a `TypeVar`, `mode` could have this signature:

Example 8-17. `mode_float.py`: `mode` that operates on `float` and subtypes.[13]

```
from collections import Counter
from collections.abc import Iterable

def mode(data: Iterable[float]) -> float:
    pairs = Counter(data).most_common(1)
    if len(pairs) == 0:
        raise ValueError('no mode for empty data')
    return pairs[0][0]
```

Many uses of `mode` involve `int` or `float` values, but Python has other numerical types, and it is desirable that the return type follows the element type of the given `Iterable`. We can improve that signature using `TypeVar`. Let's start with a simple but wrong parameterized signature:

```
from collections.abc import Iterable
from typing import TypeVar
```

```
T = TypeVar('T')

def mode(data: Iterable[T]) -> T:
```

When it first appears in the signature, the type parameter `T` can be any type. The second time it appears, it will mean the same type as the first.

Therefore, every iterable is *consistent-with* `Iterable[T]`, including iterables of unhashable types that `collections.Counter` cannot handle. We need to restrict the possible types assigned to `T`. We'll see two ways of doing that in the next two sections.

Restricted TypeVar

`TypeVar` accepts extra positional arguments to restrict the type parameter. We can improve the signature of `mode` to accept specific number types like this:

```
from collections.abc import Iterable
from decimal import Decimal
from fractions import Fraction
from typing import TypeVar

NumberT = TypeVar('NumberT', float, Decimal, Fraction)

def mode(data: Iterable[NumberT]) -> NumberT:
```

That's better than before, and it was the signature for `mode` in the `statistics.pyi` stub file on `typeshed` on May 25, 2020.

However, the `statistics.mode` documentation includes this example:

```
>>> mode(["red", "blue", "blue", "red", "green", "red", "red"])
'red'
```

In a hurry, we could just add `str` to the `NumberT` definition:

```
NumberT = TypeVar('NumberT', float, Decimal, Fraction, str)
```

That certainly works, but `NumberT` is badly misnamed if it accepts `str`. More importantly, we can't keep listing types forever as we realize `mode` can deal with them. We can do better with another feature of `TypeVar`, introduced next.

Bounded TypeVar

Looking at the body of `mode` in Example 8-17, we see that the `Counter` class is used for ranking. Counter is based on `dict`, therefore the element type of the `data` iterable must be hashable.

At first, this signature may seem to work:

```
from collections.abc import Iterable, Hashable

def mode(data: Iterable[Hashable]) -> Hashable:
```

Now the problem is that the type of the returned item is `Hashable`: an ABC that implements only the `__hash__` method. So the type checker will not let us do anything with the return value except call `hash()` on it. Not very useful.

The solution is another optional parameter of `TypeVar`: the `bound` keyword parameter. It sets an upper boundary for the acceptable types. In Example 8-18, we have `bound=Hashable`, which means the type parameter may be `Hashable` or any *subtype-of* it.[14]

Example 8-18. `mode_hashable.py`: same as Example 8-17, with a more flexible signature.

```
from collections import Counter
from collections.abc import Iterable, Hashable
from typing import TypeVar

HashableT = TypeVar('HashableT', bound=Hashable)

def mode(data: Iterable[HashableT]) -> HashableT:
    pairs = Counter(data).most_common(1)
    if len(pairs) == 0:
        raise ValueError('no mode for empty data')
    return pairs[0][0]
```

To summarize:

- A restricted type variable will be set to one of the types named in the `TypeVar` declaration.
- A bounded type variable will be set to the inferred type of the expression—as long as the inferred type is *consistent-with* the boundary declared in the `bound=` keyword argument of `TypeVar`.

> **NOTE**
>
> It is unfortunate that the keyword argument to declare a bounded `TypeVar` is named `bound=`, because the verb "to bind" is commonly used to mean setting the value of a variable, which in the reference semantics of Python is best described as binding a name to the value. It would have been less confusing if the keyword argument was named `boundary=`.

The `typing.TypeVar` constructor has other optional parameters—`covariant` and `contravariant`—that we'll cover in Chapter 15, "Variance".

Let's conclude this introduction to `TypeVar` with `AnyStr`.

The `AnyStr` predefined type variable

The `typing` module includes a predefined `TypeVar` named `AnyStr`. It's defined like this:

```
AnyStr = TypeVar('AnyStr', bytes, str)
```

`AnyStr` is used in many functions that accept either `bytes` or `str`, and return values of the given type.

Now, on to `typing.Protocol`, a new feature of Python 3.8 that can support more Pythonic use of type hints.

Static Protocols

> **NOTE**
>
> In Object-Oriented programming, the concept of a "protocol" as an informal interface is as old as Smalltalk, and is an essential part of Python from the beginning. However, in the context of type hints, a protocol is a `typing.Protocol` subclass defining an interface that a type checker can verify. Both kinds of protocols are covered in Chapter 13. This is just a brief introduction in the context of function annotations.

The `Protocol` type as presented in PEP 544—Protocols: Structural subtyping (static duck typing) is similar to interfaces in Go: a protocol type is defined by specifying one or more methods, and the type checker verifies that those methods are implemented where that protocol type is required.

In Python, a protocol definition is written as a `typing.Protocol` subclass. However, classes that *implement* a protocol don't need to inherit, register or declare any relationship with the class that *defines* the protocol. It's up to the type checker to find the available protocol types and enforce their usage.

Here is a problem that can be solved with the help of `Protocol` and `TypeVar`. Suppose you want to create a function `top(it, n)` that returns the largest `n` elements of the iterable `it`:

```
>>> top([4, 1, 5, 2, 6, 7, 3], 3)
[7, 6, 5]
>>> l = 'mango pear apple kiwi banana'.split()
>>> top(l, 3)
['pear', 'mango', 'kiwi']
>>>
>>> l2 = [(len(s), s) for s in l]
>>> l2
[(5, 'mango'), (4, 'pear'), (5, 'apple'), (4, 'kiwi'), (6,
'banana')]
>>> top(l2, 3)
[(6, 'banana'), (5, 'mango'), (5, 'apple')]
```

A parameterized generic `top` would look like this:

Example 8-19. `top` function with an undefined `T` type parameter.

```
def top(series: Iterable[T], length: int) -> list[T]:
    ordered = sorted(series, reverse=True)
    return ordered[:length]
```

The problem is how to constrain `T`? It cannot be `Any` or `object`, because the `series` must work with `sorted`. The `sorted` built-in actually accepts `Iterable[Any]`, but that's because the optional parameter `key` takes a function that computes an arbitrary sort key from each element. What happens if you give `sorted` a list of plain objects but don't provide a `key` argument? Let's try that:

```
>>> l = [object() for _ in range(4)]
>>> l
[<object object at 0x10fc2fca0>, <object object at 0x10fc2fbb0>,
<object object at 0x10fc2fbc0>, <object object at 0x10fc2fbd0>]
>>> sorted(l)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: '<' not supported between instances of 'object' and
'object'
```

The error message shows that `sorted` uses the `<` operator on the elements of the iterable. Is this all it takes? Let's do another quick experiment:[15]

```
>>> class Spam:
...     def __init__(self, n): self.n = n
...     def __lt__(self, other): return self.n < other.n
...     def __repr__(self): return f'Spam({self.n})'
...
>>> l = [Spam(n) for n in range(5, 0, -1)]
>>> l
[Spam(5), Spam(4), Spam(3), Spam(2), Spam(1)]
>>> sorted(l)
[Spam(1), Spam(2), Spam(3), Spam(4), Spam(5)]
```

That confirms it: I can `sort` a list of `Spam` because `Spam` implements `__lt__`—the special method that supports the `<` operator.

So the `T` type parameter in Example 8-19 should be limited to types that implement `__lt__`. In Example 8-18 we needed a type parameter that implemented `__hash__`, so we were able to use `typing.Hashable` as the upper bound for the type parameter. But now there is no suitable type in `typing` or `abc` to use, so we need to create it.

Here is the new `SupportsLessThan` type, a `Protocol`:

Example 8-20. `comparable.py`: definition of a `SupportsLessThan` `Protocol` type:

```
from typing import Protocol, Any

class SupportsLessThan(Protocol):  ❶
    def __lt__(self, other: Any) -> bool: ...  ❷
```

❶ A protocol is a subclass of `typing.Protocol`.

❷ The body of the protocol has one or more method definitions, with `...` in their bodies.

A type `T` is *consistent-with* a protocol `P` if `T` implements all the methods defined in `P`, with matching type signatures.

Given `SupportsLessThan`, we can now define this working version of `top`:

Example 8-21. `top.py`: definition of the `top` function using a `TypeVar` with `bound=SupportsLessThan`:

```
from collections.abc import Iterable
from typing import TypeVar

from comparable import SupportsLessThan

LT = TypeVar('LT', bound=SupportsLessThan)

def top(series: Iterable[LT], length: int) -> list[LT]:
    ordered = sorted(series, reverse=True)
    return ordered[:length]
```

Let’s test-drive `top`. Example 8-22 shows part of a test suite for use with `pytest`. It tries calling `top` first with a generator expression that yields `tuple[int, str]`, and then with a list of `object`. With the list of `object`, we expect to get a `TypeError` exception.

Example 8-22. `top_test.py`: partial listing of the test suite for `top`

```
from collections.abc import Iterator
from typing import TYPE_CHECKING  ❶

import pytest

from top import top

# several lines omitted

def test_top_tuples() -> None:
    fruit = 'mango pear apple kiwi banana'.split()
    series: Iterator[tuple[int, str]] = (  ❷
        (len(s), s) for s in fruit)
    length = 3
    expected = [(6, 'banana'), (5, 'mango'), (5, 'apple')]
    result = top(series, length)
    if TYPE_CHECKING:  ❸
        reveal_type(series)  ❹
        reveal_type(expected)
        reveal_type(result)
    assert result == expected

# intentional type error
def test_top_objects_error() -> None:
    series = [object() for _ in range(4)]
    if TYPE_CHECKING:
        reveal_type(series)
    with pytest.raises(TypeError) as excinfo:
        top(series, 3)  ❺
    assert "'<' not supported" in str(excinfo.value)
```

❶ The `typing.TYPE_CHECKING` constant is always `False` at runtime, but type checkers pretend it is `True` when they are type checking.

❷ Explicit type declaration for the `series` variable, to make the Mypy output easier to read.[16]], as we'll see in "Generic Iterable Types".]

❸ This `if` prevents the next three lines from executing when the test runs.

❹ `reveal_type()` cannot be called at runtime, because it is not a regular function but a Mypy debugging facility—that's why there is no `import` for it. Mypy will output one debugging message for each `reveal_type()` pseudo function call, showing the inferred type of the argument.

❺ This line will be flagged as an error by Mypy.

The above tests pass—but they would pass anyway, with or without type hints in *top.py*. More to the point, if I check that test file with Mypy, I see that the `TypeVar` is working as intended. See the `mypy` command output in Example 8-23.

> **WARNING**
>
> As of Mypy 0.910 (July 2021), the output of `reveal_type` does not show precisely the types I declared in some cases, but compatible types instead. For example, I did not use `typing.Iterator` but `abc.Iterator`. Please ignore this detail. The Mypy output is still useful. I will pretend this issue of Mypy is fixed when discussing the output.

Example 8-23. Output of `mypy top_test.py` (lines split for readability)

```
…/comparable/ $ mypy top_test.py
top_test.py:32: note:
    Revealed type is "typing.Iterator[Tuple[builtins.int,
builtins.str]]" ❶
top_test.py:33: note:
    Revealed type is "builtins.list[Tuple[builtins.int,
builtins.str]]"
top_test.py:34: note:
    Revealed type is "builtins.list[Tuple[builtins.int,
builtins.str]]" ❷
top_test.py:41: note:
    Revealed type is "builtins.list[builtins.object*]" ❸
top_test.py:43: error:
    Value of type variable "LT" of "top" cannot be "object"  ❹
Found 1 error in 1 file (checked 1 source file)
```

1. In `test_top_tuples`, `reveal_type(series)` shows it is an `Iterator[tuple[int, str]]`—which I explicitly declared.

2. `reveal_type(result)` confirms that the type returned by the `top` call is what I wanted: given the type of `series`, the `result` is `list[tuple[int, str]]`.

3. In `test_top_objects_error`, `reveal_type(series)` shows it is `list[object*]`. Mypy puts a `*` after any type that was inferred: I did not annotate the type of `series` in this test.

4. Mypy flags the error that this test intentionally triggers: the element type of the `Iterable` `series` cannot be `object` (it must be of type `SupportsLessThan`).

A key advantage of a protocol type over ABCs is that a type doesn't need any special declaration to *consistent-with* a protocol type. This allows a protocol to be created leveraging pre-existing types, or types implemented in code that we do not control. I don't need to derive or register `str`, `tuple`, `float`, `set`, etc. with `SupportsLessThan` to use them where a `SupportsLessThan` parameter is expected. They only need to implement `__lt__`. And the type checker will still be able do its job, because `SupportsLessThan` is explicitly defined as a `Protocol`—in contrast with the implicit protocols that are common with duck typing, which are invisible to the type checker.

The special `Protocol` class was introduced in PEP 544—Protocols: Structural subtyping (static duck typing). Example 8-21 demonstrates why this feature is known as *static duck typing*: the solution to annotate the `series` parameter of `top` was to say "The nominal type of `series` doesn't matter, as long as it implements the `__lt__` method". Python's duck typing always allowed us to say that implicitly, leaving static type checkers clueless. A type checker can't read CPython's source code in C, or perform console experiments to find out that `sorted` only requires that the elements support `<`.

Now we can make duck typing explicit for static type checkers. That's why it makes sense to say that `typing.Protocol` gives us *static duck typing*.[17]

There's more to see about `typing.Protocol`. We'll come back to it in Part IV, where Chapter 13 contrasts structural typing, duck typing, and ABCs—another approach to formalizing protocols. In addition, "Overloaded signatures" (Chapter 15) explains how to declare overloaded function signatures with `@typing.overload`, and includes an extensive example using `typing.Protocol` and a bounded `TypeVar`.

> **NOTE**
>
> `typing.Protocol` makes it possible to annotate the `double` function presented in "Types are defined by supported operations" without losing functionality. The key is to define a protocol class with the `__mul__` method. I invite you to do that as an exercise. The solution appears in "The typed double function" (Chapter 13).

Callable

To annotate callback parameters or function objects returned by higher-order functions, the `typing` module provides the `Callable` type, which is parameterized like this:

```
Callable[[ParamType1, ParamType2], ReturnType]
```

The parameter list—`[ParamType1, ParamType2]`—can have 0 or more types.

Here is an example in context:

```
def repl(input_fn: Callable[[Any], str] = input) -> None:
```

The `repl` function is part of a simple interactive interpreter.[18]

During normal usage, the `repl` function uses Python's `input` built-in to read expressions from the user. However, for automated testing or for integration with other input sources, `repl` accepts an optional `input_fn` parameter: a `Callable` with the same parameter and return types as `input`.

The built-in `input()` has this signature on typeshed:

```
def input(__prompt: Any = ...) -> str: ...
```

That function is *consistent-with* this `Callable` type hint:

```
Callable[[Any], str]
```

As another example, in Chapter 10, the `Order.__init__` method in Example 10-3 uses this signature:

```
class Order:

    def __init__(
        self,  ❶
        customer: Customer,
        cart: Sequence[LineItem],
        promotion: Optional[Callable[['Order'], float]] = None,
❷
    ) -> None:  ❸
```

❶ `self` rarely needs a type hint.[19].

❷ `promotion` may be `None`, or `Callable[[Order], float]`: a function that takes an `Order` and returns `float`.

❸ `__init__` always returns `None`, but I recommend adding the return type hint for it anyway.[20]

Note that the `Order` type appears as the string `'Order'` in the `Callable` type hint, otherwise Python would raise `NameError: name`

`'Order' is not defined`—because the `Order` class is not defined until Python reads the whole body of the class—an issue we'll discuss in Chapter 25: *Class Metaprogramming*.

> **TIP**
>
> PEP 563—Postponed Evaluation of Annotations was implemented in Python 3.7 to support forward references in annotations, avoiding the need to write `Order` as string in the previous example. However, that feature is only enabled when `from __future__ import annotations` is used at the top of the module, to avoid breaking code that depend on reading annotations at runtime, like the *pydantic* and *FastAPI* packages—to name just two examples. The PEP 563 behavior was planned to become default in Python 3.10 but this has been postponed—pun intended—while a compromise is reached between those who care about using annotations at runtime and those who don't. See this message from Python's Steering Council for more: *PEP 563 and Python 3.10*.

There is no syntax to annotate optional or keyword arguments in `Callable[]`. The documentation says "such function types are rarely used as callback types". If you need a type hint to match a function with a dynamic signature, replace the whole parameter list with `...`, like this: `Callable[..., ReturnType]`.

`NoReturn`

This is a special type used only to annotate the return type of functions that never return. Usually, they exist to raise exceptions. There are dozens of such functions in the standard library.

For example: `sys.exit()` raises `SystemExit`, to terminate the Python process.

Its signature in `typeshed` is:

```
def exit(__status: object = ...) -> NoReturn: ...
```

The `__status` parameter is positional-only, and it has a default value. Stub files don't spell out the default values: they use `...` instead. The type of `__status` is `object` which means it may also be `None`, therefore it would be redundant to mark it `Optional[object]`.

In Chapter 25, Example 25-6 uses `NoReturn` in the `__flag_unknown_attrs`, a method designed to produce a user friendly and comprehensive error message, and then raise `AttributeError`.

The last section in this epic chapter is about positional and variadic parameters.

Annotating positional-only and variadic parameters

Recall the `tag` function from Example 7-9. The last time we saw its signature was in section "Positional-only parameters":

```
def tag(name, /, *content, class_=None, **attrs):
```

Here is `tag`, fully annotated, written in several lines—a common convention for long signatures, with line breaks the way the *blue* formatter would do it:

```
from typing import Optional

def tag(
    name: str,
    /,
    *content: str,
    class_: Optional[str] = None,
    **attrs: str,
) -> str:
```

Note the type hint `*content: str` for the arbitrary positional parameters: this means all those arguments must be of type `str`. The type of the `content` local variable in the function body will be `tuple[str, ...]`.

The type hint for the arbitrary keyword arguments is `**attrs: str` in this example, therefore the type of `attrs` inside the function will be `dict[str, str]`. For a type hint like `**attrs: float`, the type of `attrs` in the functin would be `dict[str, float]`.

If the `attrs` parameter must accept values of different types, you'll need to use a `Union[]` or `Any`: `**attrs: Any`.

The `/` notation for positional-only parameters is only available in Python ≥ 3.8. In Python 3.7 or earlier, that's a syntax error. The PEP 484 convention is to prefix each positional-only parameter name with two underscores. Here is the `tag` signature again, now in two lines, using the PEP 484 convention:

```
from typing import Optional

def tag(__name: str, *content: str, class_: Optional[str] = None,
        **attrs: str) -> str:
```

Mypy understands and enforces both ways of declaring positional-only parameters.

To close this chapter, let's briefly consider the limits of type hints and the static type system they support.

Flawed Typing and Strong Testing

Maintainers of large corporate codebases report that many bugs are found by static type checkers and fixed more cheaply than if the bugs were discovered only after the code is running in production.

However, it's essential to note that automated testing was standard practice and widely adopted long before static typing was introduced in the companies that I know about.

Even in the contexts where they are most beneficial, static typing cannot be trusted as the ultimate arbiter of correctness. It’s not hard to discover:

- False positives: tools report type errors on code that is correct.
- False negatives: tools don’t report type errors on code that is incorrect.

Also, if we are forced to type check everything, we lose some of the expressive power of Python:

- Some handy features can’t be statically checked. For example: argument unpacking like `config(**settings)`.
- Advanced features like properties, descriptors, metaclasses, and metaprogramming in general are poorly supported or beyond comprehension for type checkers.
- Type checkers lag behind Python releases, rejecting or even crashing while analysing code with new language features—for more than a year in some cases.

Common data constraints cannot be expressed in the type system—even simple ones. For example: type hints are unable to ensure “quantity must be an integer > 0” or “label must be a string with 6 to 12 ASCII letters.” In general, type hints are not helpful to catch errors in business logic.

Given those caveats, type hints cannot be the mainstay of software quality, and making them mandatory without exception would amplify its downsides.

Consider a static type checker as one of the tools in a modern CI pipeline, along with test runners, linters, etc. The point of a CI pipeline is to reduce sofware failures, and automated tests catch many bugs that are beyond the reach of type hints. Any code you can write in Python, you can test in Python—with or without type hints.

NOTE

The title and conclusion of this section were inspired by Bruce Eckel's article Strong Typing vs. Strong Testing, also published in the anthology The Best Software Writing I edited by Joel Spolky. Bruce is a fan of Python and author of books about C++, Java, Scala, and Kotlin. In that post, he tells how he was a static typing advocate until he learned Python and concluded: "If a Python program has adequate unit tests, it can be as robust as a C++, Java, or C# program with adequate unit tests (although the tests in Python will be faster to write)."

This wraps up our coverage of Python's type hints for now. They are also the main focus of Chapter 15, which covers generic classes, variance, overloaded signatures, type casting, and more. Meanwhile, type hints will make guest appearances in several examples throughout the book.

Chapter summary

We started with a brief introduction to the concept of gradual typing and then switched to a hands-on approach. It’s hard to see how gradual typing works without a tool that actually reads the type hints, so we developed an annotated function guided by Mypy error reports. That section ended with another practical matter: how to annotate code that must run under Python 2.7 and 3.x.

Back to the idea of gradual typing, we explored how it is a hybrid of Python’s traditional duck typing and the nominal typing more familiar to users of Java, C++ and other statically typed languages.

Most of the chapter was devoted to presenting the major groups of types used in annotations. Many of the types we covered are related to familiar Python object types, such as collections, tuples, and callables—extended to support generic notation like `Sequence[float]`. Many of those types are temporary surrogates implemented in the `typing` module before the standard types were changed to support generics in Python 3.9.

Some of the types are special entities. `Any`, `Optional`, `Union`, and `NoReturn` have nothing to do with actual objects in memory, but exist only in the abstract domain of the type system.

We studied parameterized generics and type variables, which bring more flexibility to type hints without sacrificing type safety.

Parameterized generics become even more expressive with the use of `Protocol`. Because it appeared only in Python 3.8, `Protocol` is not widely used yet—but it is hugely important. `Protocol` enables static duck typing: the essential bridge between Python’s duck typed core and the nominal typing that allows static type checkers to catch bugs.

While covering some of these types we experimented with Mypy to see type checking errors and inferred types with the help of Mypy’s magic `reveal_type()` function.

The final section covered how to annotate positional-only and variadic parameters.

Type hints are a complex and evolving topic. Fortunately, they are an optional feature. Let us keep Python accessible to the widest user base and stop preaching that all Python code should have type hints—as I've seen in public sermons by typing evangelists.

Our BDFL emeritus led this push towards type hints in Python, so it's only fair that this chapter starts and ends with his words:

> *I wouldn't like a version of Python where I was morally obligated to add type hints all the time. I really do think that type hints have their place but there are also plenty of times that it's not worth it, and it's so wonderful that you can choose to use them.*[21]
>
> —Guido van Rossum

Further Reading

Bernát Gábor wrote in his excellent post The state of type hints in Python:

> *Type hints should be used whenever unit tests are worth writing.*

I am a big fan of testing, but I also do a lot exploratory coding. When I am exploring, tests and type hints are not helpful. They are a drag.

Gábor's post is one of the best introductions to Python's type hints that I found, along with Geir Arne Hjelle's Python Type Checking (Guide). Hypermodern Python Chapter 4: Typing by Claudio Jolowicz is a shorter introduction that also covers runtime type checking validation.

For deeper coverage, the Mypy documentation is the best source. It is valuable regardless of the type checker you are using, because it has tutorial and reference pages about Python typing in general—not just about the Mypy tool itself. There you will also find a handy cheat sheets and a very useful page about Common issues and solutions.

The `typing` module documentation is a good quick reference, but it doesn't go into much detail. The ultimate references are the PEP documents related to typing. There are more than 20 of them already. The intended audience of PEPs are Python core developers and Python's Steering Council, so they assume a lot of prior knowledge and are certainly not light reading.

As mentioned, Chapter 15 covers more typing topics, and "Further Reading" provides additional references, including Table 15-1, listing typing PEPs approved or under discussion as of March 2021.

Awesome Python Typing is a valuable collection of links to tools and references.

SOAPBOX

Just ride

> *Forget the ultralight, uncomfortable bikes, flashy jerseys, clunky shoes that clip onto tiny pedals, the grinding out of endless miles. Instead, ride like you did when you were a kid—just get on your bike and discover the pure joy of riding it.*
>
> —Grant Petersen, Just Ride: A Radically Practical Guide to Riding Your Bike

If coding is not your whole profession, but a useful tool in you profession, or something you do to learn, tinker and enjoy, you probably don't need type hints anymore than most bikers need shoes with stiff soles and metal cleats.

Just code.

The cognitive effect of typing

I worry about the effect type hints will have on Python coding style.

I agree that users of most APIs benefit from type hints. But Python attracted me—among other reasons—because it provides functions that are so powerful that they replace entire APIs, and we can write similarly powerful functions ourselves. Consider the `max()` built-in. It's powerful yet easy to understand. But I will show in "Max Overload" that it takes 14 lines of type hints to properly annotate it—not counting a `typing.Protocol` and a few `TypeVar` definitions to support those type hints.

I am concerned that strict enforcement of type hints in libraries will discourage programmers from even considering writing such functions in the future.

According to the English Wikipedia, Linguistic Relativity—a.k.a. the Sapir–Whorf hypothesis— is a "principle claiming that the structure of a language affects its speakers’ world view or cognition. Wikipedia further explains:

- The *strong* version says that language *determines* thought and that linguistic categories limit and determine cognitive categories.
- The *weak* version says that linguistic categories and usage only *influence* thought and decisions.

Linguists generally agree the strong version is false, but there is empirical evidence supporting the weak version.

I am not aware of specific studies with programming languages, but in my experience they’ve had a big impact on how I approach problems. The first programming language I used professionally was Applesoft BASIC in the age of 8-bit computers. Recursion was not directly supported by BASIC—you had to roll your own call stack to use it. So I never considered using recursive algorithms or data structures. I knew at some conceptual level such things existed, but they weren’t part of my problem-solving toolbox.

Decades later when I started with Elixir, I enjoyed solving problems with recursion and overused it—until I discovered that many of my solutions would be simpler if I used existing functions from the Elixir `Enum` and `Stream` modules. I learned that idiomatic Elixir application-level code rarely has explicit recursive calls, but use enums and streams that implement recursion under the hood.

Linguistic Relativity could explain the widespread idea (also unproven) that learning different programming languages makes you a better programmer, particularly when the languages support different programming paradigms. Practicing Elixir made me more likely to apply functional patterns when I write Python or Go code.

Now, back to Earth.

The `requests` package would probably have a very different API if Kenneth Reitz was determined (or told by his boss) to annotate all its functions. His goal was to write an API that was easy to use, flexible, and powerful. He succeeded, given the amazing popularity of `requests`—in May 2020, it's #4 on PyPI Stats, with 2.6 million downloads a day. #1 is `urllib3`, a dependency of `requests`.

In 2017, the `requests` maintainers decided not to spend their time writing type hints. One of the maintainers, Cory Benfield, had written an e-mail stating:

> *I think that libraries with Pythonic APIs are the least likely to take up this typing system because it will provide the least value to them.*

In that message, Benfield gave this extreme example of a tentative type definition for the `files` keyword argument of `requests.request()`:

```
Optional[
  Union[
    Mapping[
      basestring,
      Union[
        Tuple[basestring, Optional[Union[basestring, file]]],
        Tuple[basestring, Optional[Union[basestring, file]],
              Optional[basestring]],
        Tuple[basestring, Optional[Union[basestring, file]],
              Optional[basestring], Optional[Headers]]
      ]
    ],
    Iterable[
      Tuple[
        basestring,
        Union[
          Tuple[basestring, Optional[Union[basestring,
file]]],
          Tuple[basestring, Optional[Union[basestring, file]],
                Optional[basestring]],
          Tuple[basestring, Optional[Union[basestring, file]],
                Optional[basestring], Optional[Headers]]
      ]
    ]
```

```
    ]
  ]
```

And that assumes this definition:

```
  Headers = Union[
    Mapping[basestring, basestring],
    Iterable[Tuple[basestring, basestring]],
  ]
```

Do you think `requests` would be the way it is if the maintainers insisted on 100% type hint coverage? SQLAlchemy is another important package that doesn't play well with type hints.

What makes these libraries great is embracing the dynamic nature of Python.

While there are benefits to type hints, there is also a price to pay.

First, there is the significant investment of understanding how the type system works. That's a one-time cost.

But there is also a recurring cost, forever.

We lose some of the expressive power of Python if we insist on type checking everything. Beautiful features like argument unpacking—e.g. `config(**settings)`—are beyond comprehension for type checkers.

If you want to have a call like `config(**settings)` type checked, you must spell every argument out. That brings me memories of Turbo Pascal code I wrote 35 years ago.

Libraries that use metaprogramming are hard or impossible to annotate. Surely metaprogramming can be abused, but it's also what makes many Python packages a joy to use.

If type hints are mandated top down without exceptions in large companies, I bet soon we'll see people using code generation to reduce boilerplate in Python source-code—a common practice with less dynamic languages.

For some projects and contexts, type hints just don't make sense. Even in contexts where they mostly make sense, they don't make sense all the time. Any reasonable policy about the use of type hints must have exceptions.

Alan Kay—the Turing Award laureate who pioneered Object Oriented Programming—once said:

> *Some people are completely religious about type systems and as a mathematician I love the idea of type systems, but nobody has ever come up with one that has enough scope.*[22]

Thank Guido for optional typing. Let's use it as intended, and not aim to annotate everything into strict conformity to a coding style that looks like Java 1.5.

Duck typing FTW

Duck typing fits my brain, and static duck typing is a good compromise allowing static type checking without losing a lot of flexibility that some nominal type systems only provide with a lot of complexity—if ever.

Before PEP 544, this whole idea of type hints seemed utterly unpythonic to me. I was very glad to see `typing.Protocol` land in Python. It brings balance to the force.

Generics or specifics?

From a Python perspective, the typing usage of the term "generic" is backwards. Common meanings of "generic" are "applicable to an entire class or group" or "without a brand name."

Consider `list` versus `list[str]`. The first is generic: it accepts any object. The second is specific: it only accepts `str`.

> The term makes sense in Java, though. Before Java 1.5, all Java collections (except the magic `array`) were "specific": they could only hold `Object` references, so we had to cast the items that came out of a collection to use them. With Java 1.5, collections got type parameters, and became "generic."

---

1 PEP 484—Type Hints, section *Rationale and Goals*; bold emphasis retained from the original.

2 A just-in-time compiler like the one in PyPy has much better data than type hints: it monitors the Python program as it runs, detects the concrete types in use, and generates optimized machine code for those concrete types.

3 For example, recursive types are not supported as of July 2021—see `typing` module issue #182 Define a JSON type and Mypy issue #731 Support recursive types

4 Python doesn't provide syntax to control the set of possible values for a type—except in `Enum` types. For example, using type hints you can't define `Quantity` as an integer between 1 and 1000, or `AirportCode` as a 3-letter combination. NumPy offers `uint8`, `int16` and other machine-oriented numeric types, but in the Python standard library we only have types with very small sets of values (`NoneType`, `bool`) or extremely large sets (`float`, `int`, `str`, all possible tuples etc.).

5 Duck typing is a weaker form of *structural typing*, which Python ≥ 3.8 also supports with the introduction of `typing.Protocol`. This is covered later in this chapter—in "Static Protocols"—with more details in Chapter 13.

6 Inheritance is often overused and hard to justify in examples that are realistic yet simple, so please accept this animal example as a quick illustration of subtyping.

7 MIT Professor, programming language designer, and Turing Award recipient. Wikipedia: Barbara Liskov.

8 To be more precise, `ord` only accepts `str` or `bytes` with `len(s) == 1`. But the type system currently can't express this constraint.

9 In ABC—the language that most influenced the initial design of Python—each list was constrained to accept values of a single type: the type of the first item you put into it.

10 One of my contributions to the `typing` module documentation was to add dozens of deprecation warnings as I reorganized the entries below Module Contents into subsections, under the supervision of Guido van Rossum.

11 I use `:=` when it makes sense in a few examples, but I don't cover it in the book. Please see PEP 572—Assignment Expressions for all the gory details.

12 Actually, `dict` is a virtual subclass of `abc.MutableMapping`. The concept of a virtual subclass is explained in Chapter 13. For now, know that `issubclass(dict, abc.MutableMapping)` is `True`, despite the fact that `dict` is implemented in C and does not inherit anything from `abc.MutableMapping`, but only from `object`.

13 The implementation here is simpler than the one in the Python standard library `statistics` module.

14 I contributed this solution to typeshed, and that's how `mode` is annotated on `statistics.pyi` as of May 26, 2020.

15 How wonderful it is to open an interactive console and rely on duck typing to explore language features like I just did. I badly miss this kind of exploration when I use languages that don't support it.

16 Without this type hint, Mypy would infer the type of `series` as `Generator[Tuple[builtins.int, builtins.str*], None, None]`, which is verbose but *consistent-with* `Iterator[tuple[int, str`

17 I don't know who invented the term *static duck typing*, but it became more popular with the success of the Go language, which has interface semantics that are more like Python's protocols than the nominal interfaces of Java.

18 REPL stands for read-eval-print-loop, the common code pattern in interactive interpreters.

19 We'll see cases where `self` is annotated in Chapter 15, "Implementing a generic class"

20 As special case for `__init__`, if at least one parameter has a type hint, Mypy does not complain about the missing return type, by default. But if you forget this rule, and `__init__` is completely untyped, then it will not be type checked.

21 From YouTube video of *Type Hints by Guido van Rossum (March 2015)*. Quote starts at 13'40". I did some light editing for clarity.

22 Source: A Conversation with Alan Kay.

Chapter 9. Decorators and Closures

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 9th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *There's been a number of complaints about the choice of the name "decorator" for this feature. The major one is that the name is not consistent with its use in the GoF book.*[1] *The name decorator probably owes more to its use in the compiler area—a syntax tree is walked and annotated.*
>
> —PEP 318 — Decorators for Functions and Methods

Function decorators let us "mark" functions in the source code to enhance their behavior in some way. This is powerful stuff, but mastering it requires understanding closures—which is what happens when functions capture variables defined outside of their bodies.

The most obscure reserved keyword in Python is `nonlocal`, introduced in Python 3.0. You can have a profitable life as a Python programmer without ever using it if you adhere to a strict regimen of class-centered object orientation. However, if you want to implement your own function decorators, you must understand closures, and then the need for `nonlocal` becomes obvious.

Aside from their application in decorators, closures are also essential for any type of programming using callbacks, and for coding in a functional style when it makes sense.

The end goal of this chapter is to explain exactly how function decorators work, from the simplest registration decorators to the rather more complicated parameterized ones. However, before we reach that goal we need to cover:

- How Python evaluates decorator syntax
- How Python decides whether a variable is local
- Why closures exist and how they work
- What problem is solved by `nonlocal`

With this grounding, we can tackle further decorator topics:

- Implementing a well-behaved decorator
- Powerful decorators in the standard library: `@cache`, `@lru_cache`, and `@singledispatch`
- Implementing a parameterized decorator

What's new in this chapter

The caching decorator `functools.cache`—new in Python 3.9—is simpler than the traditional `functools.lru_cache`, so I present it first. The latter is covered in "Using lru_cache", including the simplified form added in Python 3.8.

Section "Single Dispatch Generic Functions" was expanded and now uses type hints, the preferred way to use `functools.singledispatch` since Python 3.7.

“Parameterized Decorators” now includes a class-based example, Example 9-27.

I moved Chapter 10—*Design Patterns with First-Class Functions*—to the end of part III to improve the flow of the book. Section “Decorator-Enhanced Strategy Pattern” is now in that chapter, along with other variations of the Strategy design pattern using callables.

We start with a very gentle introduction to decorators, and then proceed with the rest of the items listed in the chapter opening.

Decorators 101

A decorator is a callable that takes another function as argument (the decorated function).

A decorator may perform some processing with the decorated function, and returns it or replaces it with another function or callable object.[2]

In other words, assuming an existing decorator named `decorate`, this code:

```
@decorate
def target():
    print('running target()')
```

Has the same effect as writing this:

```
def target():
    print('running target()')

target = decorate(target)
```

The end result is the same: at the end of either of these snippets, the `target` name is bound to whatever function is returned by `decorate(target)`—which may be the function initially named `target`, or may be a different function.

To confirm that the decorated function is replaced, see the console session in Example 9-1.

Example 9-1. A decorator usually replaces a function with a different one

```
>>> def deco(func):
...     def inner():
...         print('running inner()')
...     return inner  ❶
...
>>> @deco
... def target():  ❷
...     print('running target()')
...
>>> target()  ❸
running inner()
>>> target  ❹
<function deco.<locals>.inner at 0x10063b598>
```

❶ `deco` returns its `inner` function object.

❷ `target` is decorated by `deco`.

❸ Invoking the decorated `target` actually runs `inner`.

❹ Inspection reveals that `target` is a now a reference to `inner`.

Strictly speaking, decorators are just syntactic sugar. As we just saw, you can always simply call a decorator like any regular callable, passing another function. Sometimes that is actually convenient, especially when doing *metaprogramming*—changing program behavior at runtime.

Three essential facts make a good summary of decorators:

1. A decorator is a function or another callable.
2. A decorator may replace the decorated function with a different one.
3. Decorators are executed immediately when a module is loaded.

Now let's focus on the third point.

When Python Executes Decorators

A key feature of decorators is that they run right after the decorated function is defined. That is usually at *import time* (i.e., when a module is loaded by Python). Consider *registration.py* in Example 9-2.

Example 9-2. The registration.py module

```
registry = []  ❶

def register(func):  ❷
    print(f'running register({func})')  ❸
    registry.append(func)  ❹
    return func  ❺

@register  ❻
def f1():
    print('running f1()')

@register
def f2():
    print('running f2()')

def f3():  ❼
    print('running f3()')

def main():  ❽
    print('running main()')
    print('registry ->', registry)
    f1()
    f2()
    f3()

if __name__ == '__main__':
    main()  ❾
```

❶ `registry` will hold references to functions decorated by `@register`.

❷ `register` takes a function as argument.

❸ Display what function is being decorated, for demonstration.

❹ Include `func` in `registry`.

❺ Return `func`: we must return a function; here we return the same received as argument.

❻ `f1` and `f2` are decorated by `@register`.

❼ `f3` is not decorated.

❽ `main` displays the `registry`, then calls `f1()`, `f2()`, and `f3()`.

❾ `main()` is only invoked if *registration.py* runs as a script.

The output of running *registration.py* as a script looks like this:

```
$ python3 registration.py
running register(<function f1 at 0x100631bf8>)
running register(<function f2 at 0x100631c80>)
running main()
registry -> [<function f1 at 0x100631bf8>, <function f2 at
0x100631c80>]
running f1()
running f2()
running f3()
```

Note that `register` runs (twice) before any other function in the module. When `register` is called, it receives the decorated function object as an argument—for example, `<function f1 at 0x100631bf8>`.

After the module is loaded, the `registry` list holds references to the two decorated functions: `f1` and `f2`. These functions, as well as `f3`, are only executed when explicitly called by `main`.

If *registration.py* is imported (and not run as a script), the output is this:

```
>>> import registration
running register(<function f1 at 0x10063b1e0>)
running register(<function f2 at 0x10063b268>)
```

At this time, if you inspect `registry`, this is what you see:

```
>>> registration.registry
[<function f1 at 0x10063b1e0>, <function f2 at 0x10063b268>]
```

The main point of Example 9-2 is to emphasize that function decorators are executed as soon as the module is imported, but the decorated functions only run when they are explicitly invoked. This highlights the difference between what Pythonistas call *import time* and *runtime*.

Registration decorators

Considering how decorators are commonly employed in real code, Example 9-2 is unusual in two ways:

- The decorator function is defined in the same module as the decorated functions. A real decorator is usually defined in one module and applied to functions in other modules.
- The `register` decorator returns the same function passed as argument. In practice, most decorators define an inner function and return it.

Even though the `register` decorator in Example 9-2 returns the decorated function unchanged, that technique is not useless. Similar decorators are used in many Python frameworks to add functions to some central registry—for example, a registry mapping URL patterns to functions that generate HTTP responses. Such registration decorators may or may not change the decorated function.

We will see a registration decorator applied in “Decorator-Enhanced Strategy Pattern” (Chapter 10).

Most decorators do change the decorated function. They usually do it by defining an inner function and returning it to replace the decorated function. Code that uses inner functions almost always depends on closures to operate correctly. To understand closures, we need to take a step back and review how variable scopes work in Python.

Variable Scope Rules

In Example 9-3, we define and test a function that reads two variables: a local variable `a`—defined as function parameter—and variable `b` that is not defined anywhere in the function.

Example 9-3. Function reading a local and a global variable

```
>>> def f1(a):
...     print(a)
...     print(b)
...
>>> f1(3)
3
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "<stdin>", line 3, in f1
NameError: global name 'b' is not defined
```

The error we got is not surprising. Continuing from Example 9-3, if we assign a value to a global `b` and then call `f1`, it works:

```
>>> b = 6
>>> f1(3)
3
6
```

Now, let's see an example that may surprise you.

Take a look at the `f2` function in Example 9-4. Its first two lines are the same as `f1` in Example 9-3, then it makes an assignment to `b`. But it fails at the second `print`, before the assignment is made.

Example 9-4. Variable b is local, because it is assigned a value in the body of the function

```
>>> b = 6
>>> def f2(a):
...     print(a)
...     print(b)
...     b = 9
...
>>> f2(3)
3
```

```
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "<stdin>", line 3, in f2
UnboundLocalError: local variable 'b' referenced before assignment
```

Note that the output starts with `3`, which proves that the `print(a)` statement was executed. But the second one, `print(b)`, never runs. When I first saw this I was surprised, thinking that `6` should be printed, because there is a global variable `b` and the assignment to the local `b` is made after `print(b)`.

But the fact is, when Python compiles the body of the function, it decides that `b` is a local variable because it is assigned within the function. The generated bytecode reflects this decision and will try to fetch `b` from the local scope. Later, when the call `f2(3)` is made, the body of `f2` fetches and prints the value of the local variable `a`, but when trying to fetch the value of local variable `b` it discovers that `b` is unbound.

This is not a bug, but a design choice: Python does not require you to declare variables, but assumes that a variable assigned in the body of a function is local. This is much better than the behavior of JavaScript, which does not require variable declarations either, but if you do forget to declare that a variable is local (with `var`), you may clobber a global variable without knowing.

If we want the interpreter to treat `b` as a global variable and still assign a new value to it within the function, we use the `global` declaration:

```
>>> b = 6
>>> def f3(a):
...     global b
...     print(a)
...     print(b)
...     b = 9
...
>>> f3(3)
3
6
>>> b
9
```

In the examples above we can see two scopes in action:

1. A module global scope, made of names assigned to values outside of any class or function block.
2. Function local scopes, made of names assigned to values as parameters, or directly in the body of the function.

There is one other scope where variables can come from, which we call *nonlocal* and is fundamental for closres; we'll see it in a bit.

After this closer look at how variable scopes work in Python, we can tackle closures in the next section, "Closures". If you are curious about the bytecode differences between the functions in Examples 9-3 and 9-4, see the following sidebar.

COMPARING BYTECODES

The `dis` module provides an easy way to disassemble the bytecode of Python functions. Read Examples 9-5 and 9-6 to see the bytecodes for `f1` and `f2` from Examples 9-3 and 9-4.

Example 9-5. Disassembly of the f1 function from Example 9-3

```
>>> from dis import dis
>>> dis(f1)
  2           0 LOAD_GLOBAL              0 (print)  ❶
              3 LOAD_FAST                0 (a)  ❷
              6 CALL_FUNCTION            1 (1 positional, 0
keyword pair)
              9 POP_TOP

  3          10 LOAD_GLOBAL              0 (print)
             13 LOAD_GLOBAL              1 (b)  ❸
             16 CALL_FUNCTION            1 (1 positional, 0
keyword pair)
             19 POP_TOP
             20 LOAD_CONST               0 (None)
             23 RETURN_VALUE
```

❶ Load global name `print`.

❷ Load local name `a`.

❸ Load global name `b`.

Contrast the bytecode for `f1` shown in Example 9-5 with the bytecode for `f2` in Example 9-6.

Example 9-6. Disassembly of the f2 function from Example 9-4

```
>>> dis(f2)
  2           0 LOAD_GLOBAL              0 (print)
              3 LOAD_FAST                0 (a)
              6 CALL_FUNCTION            1 (1 positional, 0
keyword pair)
              9 POP_TOP

  3          10 LOAD_GLOBAL              0 (print)
```

```
             13 LOAD_FAST                1 (b)   ❶
             16 CALL_FUNCTION            1 (1 positional, 0
keyword pair)
             19 POP_TOP

  4          20 LOAD_CONST               1 (9)
             23 STORE_FAST               1 (b)
             26 LOAD_CONST               0 (None)
             29 RETURN_VALUE
```

❶ Load *local* name `b`. This shows that the compiler considers `b` a local variable, even if the assignment to `b` occurs later, because the nature of the variable—whether it is local or not—cannot change in the body of the function.

The CPython VM that runs the bytecode is a stack machine, so `LOAD` and `POP` operations refer to the stack. It is beyond the scope of this book to further describe the Python opcodes, but they are documented along with the `dis` module in dis — Disassembler for Python bytecode.

Closures

In the blogosphere, closures are sometimes confused with anonymous functions. Many confuse them because of the parallel history of those features: defining functions inside functions is not so common or convenient, until you have anonymous functions. And closures only matter when you have nested functions. So a lot of people learn both concepts at the same time.

Actually, a closure is a function—let's call it `f`—with an extended scope that encompasses variables referenced in the body of `f` that are not global variables nor local variables of `f`. Such variables must come from the local scope of an outer function which encompasses `f`.

It does not matter whether the function is anonymous or not; what matters is that it can access nonglobal variables that are defined outside of its body.

This is a challenging concept to grasp, and is better approached through an example.

Consider an `avg` function to compute the mean of an ever-growing series of values; for example, the average closing price of a commodity over its entire history. Every day a new price is added, and the average is computed taking into account all prices so far.

Starting with a clean slate, this is how `avg` could be used:

```
>>> avg(10)
10.0
>>> avg(11)
10.5
>>> avg(12)
11.0
```

Where does `avg` come from, and where does it keep the history of previous values?

For starters, Example 9-7 is a class-based implementation.

Example 9-7. average_oo.py: A class to calculate a running average

```
class Averager():

    def __init__(self):
        self.series = []

    def __call__(self, new_value):
        self.series.append(new_value)
        total = sum(self.series)
        return total / len(self.series)
```

The `Averager` class creates instances that are callable:

```
>>> avg = Averager()
>>> avg(10)
10.0
>>> avg(11)
10.5
```

```
>>> avg(12)
11.0
```

Now, Example 9-8 is a functional implementation, using the higher-order function `make_averager`.

Example 9-8. average.py: A higher-order function to calculate a running average

```
def make_averager():
    series = []

    def averager(new_value):
        series.append(new_value)
        total = sum(series)
        return total / len(series)

    return averager
```

When invoked, `make_averager` returns an `averager` function object. Each time an `averager` is called, it appends the passed argument to the series, and computes the current average, as shown in Example 9-9.

Example 9-9. Testing Example 9-8

```
>>> avg = make_averager()
>>> avg(10)
10.0
>>> avg(11)
10.5
>>> avg(12)
11.0
```

Note the similarities of the examples: we call `Averager()` or `make_averager()` to get a callable object `avg` that will update the historical series and calculate the current mean. In Example 9-7, `avg` is an instance of `Averager`, and in Example 9-8 it is the inner function, `averager`. Either way, we just call `avg(n)` to include `n` in the series and get the updated mean.

It's obvious where the `avg` of the `Averager` class keeps the history: the `self.series` instance attribute. But where does the `avg` function in the second example find the `series`?

Note that `series` is a local variable of `make_averager` because the assignment `series = []` happens in the body of that function. But when `avg(10)` is called, `make_averager` has already returned, and its local scope is long gone.

Within `averager`, `series` is a *free variable*. This is a technical term meaning a variable that is not bound in the local scope. See Figure 9-1.

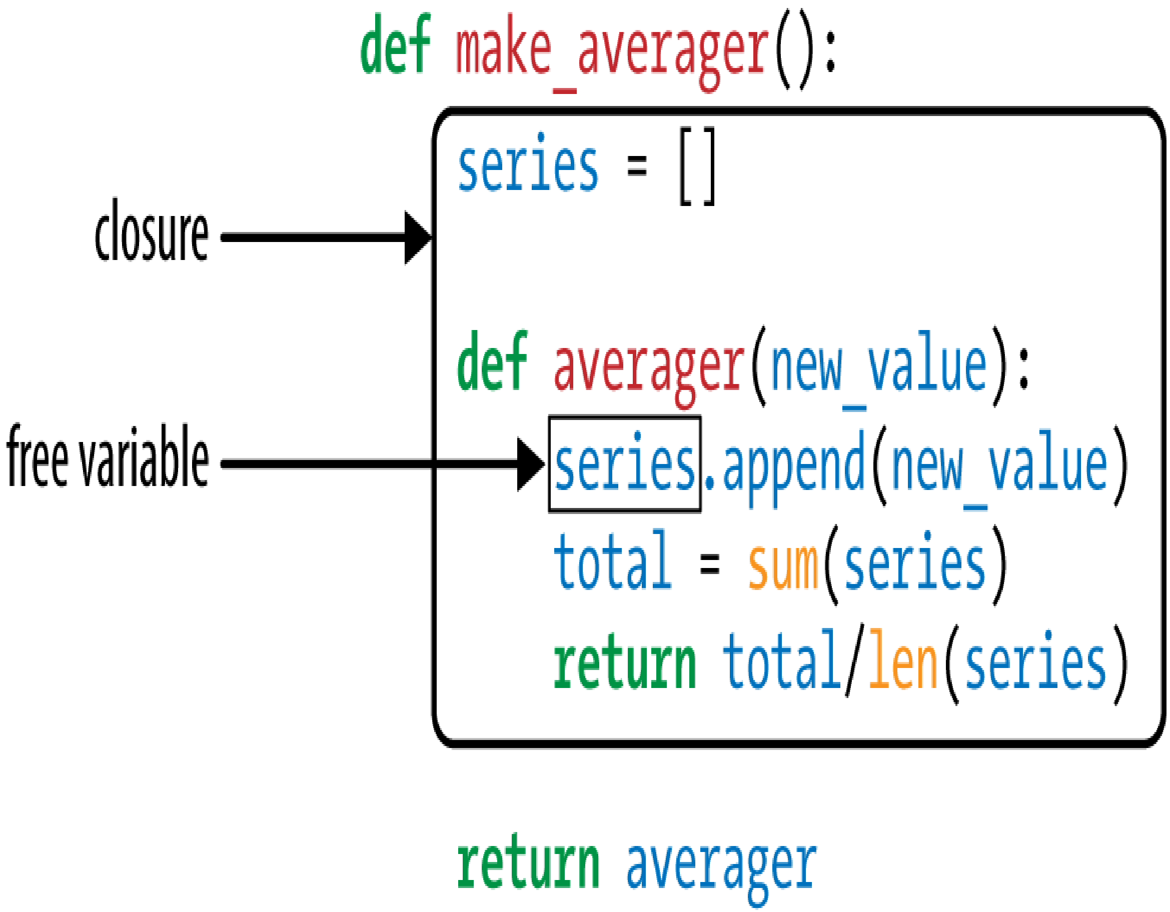


Figure 9-1. The closure for averager extends the scope of that function to include the binding for the free variable series.

Inspecting the returned `averager` object shows how Python keeps the names of local and free variables in the `__code__` attribute that represents the compiled body of the function. Example 9-10 demonstrates.

Example 9-10. Inspecting the function created by make_averager in Example 9-8

```
>>> avg.__code__.co_varnames
('new_value', 'total')
>>> avg.__code__.co_freevars
('series',)
```

The value for `series` is kept in the `__closure__` attribute of the returned function `avg`. Each item in `avg.__closure__` corresponds to a name in `avg.__code__.co_freevars`. These items are `cells`, and they have an attribute called `cell_contents` where the actual value can be found. Example 9-11 shows these attributes.

Example 9-11. Continuing from Example 9-9

```
>>> avg.__code__.co_freevars
('series',)
>>> avg.__closure__
(<cell at 0x107a44f78: list object at 0x107a91a48>,)
>>> avg.__closure__[0].cell_contents
[10, 11, 12]
```

To summarize: a closure is a function that retains the bindings of the free variables that exist when the function is defined, so that they can be used later when the function is invoked and the defining scope is no longer available.

Note that the only situation in which a function may need to deal with external variables that are nonglobal is when it is nested in another function and those variables are part of the local scope of the outer function.

The `nonlocal` Declaration

Our previous implementation of `make_averager` was not efficient. In Example 9-8, we stored all the values in the historical series and computed their `sum` every time `averager` was called. A better implementation would only store the total and the number of items so far, and compute the mean from these two numbers.

Example 9-12 is a broken implementation, just to make a point. Can you see where it breaks?

Example 9-12. A broken higher-order function to calculate a running average without keeping all history

```
def make_averager():
    count = 0
    total = 0

    def averager(new_value):
        count += 1
        total += new_value
        return total / count

    return averager
```

If you try Example 9-12, here is what you get:

```
>>> avg = make_averager()
>>> avg(10)
Traceback (most recent call last):
  ...
UnboundLocalError: local variable 'count' referenced before
assignment
>>>
```

The problem is that the statement `count += 1` actually means the same as `count = count + 1`, when `count` is a number or any immutable type. So we are actually assigning to `count` in the body of `averager`, and that makes it a local variable. The same problem affects the `total` variable.

We did not have this problem in Example 9-8 because we never assigned to the `series` name; we only called `series.append` and invoked `sum` and `len` on it. So we took advantage of the fact that lists are mutable.

But with immutable types like numbers, strings, tuples, etc., all you can do is read, never update. If you try to rebind them, as in `count = count + 1`, then you are implicitly creating a local variable `count`. It is no longer a free variable, and therefore it is not saved in the closure.

To work around this, the `nonlocal` keyword was introduced in Python 3. It lets you declare a variable as a free variable even when it is assigned within the function. If a new value is assigned to a `nonlocal` variable, the binding stored in the closure is changed. A correct implementation of our newest `make_averager` looks like Example 9-13.

Example 9-13. Calculate a running average without keeping all history (fixed with the use of nonlocal)

```
def make_averager():
    count = 0
    total = 0

    def averager(new_value):
        nonlocal count, total
        count += 1
        total += new_value
        return total / count

    return averager
```

After studing the use of `nonlocal`, let's summarize how Python's variable lookup works.[3]

The Python bytecode compiler determines when the function is defined how to fetch a variable `x` that appears in it, based on these rules:

- If there is a `global x` declaration, `x` comes from and is assigned to the `x` global variable the module.[4]
- If there is a `nonlocal x` declaration, `x` comes from and is assigned to the `x` local variable of the nearest surrounding function where `x` is defined.
- If `x` is a parameter or is assigned a value in the function body, then `x` is local variable.
- If `x` is referenced but is not assigned and is not a parameter:
- `x` will be looked up in the local scopes of the surrounding function bodies (nonlocal scopes);
- If not found in sorrounding scopes, it will be read from the module global scope;

- If not found in the global scope, it will be read from `__builtins__.__dict__`.

Now that we have Python closures covered, we can effectively implement decorators with nested functions.

Implementing a Simple Decorator

Example 9-14 is a decorator that clocks every invocation of the decorated function and displays the elapsed time, the arguments passed, and the result of the call.

Example 9-14. `clockdeco0.py`: simple decorator to show the running time of functions

```
import time


def clock(func):
    def clocked(*args):  ❶
        t0 = time.perf_counter()
        result = func(*args)  ❷
        elapsed = time.perf_counter() - t0
        name = func.__name__
        arg_str = ', '.join(repr(arg) for arg in args)
        print(f'[{elapsed:0.8f}s] {name}({arg_str}) -> {result!r}')
        return result
    return clocked  ❸
```

❶ Define inner function `clocked` to accept any number of positional arguments.

❷ This line only works because the closure for `clocked` encompasses the `func` free variable.

❸ Return the inner function to replace the decorated function.

Example 9-15 demonstrates the use of the `clock` decorator.

Example 9-15. Using the clock decorator

```
import time
from clockdeco0 import clock

@clock
def snooze(seconds):
    time.sleep(seconds)

@clock
def factorial(n):
    return 1 if n < 2 else n*factorial(n-1)

if __name__ == '__main__':
    print('*' * 40, 'Calling snooze(.123)')
    snooze(.123)
    print('*' * 40, 'Calling factorial(6)')
    print('6! =', factorial(6))
```

The output of running Example 9-15 looks like this:

```
$ python3 clockdeco_demo.py
**************************************** Calling snooze(.123)
[0.12363791s] snooze(0.123) -> None
**************************************** Calling factorial(6)
[0.00000095s] factorial(1) -> 1
[0.00002408s] factorial(2) -> 2
[0.00003934s] factorial(3) -> 6
[0.00005221s] factorial(4) -> 24
[0.00006390s] factorial(5) -> 120
[0.00008297s] factorial(6) -> 720
6! = 720
```

How It Works

Remember that this code:

```
@clock
def factorial(n):
    return 1 if n < 2 else n*factorial(n-1)
```

Actually does this:

```
def factorial(n):
    return 1 if n < 2 else n*factorial(n-1)
```

```
factorial = clock(factorial)
```

So, in both examples, `clock` gets the `factorial` function as its `func` argument (see Example 9-14). It then creates and returns the `clocked` function, which the Python interpreter assigns to `factorial` (behind the scenes, in the first example). In fact, if you import the `clockdeco_demo` module and check the `__name__` of `factorial`, this is what you get:

```
>>> import clockdeco_demo
>>> clockdeco_demo.factorial.__name__
'clocked'
>>>
```

So `factorial` now actually holds a reference to the `clocked` function. From now on, each time `factorial(n)` is called, `clocked(n)` gets executed. In essence, `clocked` does the following:

1. Records the initial time `t0`.
2. Calls the original `factorial` function, saving the result.
3. Computes the elapsed time.
4. Formats and displays the collected data.
5. Returns the result saved in step 2.

This is the typical behavior of a decorator: it replaces the decorated function with a new function that accepts the same arguments and (usually) returns whatever the decorated function was supposed to return, while also doing some extra processing.

> **TIP**
>
> In *Design Patterns* by Gamma et al., the short description of the Decorator pattern starts with: "Attach additional responsibilities to an object dynamically." Function decorators fit that description. But at the implementation level, Python decorators bear little resemblance to the classic Decorator described in the original *Design Patterns* work. "Soapbox" has more on this subject.

The `clock` decorator implemented in Example 9-14 has a few shortcomings: it does not support keyword arguments, and it masks the `__name__` and `__doc__` of the decorated function. Example 9-16 uses the `functools.wraps` decorator to copy the relevant attributes from `func` to `clocked`. Also, in this new version, keyword arguments are correctly handled.

Example 9-16. `clockdeco.py`: an improved clock decorator

```
import time
import functools


def clock(func):
    @functools.wraps(func)
    def clocked(*args, **kwargs):
        t0 = time.perf_counter()
        result = func(*args, **kwargs)
        elapsed = time.perf_counter() - t0
        name = func.__name__
        arg_lst = [repr(arg) for arg in args]
        arg_lst.extend(f'{k}={v!r}' for k, v in kwargs.items())
        arg_str = ', '.join(arg_lst)
        print(f'[{elapsed:0.8f}s] {name}({arg_str}) -> {result!r}')
        return result
    return clocked
```

`functools.wraps` is just one of the ready-to-use decorators in the standard library. In the next section, we'll meet the most impressive decorator that `functools` provides: `cache`.

Decorators in the Standard Library

Python has three built-in functions that are designed to decorate methods: `property`, `classmethod`, and `staticmethod`. We will discuss `property` in "Using a Property for Attribute Validation" and the others in "`classmethod` Versus `staticmethod`".

In Example 9-16 we saw another important decorator: `functools.wraps`, a helper for building well-behaved decorators. Some of the most interesting decorators in the standard library are `cache`, `lru_cache`, and `singledispatch`—all from the `functools` module. We'll cover them next.

Memoization with functools.cache

The `functools.cache` decorator implements memoization:[5] an optimization technique that works by saving the results of previous invocations of an expensive function, avoiding repeat computations on previously used arguments.

> **TIP**
>
> `functools.cache` was added in Python 3.9. If you need to run these examples in Python 3.8, replace `@cache` with `@lru_cache`. For prior versions of Python, you must invoke the decorator, writing `@lru_cache()`, as explained in "Using lru_cache"

A good demonstration is to apply `@cache` to the painfully slow recursive function to generate the *n*th number in the Fibonacci sequence, as shown in Example 9-17.

Example 9-17. The very costly recursive way to compute the nth number in the Fibonacci series

```
from clockdeco import clock


@clock
def fibonacci(n):
    if n < 2:
        return n
```

```
    return fibonacci(n - 2) + fibonacci(n - 1)


if __name__ == '__main__':
    print(fibonacci(6))
```

Here is the result of running *fibo_demo.py*. Except for the last line, all output is generated by the `clock` decorator:

```
$ python3 fibo_demo.py
[0.00000042s] fibonacci(0) -> 0
[0.00000049s] fibonacci(1) -> 1
[0.00006115s] fibonacci(2) -> 1
[0.00000031s] fibonacci(1) -> 1
[0.00000035s] fibonacci(0) -> 0
[0.00000030s] fibonacci(1) -> 1
[0.00001084s] fibonacci(2) -> 1
[0.00002074s] fibonacci(3) -> 2
[0.00009189s] fibonacci(4) -> 3
[0.00000029s] fibonacci(1) -> 1
[0.00000027s] fibonacci(0) -> 0
[0.00000029s] fibonacci(1) -> 1
[0.00000959s] fibonacci(2) -> 1
[0.00001905s] fibonacci(3) -> 2
[0.00000026s] fibonacci(0) -> 0
[0.00000029s] fibonacci(1) -> 1
[0.00000997s] fibonacci(2) -> 1
[0.00000028s] fibonacci(1) -> 1
[0.00000030s] fibonacci(0) -> 0
[0.00000031s] fibonacci(1) -> 1
[0.00001019s] fibonacci(2) -> 1
[0.00001967s] fibonacci(3) -> 2
[0.00003876s] fibonacci(4) -> 3
[0.00006670s] fibonacci(5) -> 5
[0.00016852s] fibonacci(6) -> 8
8
```

The waste is obvious: `fibonacci(1)` is called eight times, `fibonacci(2)` five times, etc. But adding just two lines to use `cache`, performance is much improved. See Example 9-18.

Example 9-18. Faster implementation using caching

```
import functools

from clockdeco import clock
```

```python
@functools.cache  ❶
@clock  ❷
def fibonacci(n):
    if n < 2:
        return n
    return fibonacci(n - 2) + fibonacci(n - 1)


if __name__ == '__main__':
    print(fibonacci(6))
```

❶ This line works with Python 3.9 or later. See "Using lru_cache" for alternatives supporting earlier versions of Python.

❷ This is an example of stacked decorators: `@cache` is applied on the function returned by `@clock`.

> **STACKED DECORATORS**
>
> To make sense of stacked decorators, recall that the @ is syntax sugar for applying the decorator function to the function below it. If there's more than one decorator, they behave like nested function calls. This:
>
> ```python
> @alpha
> @beta
> def my_fn():
>     ...
> ```
>
> Is the same as this:
>
> ```python
> my_fn = alpha(beta(my_fn))
> ```
>
> In other words, the `beta` decorator is applied first, and the function it returns is then passed to `alpha`.

Using `cache` in Example 9-18, the `fibonacci` function is called only once for each value of `n`:

```
$ python3 fibo_demo_lru.py
[0.00000043s] fibonacci(0) -> 0
[0.00000054s] fibonacci(1) -> 1
[0.00006179s] fibonacci(2) -> 1
[0.00000070s] fibonacci(3) -> 2
[0.00007366s] fibonacci(4) -> 3
[0.00000057s] fibonacci(5) -> 5
[0.00008479s] fibonacci(6) -> 8
8
```

In another test, to compute `fibonacci(30)`, Example 9-18 made the 31 calls needed in 0.00017s—total time–while the uncached Example 9-17 took 12.09s on an Intel Core i7 notebook, because it called `fibonacci(1)` 832,040 times, in a total of 2,692,537 calls.

All the arguments taken by the decorated function must be *hashable*, because the underlying `lru_cache` uses a `dict` to store the results, and the keys are made from the positional and keyword arguments used in the calls.

Besides making silly recursive algorithms viable, `@cache` really shines in applications that need to fetch information from remote APIs.

> **WARNING**
>
> `functools.cache` can consume all available memory if there is a very large number of cache entries. I consider it more suitable for use in short lived command-line scripts. In long running processes, I recommend using `functools.lru_cache` with a suitable `maxsize` parameter, as explained in the next section.

Using lru_cache

The `functools.cache` decorator is actually a simple wrapper around the older `functools.lru_cache` function, which is more flexible and compatible with Python 3.8 and earlier versions.

The main advantage of `@lru_cache` is that its memory usage is bounded by the `maxsize` parameter, which has a rather conservative default value of 128—which means the cache will hold at most 128 entries at any time.

The acronym LRU stands for Least Recently Used, meaning that older entries that have not been read for a while are discarded to make room for new ones.

Since Python 3.8 `lru_cache` can be applied in two ways. This is how to use it in the simplest way:

```
@lru_cache
def costly_function(a, b):
    ...
```

The other way—available since Python 3.2—is to invoke it as a function—with `()`:

```
@lru_cache()
def costly_function(a, b):
    ...
```

In both cases above, the default parameters would be used. They are:

`maxsize=128`

Sets the maximum number of entries to be stored. After the cache is full, the least recently used entry is discarded to make room for each new entry. For optimal performance, `maxsize` should be a power of 2. If you pass `maxsize=None` the LRU logic is disabled, so the cache works faster but entries are never discarded, which may consume too much memory. That’s what `@functools.cache` does.

`typed=False`

Determines whether results of different argument types are stored separately. For example, in the default setting, float and integer arguments that are considered equal are stored only once, so there would be a single entry for the calls `f(1)` and `f(1.0)`. If `typed=True`, those arguments would produce different entries, possibly storing distinct results.

Here is an example invoking `@lru_cache` with non-default parameters:

```
@lru_cache(maxsize=2**20, typed=True)
def costly_function(a, b):
    ...
```

Now let's study another powerful decorator: `functools.singledispatch`.

Single Dispatch Generic Functions

Imagine we are creating a tool to debug web applications. We want to generate HTML displays for different types of Python objects.

We could start with a function like this:

```
import html

def htmlize(obj):
    content = html.escape(repr(obj))
    return f'<pre>{content}</pre>'
```

That will work for any Python type, but now we want to extend it to generate custom displays for some types. Some examples:

- `str`: replace embedded newline characters with `'<br/>\n'` and use `<p>` tags instead of `<pre>`.
- `int`: show the number in decimal and hexadecimal (with a special case for `bool`).
- `list`: output an HTML list, formatting each item according to its type.
- `float` and `Decimal`: output the value as usual, but also in the form of a fraction (why not?).

The behavior we want is shown in Example 9-19.

Example 9-19. `htmlize()` generates HTML tailored to different object types

```
>>> htmlize({1, 2, 3})  ❶
'<pre>{1, 2, 3}</pre>'
>>> htmlize(abs)
'<pre>&lt;built-in function abs&gt;</pre>'
>>> htmlize('Heimlich & Co.\n- a game')  ❷
'<p>Heimlich &amp; Co.<br/>\n- a game</p>'
>>> htmlize(42)  ❸
'<pre>42 (0x2a)</pre>'
>>> print(htmlize(['alpha', 66, {3, 2, 1}]))  ❹
<ul>
<li><p>alpha</p></li>
<li><pre>66 (0x42)</pre></li>
<li><pre>{1, 2, 3}</pre></li>
</ul>
>>> htmlize(True)  ❺
'<pre>True</pre>'
>>> htmlize(fractions.Fraction(2, 3))  ❻
'<pre>2/3</pre>'
>>> htmlize(2/3)  ❼
'<pre>0.6666666666666666 (2/3)</pre>'
>>> htmlize(decimal.Decimal('0.02380952'))
'<pre>0.02380952 (1/42)</pre>'
```

❶ The original function is registered for `object`, so it serves as a catch-all to handle argument types that don't match the other implementations.

❷ `str` objects are also HTML-escaped but wrapped in `<p></p>` with `<br/>` line breaks inserted before each `'\n'`.

❸ An `int` is shown in decimal and hexadecimal, inside `<pre></pre>`.

❹ Each list item is formatted according to its type, and the whole sequence rendered as an HTML list.

❺ Although `bool` is an `int` subtype, it gets special treatment.

❻ Show `Fraction` as a fraction.

❼ Show `float` and `Decimal` with an approximate fractional equivalent.

Function `singledispatch`

Because we don't have Java-style method overloading in Python, we can't simply create variations of `htmlize` with different signatures for each data type we want to handle differently. A possible solution in Python would be to turn `htmlize` into a dispatch function, with a chain of `if/elif/`… or `match/case/`… calling specialized functions like `htmlize_str`, `htmlize_int`, etc. This is not extensible by users of our module, and is unwieldy: over time, the `htmlize` dispatcher would become too big, and the coupling between it and the specialized functions would be very tight.

The `functools.singledispatch` decorator allows different modules to contribute to the overall solution, and lets you easily provide a specialized functions even for types that belong to third party packages that you can't edit. If you decorate a plain function with `@singledispatch`, it becomes the entry point for a *generic function*: a group of functions to perform the same operation in different ways, depending on the type of the first argument. This is what is meant by the term single-dispatch. If more arguments were used to select the specific functions, we'd have multiple-dispatch. Example 9-20 shows how.

> **WARNING**
>
> `functools.singledispatch` exists since Python 3.4, but it only supports type hints since Python 3.7. The last two functions in Example 9-20 illustrate the syntax that works in all versions of Python since 3.4.

Example 9-20. `@singledispatch` creates a custom `@htmlize.register` to bundle several functions into a generic function

```
from functools import singledispatch
from collections import abc
import fractions
```

```
import decimal
import html
import numbers

@singledispatch  ❶
def htmlize(obj: object) -> str:
    content = html.escape(repr(obj))
    return f'<pre>{content}</pre>'

@htmlize.register  ❷
def _(text: str) -> str:  ❸
    content = html.escape(text).replace('\n', '<br/>\n')
    return f'<p>{content}</p>'

@htmlize.register  ❹
def _(seq: abc.Sequence) -> str:
    inner = '</li>\n<li>'.join(htmlize(item) for item in seq)
    return '<ul>\n<li>' + inner + '</li>\n</ul>'

@htmlize.register  ❺
def _(n: numbers.Integral) -> str:
    return f'<pre>{n} (0x{n:x})</pre>'

@htmlize.register  ❻
def _(n: bool) -> str:
    return f'<pre>{n}</pre>'

@htmlize.register(fractions.Fraction)  ❼
def _(x) -> str:
    frac = fractions.Fraction(x)
    return f'<pre>{frac.numerator}/{frac.denominator}</pre>'

@htmlize.register(decimal.Decimal)  ❽
@htmlize.register(float)
def _(x) -> str:
    frac = fractions.Fraction(x).limit_denominator()
    return f'<pre>{x} ({frac.numerator}/{frac.denominator})</pre>'
```

❶ `@singledispatch` marks the base function that handles the `object` type.

❷ Each specialized function is decorated with `@«base».register`

❸ The type of the first argument given at runtime determines when this particular function definition will be used. The name of the specialized functions is irrelevant; _ is a good choice to make this clear.[6]

❹ For each additional type to get special treatment, register a new function with a matching type hint in the first parameter.

❺ The `numbers` ABCs are useful for use with `singledispatch`.[7]

❻ `bool` is a *subtype-of* `numbers.Integral`, but the `singledispatch` logic seeks the implementation with the most specific matching type, regardless of the order they appear in the code.

❼ If you don't want to, or cannot, add type hints to the decorated function, you can pass a type to the `@«base».register` decorator. This syntax works in Python 3.4 or later.

❽ The `@«base».register` decorator returns the undecorated function, so it's possible to stack them to register two or more types on the same implementation.[8]

When possible, register the specialized functions to handle ABCs (abstract classes) such as `numbers.Integral` and `abc.MutableSequence` instead of concrete implementations like `int` and `list`. This allows your code to support a greater variety of compatible types. For example, a Python extension can provide alternatives to the `int` type with fixed bit lengths as subclasses of `numbers.Integral`.[9]

> **TIP**
>
> Using ABCs or `typing.Protocol` with `@singledispatch` allows your code to support existing or future classes that are actual or virtual subclasses of those ABCs, or that implement those protocols. The use of ABCs and the concept of a virtual subclass are subjects of Chapter 13.

A notable quality of the `singledispatch` mechanism is that you can register specialized functions anywhere in the system, in any module. If you later add a module with a new user-defined type, you can easily provide a new custom function to handle that type. And you can write custom functions for classes that you did not write and can't change.

`singledispatch` is a well-thought-out addition to the standard library, and it offers more features than I can describe here. PEP 443 — Single-dispatch generic functions is a good reference—but it doesn't mention the use of type hints, which were added later. The `functools` module documentation has improved and more up-to-date coverage with several examples in its `singledispatch` entry.

> **NOTE**
>
> `@singledispatch` is not designed to bring Java-style method overloading to Python. A single class with many overloaded variations of a method is better than a single function with a lengthy stretch of `if/elif/elif/elif` blocks. But both solutions are flawed because they concentrate too much responsibility in a single code unit—the class or the function. The advantage of `@singledispatch` is supporting modular extension: each module can register a specialized function for each type it supports. In a realistic use case, you would not have all the implementations of generic function in the same module as in Example 9-20.

We've seen some decorators that take arguments, for example, `@lru_cache()` and `htmlize.register(float)` created by `@singledispatch` in Example 9-20. The next section shows how to build decorators that accept parameters.

Parameterized Decorators

When parsing a decorator in source code, Python takes the decorated function and passes it as the first argument to the decorator function. So how do you make a decorator accept other arguments? The answer is: make a decorator factory that takes those arguments and returns a decorator, which is then applied to the function to be decorated. Confusing? Sure. Let's start with an example based on the simplest decorator we've seen: `register` in Example 9-21.

Example 9-21. Abridged registration.py module from Example 9-2, repeated here for convenience

```
registry = []

def register(func):
    print(f'running register({func})')
    registry.append(func)
    return func

@register
def f1():
    print('running f1()')

print('running main()')
print('registry ->', registry)
f1()
```

A Parameterized Registration Decorator

In order to make it easy to enable or disable the function registration performed by `register`, we'll make it accept an optional `active` parameter which, if `False`, skips registering the decorated function. Example 9-22 shows how. Conceptually, the new `register` function is not a decorator but a decorator factory. When called, it returns the actual decorator that will be applied to the target function.

Example 9-22. To accept parameters, the new register decorator must be called as a function

```
registry = set()  ❶

def register(active=True):  ❷
    def decorate(func):  ❸
        print('running register'
              f'(active={active})->decorate({func})')
        if active:   ❹
            registry.add(func)
        else:
            registry.discard(func)  ❺
```

```
        return func  ❻
    return decorate  ❼

@register(active=False)  ❽
def f1():
    print('running f1()')

@register()  ❾
def f2():
    print('running f2()')

def f3():
    print('running f3()')
```

❶ `registry` is now a `set`, so adding and removing functions is faster.

❷ `register` takes an optional keyword argument.

❸ The `decorate` inner function is the actual decorator; note how it takes a function as argument.

❹ Register `func` only if the `active` argument (retrieved from the closure) is `True`.

❺ If `not active` and `func in registry`, remove it.

❻ Because `decorate` is a decorator, it must return a function.

❼ `register` is our decorator factory, so it returns `decorate`.

❽ The `@register` factory must be invoked as a function, with the desired parameters.

❾ If no parameters are passed, `register` must still be called as a function—`@register()`—i.e., to return the actual decorator, `decorate`.

The main point is that `register()` returns `decorate`, which is then applied to the decorated function.

The code in Example 9-22 is in a *registration_param.py* module. If we import it, this is what we get:

```
>>> import registration_param
running register(active=False)->decorate(<function f1 at
0x10063c1e0>)
running register(active=True)->decorate(<function f2 at
0x10063c268>)
>>> registration_param.registry
[<function f2 at 0x10063c268>]
```

Note how only the `f2` function appears in the `registry`; `f1` does not appear because `active=False` was passed to the `register` decorator factory, so the `decorate` that was applied to `f1` did not add it to the `registry`.

If, instead of using the `@` syntax, we used `register` as a regular function, the syntax needed to decorate a function `f` would be `register()(f)` to add `f` to the `registry`, or `register(active=False)(f)` to not add it (or remove it). See Example 9-23 for a demo of adding and removing functions to the `registry`.

Example 9-23. Using the registration_param module listed in Example 9-22

```
>>> from registration_param import *
running register(active=False)->decorate(<function f1 at
0x10073c1e0>)
running register(active=True)->decorate(<function f2 at
0x10073c268>)
>>> registry  ❶
{<function f2 at 0x10073c268>}
>>> register()(f3)  ❷
running register(active=True)->decorate(<function f3 at
0x10073c158>)
<function f3 at 0x10073c158>
>>> registry  ❸
{<function f3 at 0x10073c158>, <function f2 at 0x10073c268>}
>>> register(active=False)(f2)  ❹
running register(active=False)->decorate(<function f2 at
0x10073c268>)
```

```
<function f2 at 0x10073c268>
>>> registry  ❺
{<function f3 at 0x10073c158>}
```

❶ When the module is imported, `f2` is in the `registry`.

❷ The `register()` expression returns `decorate`, which is then applied to `f3`.

❸ The previous line added `f3` to the `registry`.

❹ This call removes `f2` from the `registry`.

❺ Confirm that only `f3` remains in the `registry`.

The workings of parameterized decorators are fairly involved, and the one we've just discussed is simpler than most. Parameterized decorators usually replace the decorated function, and their construction requires yet another level of nesting. Now we will explore the architecture of one such function pyramid.

The Parameterized Clock Decorator

In this section, we'll revisit the `clock` decorator, adding a feature: users may pass a format string to control the output of the clocked function report. See Example 9-24.

> **NOTE**
>
> For simplicity, Example 9-24 is based on the initial `clock` implementation from Example 9-14, and not the improved one from Example 9-16 that uses `@functools.wraps`, adding yet another function layer.

Example 9-24. Module clockdeco_param.py: the parameterized clock decorator

```python
import time

DEFAULT_FMT = '[{elapsed:0.8f}s] {name}({args}) -> {result}'

def clock(fmt=DEFAULT_FMT):  ❶
    def decorate(func):      ❷
        def clocked(*_args): ❸
            t0 = time.perf_counter()
            _result = func(*_args)  ❹
            elapsed = time.perf_counter() - t0
            name = func.__name__
            args = ', '.join(repr(arg) for arg in _args)  ❺
            result = repr(_result)  ❻
            print(fmt.format(**locals()))  ❼
            return _result  ❽
        return clocked  ❾
    return decorate  ❿

if __name__ == '__main__':

    @clock()  ⓫
    def snooze(seconds):
        time.sleep(seconds)

    for i in range(3):
        snooze(.123)
```

❶ `clock` is our parameterized decorator factory.

❷ `decorate` is the actual decorator.

❸ `clocked` wraps the decorated function.

❹ `_result` is the actual result of the decorated function.

❺ `_args` holds the actual arguments of `clocked`, while `args` is `str` used for display.

❻ `result` is the `str` representation of `_result`, for display.

❼ Using `**locals()` here allows any local variable of `clocked` to be referenced in the `fmt`.[10]

❽ `clocked` will replace the decorated function, so it should return whatever that function returns.

❾ `decorate` returns `clocked`.

❿ `clock` returns `decorate`.

⓫ In this self test, `clock()` is called without arguments, so the decorator applied will use the default format `str`.

If you run Example 9-24 from the shell, this is what you get:

```
$ python3 clockdeco_param.py
[0.12412500s] snooze(0.123) -> None
[0.12411904s] snooze(0.123) -> None
[0.12410498s] snooze(0.123) -> None
```

To exercise the new functionality, let's have a look at Examples 9-25 and 9-26, which are two other modules using `clockdeco_param`, and the outputs they generate.

Example 9-25. clockdeco_param_demo1.py

```python
import time
from clockdeco_param import clock

@clock('{name}: {elapsed}s')
def snooze(seconds):
    time.sleep(seconds)

for i in range(3):
    snooze(.123)
```

Output of Example 9-25:

```
$ python3 clockdeco_param_demo1.py
snooze: 0.12414693832397461s
snooze: 0.1241159439086914s
snooze: 0.12412118911743164s
```

Example 9-26. clockdeco_param_demo2.py

```
import time
from clockdeco_param import clock

@clock('{name}({args}) dt={elapsed:0.3f}s')
def snooze(seconds):
    time.sleep(seconds)

for i in range(3):
    snooze(.123)
```

Output of Example 9-26:

```
$ python3 clockdeco_param_demo2.py
snooze(0.123) dt=0.124s
snooze(0.123) dt=0.124s
snooze(0.123) dt=0.124s
```

> **NOTE**
>
> Graham Dumpleton and Lennart Regebro—technical reviewer of the *First Edition*—argue that decorators are best coded as classes implementing `__call__`, and not as functions like the examples in this chapter. I agree that approach is better for non-trivial decorators, but to explain the basic idea of this language feature, functions are easier to understand. See "Further Reading", in particular Graham Dumpleton's blog and `wrapt` module for industrial-strength techniques when building decorators.

The next section shows an example in the style recommended by Dumpleton and Regebro.

A class-based `clock` decorator

As a final example, Example 9-27 lists the implementation of a parameterized `clock` decorator implemented as a class with `__call__`. Contrast Example 9-24 with Example 9-27. Which one do you prefer?

Example 9-27. Module clockdeco_cls.py: parameterized clock decorator implemented as class

```
import time
```

```python
DEFAULT_FMT = '[{elapsed:0.8f}s] {name}({args}) -> {result}'

class clock:  ❶

    def __init__(self, fmt=DEFAULT_FMT):  ❷
        self.fmt = fmt

    def __call__(self, func):  ❸
        def clocked(*_args):
            t0 = time.perf_counter()
            _result = func(*_args)  ❹
            elapsed = time.perf_counter() - t0
            name = func.__name__
            args = ', '.join(repr(arg) for arg in _args)
            result = repr(_result)
            print(self.fmt.format(**locals()))
            return _result
        return clocked
```

❶ Instead of a `clock` outer function, the `clock` class is our parameterized decorator factory. I named it with a lowercase `c` to make clear that this implementation is a drop-in replacement for the one in Example 9-24.

❷ The argument passed in the `clock(my_format)` is assigned to the `fmt` parameter here. The class constructor returns an instance of `clock`, with `my_format` stored in `self.fmt`.

❸ `__call__` makes the `clock` instance callable. When invoked, the instance replaces the decorated function with `clocked`

❹ `clocked` wraps the decorated function.

This ends our exploration of function decorators. We'll see class decorators in Chapter 25.

Chapter Summary

We covered some difficult terrain in this chapter. I tried to make the journey as smooth as possible, but we definitely entered the realm of metaprogramming.

We started with a simple `@register` decorator without an inner function, and finished with a parameterized `@clock()` involving two levels of nested functions.

Registration decorators, though simple in essence, have real applications in Python frameworks. We will apply the registration idea in one implementation of the Strategy design pattern in Chapter 10.

Understanding how decorators actually work required covering the difference between *import time* and *runtime*, then diving into variable scoping, closures, and the new `nonlocal` declaration. Mastering closures and `nonlocal` is valuable not only to build decorators, but also to code event-oriented programs for GUIs or asynchronous I/O with callbacks, and to adopt a functional style when it makes sense.

Parameterized decorators almost always involve at least two nested functions, maybe more if you want to use `@functools.wraps` to produce a decorator that provides better support for more advanced techniques. One such technique is stacked decorators, which we saw in Example 9-18. For more sophisticated decorators, a class-based implementation may be easier to read and maintain.

As examples of parametrized decorators in the standard library, we visited the powerful `@cache` and `@singledispatch` from the `functools` module.

Further Reading

Item #26 of Brett Slatkin's *Effective Python, Second Edition* (Addison-Wesley, 2019) covers best practices for function decorators and recommends always using `functools.wraps`—which we saw in Example 9-16.[11]

Graham Dumpleton has a series of in-depth blog posts about techniques for implementing well-behaved decorators, starting with "How You Implemented Your Python Decorator is Wrong". His deep expertise in this matter is also nicely packaged in the wrapt module he wrote to simplify the implementation of decorators and dynamic function wrappers, which support introspection and behave correctly when further decorated, when applied to methods and when used as attribute descriptors. Chapter 24 in *Part VI* is about descriptors.

Chapter 9, *Metaprogramming* of the *Python Cookbook, Third Edition* by David Beazley and Brian K. Jones (O'Reilly), has several recipes from elementary decorators to very sophisticated ones, including one that can be called as a regular decorator or as a decorator factory, e.g., `@clock` or `@clock()`. That's "Recipe 9.6. Defining a Decorator That Takes an Optional Argument" in that cookbook.

Michele Simionato authored a package aiming to "simplify the usage of decorators for the average programmer, and to popularize decorators by showing various non-trivial examples," according to the docs. It's available on PyPI as the decorator package.

Created when decorators were still a new feature in Python, the Python Decorator Library wiki page has dozens of examples. Because that page started years ago, some of the techniques shown have been superseded, but the page is still an excellent source of inspiration.

"Closures in Python" is a short blog post by Fredrik Lundh that explains the terminology of closures.

PEP 3104 — Access to Names in Outer Scopes describes the introduction of the `nonlocal` declaration to allow rebinding of names that are neither local nor global. It also includes an excellent overview of how this issue is resolved in other dynamic languages (Perl, Ruby, JavaScript, etc.) and the pros and cons of the design options available to Python.

On a more theoretical level, PEP 227 — Statically Nested Scopes documents the introduction of lexical scoping as an option in Python 2.1 and as a standard in Python 2.2, explaining the rationale and design choices for the implementation of closures in Python.

PEP 443 provides the rationale and a detailed description of the single-dispatch generic functions' facility. An old (March 2005) blog post by Guido van Rossum, "Five-Minute Multimethods in Python", walks through an implementation of generic functions (a.k.a. multimethods) using decorators. His code supports multiple-dispatch (i.e., dispatch based on more than one positional argument). Guido's multimethods code is interesting, but it's a didactic example. For a modern, production-ready implementation of multiple-dispatch generic functions, check out Reg by Martijn Faassen—author of the model-driven and REST-savvy Morepath web framework.

SOAPBOX

The designer of any language with first-class functions faces this issue: being first-class objects, functions are defined in a certain scope but may be invoked in other scopes. The question is: how to evaluate the free variables? The first and simplest answer is “dynamic scope.” This means that free variables are evaluated by looking into the environment where the function is invoked.

If Python had dynamic scope and no closures, we could improvise `avg`—similar to Example 9-8—like this:

```
>>> ### this is not a real Python console session! ###
>>> avg = make_averager()
>>> series = []  ❶
>>> avg(10)
10.0
>>> avg(11)  ❷
10.5
>>> avg(12)
11.0
>>> series = [1]  ❸
>>> avg(5)
3.0
```

❶ Before using `avg`, we have to define `series = []` ourselves, so we must know that `averager` (inside `make_averager`) refers to a list named `series`.

❷ Behind the scenes, `series` accumulates the values to be averaged.

❸ When `series = [1]` is executed, the previous list is lost. This could happen by accident, when handling two independent running averages at the same time.

Functions should be black boxes, with their implementation hidden from users. But with dynamic scope, if a function uses free variables, the programmer has to know its internals to set up an environment where it works correctly. After years of struggling with the LaTeX document preparation language, the excellent *Practical LaTeX* book by George Grätzer taught me that LaTeX variables use dynamic scope. That's why they were so confusing to me!

Emacs Lisp also uses dynamic scope, at least by default. See Dynamic Binding in the Emacs Lisp manual for a short explanation.

Dynamic scope is easier to implement, which is probably why it was the path taken by John McCarthy when he created Lisp, the first language to have first-class functions. Paul Graham's article "The Roots of Lisp" is an accessible explanation of John McCarthy's original paper about the Lisp language: "Recursive Functions of Symbolic Expressions and Their Computation by Machine, Part I". McCarthy's paper is a masterpiece as great as Beethoven's 9th Symphony. Paul Graham translated it for the rest of us, from mathematics to English and running code.

Paul Graham's commentary explains how tricky dynamic scoping is. Quoting from "The Roots of Lisp":

> *It's an eloquent testimony to the dangers of dynamic scope that even the very first example of higher-order Lisp functions was broken because of it. It may be that McCarthy was not fully aware of the implications of dynamic scope in 1960. Dynamic scope remained in Lisp implementations for a surprisingly long time—until Sussman and Steele developed Scheme in 1975. Lexical scope does not complicate the definition of* `eval` *very much, but it may make compilers harder to write.*

Today, lexical scope is the norm: free variables are evaluated considering the environment where the function is defined. Lexical scope complicates the implementation of languages with first-class functions, because it requires the support of closures. On the other hand, lexical scope makes source code easier to read. Most languages invented since Algol have lexical scope.

For many years, Python `lambdas` did not provide closures, contributing to the bad name of this feature among functional-programming geeks in the blogosphere. This was fixed in Python 2.2 (December 2001), but the blogosphere has a long memory. Since then, `lambda` is embarrassing only because of its limited syntax.

Python Decorators and the Decorator Design Pattern

Python function decorators fit the general description of Decorator given by Gamma et al. in *Design Patterns*: “Attach additional responsibilities to an object dynamically. Decorators provide a flexible alternative to subclassing for extending functionality.”

At the implementation level, Python decorators do not resemble the classic Decorator design pattern, but an analogy can be made.

In the design pattern, `Decorator` and `Component` are abstract classes. An instance of a concrete decorator wraps an instance of a concrete component in order to add behaviors to it. Quoting from *Design Patterns*:

> *The decorator conforms to the interface of the component it decorates so that its presence is transparent to the component’s clients. The decorator forwards requests to the component and may perform additional actions (such as drawing a border) before or after forwarding. Transparency lets you nest decorators recursively, thereby allowing an unlimited number of added responsibilities.” (p. 175)*

In Python, the decorator function plays the role of a concrete `Decorator` subclass, and the inner function it returns is a decorator instance. The returned function wraps the function to be decorated, which is analogous to the component in the design pattern. The returned function is transparent because it conforms to the interface of the component by accepting the same arguments. It forwards calls to the component and may perform additional actions either before or after it. Borrowing from the previous citation, we can adapt the last sentence to say that “Transparency lets you stack decorators, thereby allowing an unlimited number of added behaviors.”

Note that I am not suggesting that function decorators should be used to implement the Decorator pattern in Python programs. Although this can be done in specific situations, in general the Decorator pattern is best implemented with classes to represent the Decorator and the components it will wrap.

---

1 That’s the 1995 *Design Patterns* book by the so-called Gang of Four.

2 If you replace “function” with “class” in the previous sentence, you have a brief description of what a class decorator does. Class decorators are covered in Chapter 25.

3 Thanks to tech reviewer Leonardo Rochael suggesting this summary.

4 Python does not have a program global scope, only module global scopes.

5 To clarify, this is not a typo: “memoization” is a computer science term vaguely related to “memorization”, but not the same.

6 Unfortunately, Mypy 0.770 complains when it sees multiple functions with the same name…

7 Despite the warning in “The Fall of the Numeric Tower”, the `number` ABC are not deprecated and you find them in Python 3 code.

8 Maybe one day you’ll also be able to express this with single unparameterized `@htmlize.register` and type hint using `Union`, but when I tried, Python raised a `TypeError` with a message saying that `Union` is not a class. So, although PEP 484 *syntax* is supported by `@singledispatch`, the *semantics* are not there yet.

9 NumPy, for example, implements several machine-oriented integer and floating-point types.

10 Tech reviewer Miroslav Šedivý noted: “It also means that code linters will complain about unused variables since they tend to ignore uses of `locals()`.” Yes, that’s yet another example of how static checking tools discourage the use of the dynamic features that attracted me and countless programmers to Python in the first place. To make the linter happy, I could spell out each local variable twice in the call: `.format(elapsed=elapsed, name=name, args=args, result=result)`. I’d rather not. If you use static checking tools, it’s very important to know when to ignore them.

11 I wanted to make the code as simple as possible, so I did not follow Slatkin’s excellent advice in all examples.

Chapter 10. Design Patterns with First-Class Functions

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 10th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

Conformity to patterns is not a measure of goodness.[1]

—Ralph Johnson, Coauthor of the Design Patterns classic

In software engineering, a *design pattern* is a general recipe for solving a common design problem. You don't need to know design patterns to follow this chapter. I will explain the patterns used in the examples.

The use of design patterns in programming was popularized by the landmark book *Design Patterns: Elements of Reusable Object-Oriented Software* (Addison-Wesley, 1995) by Erich Gamma, Richard Helm, Ralph Johnson & John Vlissides—a.k.a. "the Gang of Four." The book is a catalog of 23 patterns consisting of arrangements of classes exemplified with code in C++, but assumed to be useful in other Object-Oriented languages as well.

Although design patterns are language-independent, that does not mean every pattern applies to every language. For example, Chapter 17 will show that it doesn't make sense to emulate the recipe of the Iterator pattern in Python, because the pattern is embedded in the language and ready to use in in the form of generators—which don't need classes to work, and require less code than the classic recipe.

The authors of *Design Patterns* acknowledge in their *Introduction* that the implementation language determines which patterns are relevant:

> *The choice of programming language is important because it influences one's point of view. Our patterns assume Smalltalk/C++-level language features, and that choice determines what can and cannot be implemented easily. If we assumed procedural languages, we might have included design patterns called "Inheritance," "Encapsulation," and "Polymorphism." Similarly, some of our patterns are supported directly by the less common object-oriented languages. CLOS has multi-methods, for example, which lessen the need for a pattern such as Visitor.*[2]

In his 1996 presentation, "Design Patterns in Dynamic Languages", Peter Norvig states that 16 out of the 23 patterns in the original *Design Patterns* book become either "invisible or simpler" in a dynamic language (slide 9). He was talking about the Lisp and Dylan languages, but many of the relevant dynamic features are also present in Python. In particular, in the context of languages with first-class functions, Norvig suggests rethinking the classic patterns known as Strategy, Command, Template Method, and Visitor.

The goal of this chapter is to show how—in some cases—functions can do the same work as classes, with code that is shorter and easier to read. We will refactor an implementation of Strategy using functions as objects, removing a lot of boilerplate code. We'll also discuss a similar approach to simplifying the Command pattern.

What's new in this chapter

I moved this chapter to the end of Part III so I could apply a registration decorator in "Decorator-Enhanced Strategy Pattern" and also use type hints in the examples. Most type hints used in this chapter are not complicated, and they do help with readability.

Case Study: Refactoring Strategy

Strategy is a good example of a design pattern that can be simpler in Python if you leverage functions as first-class objects. In the following section, we describe and implement Strategy using the "classic" structure described in *Design Patterns*. If you are familiar with the classic pattern, you can skip to "Function-Oriented Strategy" where we refactor the code using functions, significantly reducing the line count.

Classic Strategy

The UML class diagram in Figure 10-1 depicts an arrangement of classes that exemplifies the Strategy pattern.

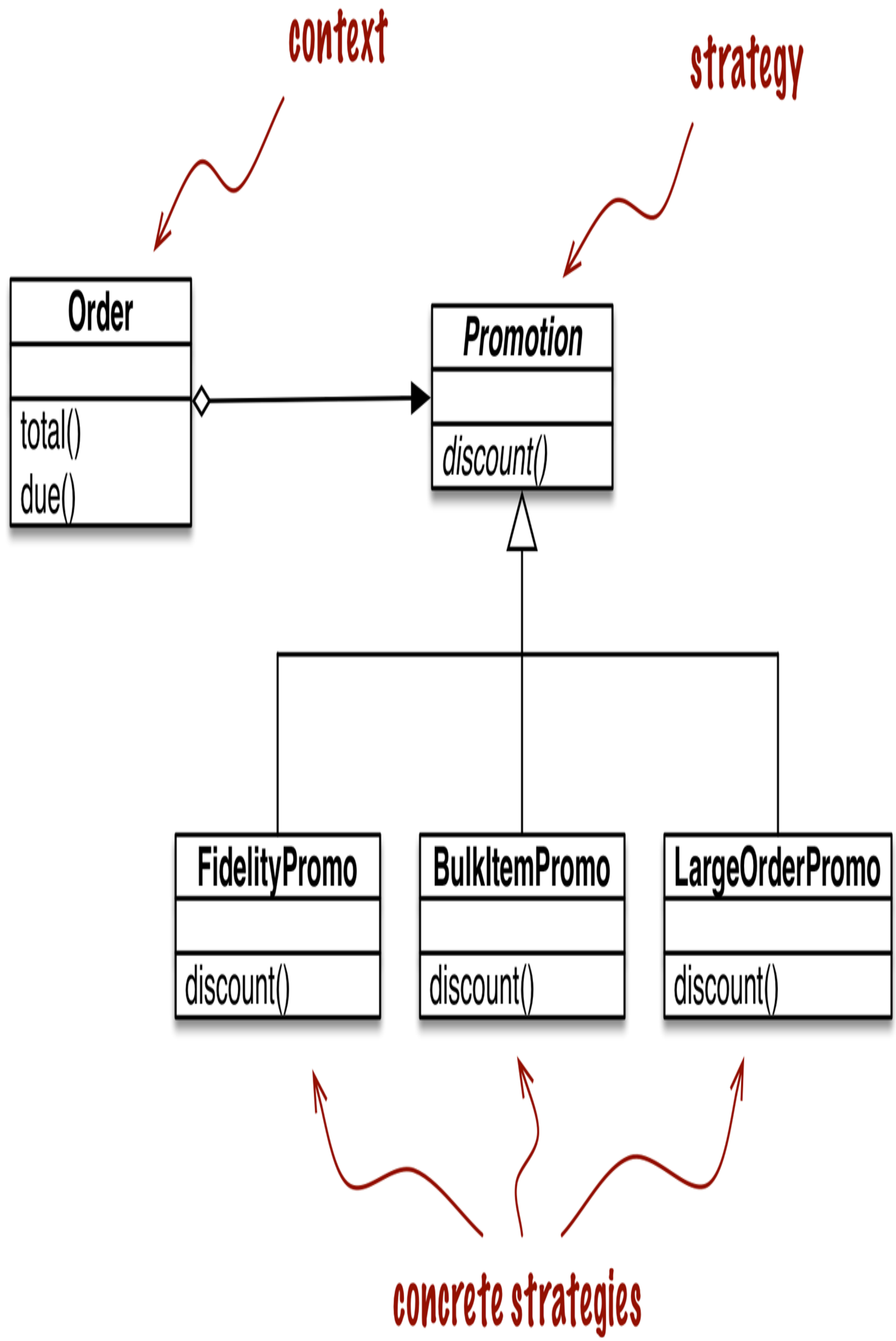

context
strategy
Order
total()
due()
Promotion
discount()
FidelityPromo
discount()
BulkItemPromo
discount()
LargeOrderPromo
discount()
concrete strategies

Figure 10-1. UML class diagram for order discount processing implemented with the Strategy design pattern

The Strategy pattern is summarized like this in *Design Patterns*:

> *Define a family of algorithms, encapsulate each one, and make them interchangeable. Strategy lets the algorithm vary independently from clients that use it.*

A clear example of Strategy applied in the ecommerce domain is computing discounts to orders according to the attributes of the customer or inspection of the ordered items.

Consider an online store with these discount rules:

- Customers with 1,000 or more fidelity points get a global 5% discount per order.
- A 10% discount is applied to each line item with 20 or more units in the same order.
- Orders with at least 10 distinct items get a 7% global discount.

For brevity, let's assume that only one discount may be applied to an order.

The UML class diagram for the Strategy pattern is depicted in Figure 10-1. Its participants are:

Context

Provides a service by delegating some computation to interchangeable components that implement alternative algorithms. In the ecommerce example, the context is an `Order`, which is configured to apply a promotional discount according to one of several algorithms.

Strategy

The interface common to the components that implement the different algorithms. In our example, this role is played by an abstract class called `Promotion`.

Concrete Strategy

> One of the concrete subclasses of Strategy. `FidelityPromo`, `BulkPromo`, and `LargeOrderPromo` are the three concrete strategies implemented.

The code in Example 10-1 follows the blueprint in Figure 10-1. As described in *Design Patterns*, the concrete strategy is chosen by the client of the context class. In our example, before instantiating an order, the system would somehow select a promotional discount strategy and pass it to the `Order` constructor. The selection of the strategy is outside the scope of the pattern.

Example 10-1. Implementation of the `Order` class with pluggable discount strategies.

```
from abc import ABC, abstractmethod
from collections.abc import Sequence
from decimal import Decimal
from typing import NamedTuple, Optional


class Customer(NamedTuple):
    name: str
    fidelity: int


class LineItem(NamedTuple):
    product: str
    quantity: int
    price: Decimal

    def total(self) -> Decimal:
        return self.price * self.quantity


class Order(NamedTuple):  # the Context
    customer: Customer
    cart: Sequence[LineItem]
    promotion: Optional['Promotion'] = None

    def total(self) -> Decimal:
        totals = (item.total() for item in self.cart)
```

```python
        return sum(totals, start=Decimal(0))

    def due(self) -> Decimal:
        if self.promotion is None:
            discount = Decimal(0)
        else:
            discount = self.promotion.discount(self)
        return self.total() - discount

    def __repr__(self):
        return f'<Order total: {self.total():.2f} due:
{self.due():.2f}>'


class Promotion(ABC):  # the Strategy: an abstract base class
    @abstractmethod
    def discount(self, order: Order) -> Decimal:
        """Return discount as a positive dollar amount"""


class FidelityPromo(Promotion):  # first Concrete Strategy
    """5% discount for customers with 1000 or more fidelity
points"""

    def discount(self, order: Order) -> Decimal:
        rate = Decimal('0.05')
        if order.customer.fidelity >= 1000:
            return order.total() * rate
        return Decimal(0)


class BulkItemPromo(Promotion):  # second Concrete Strategy
    """10% discount for each LineItem with 20 or more units"""

    def discount(self, order: Order) -> Decimal:
        discount = Decimal(0)
        for item in order.cart:
            if item.quantity >= 20:
                discount += item.total() * Decimal('0.1')
        return discount


class LargeOrderPromo(Promotion):  # third Concrete Strategy
    """7% discount for orders with 10 or more distinct items"""

    def discount(self, order: Order) -> Decimal:
        distinct_items = {item.product for item in order.cart}
        if len(distinct_items) >= 10:
```

```
            return order.total() * Decimal('0.07')
        return Decimal(0)
```

Note that in Example 10-1, I coded `Promotion` as an abstract base class (ABC), to use the `@abstractmethod` decorator and make the pattern more explicit.

Example 10-2 shows doctests used to demonstrate and verify the operation of a module implementing the rules described earlier.

Example 10-2. Sample usage of `Order` class with different promotions applied.

```
    >>> joe = Customer('John Doe', 0)  ❶
    >>> ann = Customer('Ann Smith', 1100)
    >>> cart = (LineItem('banana', 4, Decimal('.5')),  ❷
    ...         LineItem('apple', 10, Decimal('1.5')),
    ...         LineItem('watermelon', 5, Decimal(5)))
    >>> Order(joe, cart, FidelityPromo())  ❸
    <Order total: 42.00 due: 42.00>
    >>> Order(ann, cart, FidelityPromo())  ❹
    <Order total: 42.00 due: 39.90>
    >>> banana_cart = (LineItem('banana', 30, Decimal('.5')),  ❺
    ...                LineItem('apple', 10, Decimal('1.5')))
    >>> Order(joe, banana_cart, BulkItemPromo())  ❻
    <Order total: 30.00 due: 28.50>
    >>> long_cart = tuple(LineItem(str(sku), 1, Decimal(1)) ❼
    ...                   for sku in range(10))
    >>> Order(joe, long_cart, LargeOrderPromo())  ❽
    <Order total: 10.00 due: 9.30>
    >>> Order(joe, cart, LargeOrderPromo())
    <Order total: 42.00 due: 42.00>
```

❶ Two customers: `joe` has 0 fidelity points, `ann` has 1,100.

❷ One shopping cart with three line items.

❸ The `FidelityPromo` promotion gives no discount to `joe`.

❹ `ann` gets a 5% discount because she has at least 1,000 points.

❺ The `banana_cart` has 30 units of the `"banana"` product and 10 apples.

6. Thanks to the `BulkItemPromo`, `joe` gets a $1.50 discount on the bananas.

7. `long_cart` has 10 different items at $1.00 each.

8. `joe` gets a 7% discount on the whole order because of `LargerOrderPromo`.

Example 10-1 works perfectly well, but the same functionality can be implemented with less code in Python by using functions as objects. The next section shows how.

Function-Oriented Strategy

Each concrete strategy in Example 10-1 is a class with a single method, `discount`. Furthermore, the strategy instances have no state (no instance attributes). You could say they look a lot like plain functions, and you would be right. Example 10-3 is a refactoring of Example 10-1, replacing the concrete strategies with simple functions and removing the `Promo` abstract class. Only small adjustments are needed in the `Order` class.[3]

Example 10-3. `Order` class with discount strategies implemented as functions.

```
from collections.abc import Sequence
from dataclasses import dataclass
from decimal import Decimal
from typing import Optional, Callable, NamedTuple


class Customer(NamedTuple):
    name: str
    fidelity: int


class LineItem(NamedTuple):
    product: str
    quantity: int
    price: Decimal
```

```
    def total(self):
        return self.price * self.quantity

@dataclass(frozen=True)
class Order:  # the Context
    customer: Customer
    cart: Sequence[LineItem]
    promotion: Optional[Callable[['Order'], Decimal]] = None  ❶

    def total(self) -> Decimal:
        totals = (item.total() for item in self.cart)
        return sum(totals, start=Decimal(0))

    def due(self) -> Decimal:
        if self.promotion is None:
            discount = Decimal(0)
        else:
            discount = self.promotion(self)  ❷
        return self.total() - discount

    def __repr__(self):
        return f'<Order total: {self.total():.2f} due:
{self.due():.2f}>'


❸


def fidelity_promo(order: Order) -> Decimal:  ❹
    """5% discount for customers with 1000 or more fidelity
points"""
    if order.customer.fidelity >= 1000:
        return order.total() * Decimal('0.05')
    return Decimal(0)


def bulk_item_promo(order: Order) -> Decimal:
    """10% discount for each LineItem with 20 or more units"""
    discount = Decimal(0)
    for item in order.cart:
        if item.quantity >= 20:
            discount += item.total() * Decimal('0.1')
    return discount


def large_order_promo(order: Order) -> Decimal:
    """7% discount for orders with 10 or more distinct items"""
    distinct_items = {item.product for item in order.cart}
```

```
if len(distinct_items) >= 10:
    return order.total() * Decimal('0.07')
return Decimal(0)
```

❶ This type hint says: `promotion` may be `None`, or it may be a callable that takes an `Order` argument and returns a `Decimal`.

❷ To compute a discount, call the `self.promotion` callable, passing `self` as an argument. See below for the reason.

❸ No abstract class.

❹ Each strategy is a function.

> **WHY SELF.PROMOTION(SELF)**
>
> In the `Order` class, `promotion` is not a method. It's an instance attribute that happens to be callable. So the first part of the expression, `self.promotion`, retrieves that callable. To invoke it, we must provide an instance of `Order`, which in this case is `self`. That's why `self` appears twice in that expression.
>
> "Methods Are Descriptors" will explain the mechanism that binds methods to instances automatically. It does not apply to `promotion` because it is not a method.

The code in Example 10-3 is shorter than Example 10-1. Using the new `Order` is also a bit simpler, as shown in the Example 10-4 doctests.

Example 10-4. Sample usage of Order class with promotions as functions

```
>>> joe = Customer('John Doe', 0)  ❶
>>> ann = Customer('Ann Smith', 1100)
>>> cart = [LineItem('banana', 4, Decimal('.5')),
...         LineItem('apple', 10, Decimal('1.5')),
...         LineItem('watermelon', 5, Decimal(5))]
>>> Order(joe, cart, fidelity_promo)  ❷
<Order total: 42.00 due: 42.00>
>>> Order(ann, cart, fidelity_promo)
<Order total: 42.00 due: 39.90>
>>> banana_cart = [LineItem('banana', 30, Decimal('.5')),
...                LineItem('apple', 10, Decimal('1.5'))]
>>> Order(joe, banana_cart, bulk_item_promo)  ❸
```

```
<Order total: 30.00 due: 28.50>
>>> long_cart = [LineItem(str(item_code), 1, Decimal(1))
...              for item_code in range(10)]
>>> Order(joe, long_cart, large_order_promo)
<Order total: 10.00 due: 9.30>
>>> Order(joe, cart, large_order_promo)
<Order total: 42.00 due: 42.00>
```

❶ Same test fixtures as Example 10-1.

❷ To apply a discount strategy to an `Order`, just pass the promotion function as an argument.

❸ A different promotion function is used here and in the next test.

Note the callouts in Example 10-4: there is no need to instantiate a new promotion object with each new order: the functions are ready to use.

It is interesting to note that in *Design Patterns* the authors suggest: “Strategy objects often make good flyweights.”[4] A definition of the Flyweight in another part of that work states: “A flyweight is a shared object that can be used in multiple contexts simultaneously.”[5] The sharing is recommended to reduce the cost of creating a new concrete strategy object when the same strategy is applied over and over again with every new context—with every new `Order` instance, in our example. So, to overcome a drawback of the Strategy pattern—its runtime cost—the authors recommend applying yet another pattern. Meanwhile, the line count and maintenance cost of your code are piling up.

A thornier use case, with complex concrete strategies holding internal state, may require all the pieces of the Strategy and Flyweight design patterns combined. But often concrete strategies have no internal state; they only deal with data from the context. If that is the case, then by all means use plain old functions instead of coding single-method classes implementing a single-method interface declared in yet another class. A function is more lightweight than an instance of a user-defined class, and there is no need for Flyweight because each strategy function is created just once per Python process when it loads the module. A plain function is also “a shared object that can be used in multiple contexts simultaneously.”

Now that we have implemented the Strategy pattern with functions, other possibilities emerge. Suppose you want to create a “meta-strategy” that selects the best available discount for a given `Order`. In the following sections we study additional refactorings that implement this requirement using a variety of approaches that leverage functions and modules as objects.

Choosing the Best Strategy: Simple Approach

Given the same customers and shopping carts from the tests in Example 10-4, we now add three additional tests in Example 10-5.

Example 10-5. The best_promo function applies all discounts and returns the largest

```
>>> Order(joe, long_cart, best_promo)  ❶
<Order total: 10.00 due: 9.30>
>>> Order(joe, banana_cart, best_promo)  ❷
<Order total: 30.00 due: 28.50>
>>> Order(ann, cart, best_promo)  ❸
<Order total: 42.00 due: 39.90>
```

❶ `best_promo` selected the `larger_order_promo` for customer `joe`.

❷ Here `joe` got the discount from `bulk_item_promo` for ordering lots of bananas.

❸ Checking out with a simple cart, `best_promo` gave loyal customer `ann` the discount for the `fidelity_promo`.

The implementation of `best_promo` is very simple. See Example 10-6.

Example 10-6. best_promo finds the maximum discount iterating over a list of functions

```
promos = [fidelity_promo, bulk_item_promo, large_order_promo]  ❶


def best_promo(order: Order) -> Decimal:  ❷
    """Compute the best discount available"""
    return max(promo(order) for promo in promos)  ❸
```

❶ `promos`: list of the strategies implemented as functions.

❷ `best_promo` takes an instance of `Order` as argument, as do the other `*_promo` functions.

❸ Using a generator expression, we apply each of the functions from `promos` to the `order`, and return the maximum discount computed.

Example 10-6 is straightforward: `promos` is a `list` of functions. Once you get used to the idea that functions are first-class objects, it naturally follows that building data structures holding functions often makes sense.

Although Example 10-6 works and is easy to read, there is some duplication that could lead to a subtle bug: to add a new promotion strategy, we need to code the function and remember to add it to the `promos` list, or else the new promotion will work when explicitly passed as an argument to `Order`, but will not be considered by `best_promotion`.

Read on for a couple of solutions to this issue.

Finding Strategies in a Module

Modules in Python are also first-class objects, and the standard library provides several functions to handle them. The built-in `globals` is described as follows in the Python docs:

`globals()`

> Return a dictionary representing the current global symbol table. This is always the dictionary of the current module (inside a function or

method, this is the module where it is defined, not the module from which it is called).

Example 10-7 is a somewhat hackish way of using `globals` to help `best_promo` automatically find the other available `*_promo` functions.

Example 10-7. The `promos` list is built by introspection of the module global namespace

```
from decimal import Decimal
from strategy import Order
from strategy import (
    fidelity_promo, bulk_item_promo, large_order_promo  ❶
)

promos = [promo for name, promo in globals().items()  ❷
                if name.endswith('_promo') and        ❸
                   name != 'best_promo'               ❹
]


def best_promo(order: Order) -> Decimal:              ❺
    """Compute the best discount available"""
    return max(promo(order) for promo in promos)
```

❶ Import the promotion functions so they are available in the global namespace.[6]

❷ Iterate over each item in the `dict` returned by `globals()`.

❸ Select only values where the name ends with the `_promo` suffix and…

❹ Filter out `best_promo` itself, to avoid an infinite recursion when `best_promo` is called.

❺ No changes in `best_promo`.

Another way of collecting the available promotions would be to create a module and put all the strategy functions there, except for `best_promo`.

In Example 10-8, the only significant change is that the list of strategy functions is built by introspection of a separate module called `promotions`. Note that Example 10-8 depends on importing the `promotions` module as well as `inspect`, which provides high-level introspection functions.

Example 10-8. The promos list is built by introspection of a new promotions module

```
from decimal import Decimal
import inspect

from strategy import Order
import promotions


promos = [func for _, func in inspect.getmembers(promotions,
inspect.isfunction)]


def best_promo(order: Order) -> Decimal:
    """Compute the best discount available"""
    return max(promo(order) for promo in promos)
```

The function `inspect.getmembers` returns the attributes of an object —in this case, the `promotions` module—optionally filtered by a predicate (a boolean function). We use `inspect.isfunction` to get only the functions from the module.

Example 10-8 works regardless of the names given to the functions; all that matters is that the `promotions` module contains only functions that calculate discounts given orders. Of course, this is an implicit assumption of the code. If someone were to create a function with a different signature in the `promotions` module, then `best_promo` would break while trying to apply it to an order.

We could add more stringent tests to filter the functions, by inspecting their arguments for instance. The point of Example 10-8 is not to offer a complete solution, but to highlight one possible use of module introspection.

A more explicit alternative to dynamically collecting promotional discount functions would be to use a simple decorator. That's next.

Decorator-Enhanced Strategy Pattern

Recall that our main issue with Example 10-6 is the repetition of the function names in their definitions and then in the `promos` list used by the `best_promo` function to determine the highest discount applicable. The repetition is problematic because someone may add a new promotional strategy function and forget to manually add it to the `promos` list—in which case, `best_promo` will silently ignore the new strategy, introducing a subtle bug in the system. Example 10-9 solves this problem with the technique covered in "Registration decorators".

Example 10-9. The promos list is filled by the promotion decorator

```
Promotion = Callable[[Order], Decimal]

promos: list[Promotion] = []  ❶


def promotion(promo: Promotion) -> Promotion:  ❷
    promos.append(promo)
    return promo


def best_promo(order: Order) -> Decimal:
    """Compute the best discount available"""
    return max(promo(order) for promo in promos)  ❸


@promotion  ❹
def fidelity(order: Order) -> Decimal:
    """5% discount for customers with 1000 or more fidelity
points"""
    if order.customer.fidelity >= 1000:
        return order.total() * Decimal('0.05')
    return Decimal(0)


@promotion
def bulk_item(order: Order) -> Decimal:
    """10% discount for each LineItem with 20 or more units"""
```

```
    discount = Decimal(0)
    for item in order.cart:
        if item.quantity >= 20:
            discount += item.total() * Decimal('0.1')
    return discount


@promotion
def large_order(order: Order) -> Decimal:
    """7% discount for orders with 10 or more distinct items"""
    distinct_items = {item.product for item in order.cart}
    if len(distinct_items) >= 10:
        return order.total() * Decimal('0.07')
    return Decimal(0)
```

❶ The `promos` list is a module global, and starts empty.

❷ `promotion` is a registration decorator: it returns the `promo` function unchanged, after appending it to the `promos` list.

❸ No changes needed to `best_promo`, because it relies on the `promos` list.

❹ Any function decorated by `@promotion` will be added to `promos`.

This solution has several advantages over the others presented before:

- The promotion strategy functions don't have to use special names —no need for the `_promo` suffix.
- The `@promotion` decorator highlights the purpose of the decorated function, and also makes it easy to temporarily disable a promotion: just comment out the decorator.
- Promotional discount strategies may be defined in other modules, anywhere in the system, as long as the `@promotion` decorator is applied to them.

In the next section, we discuss Command—another design pattern that is sometimes implemented via single-method classes when plain functions would do.

The Command Pattern

Command is another design pattern that can be simplified by the use of functions passed as arguments. Figure 10-2 shows the arrangement of classes in the Command pattern.

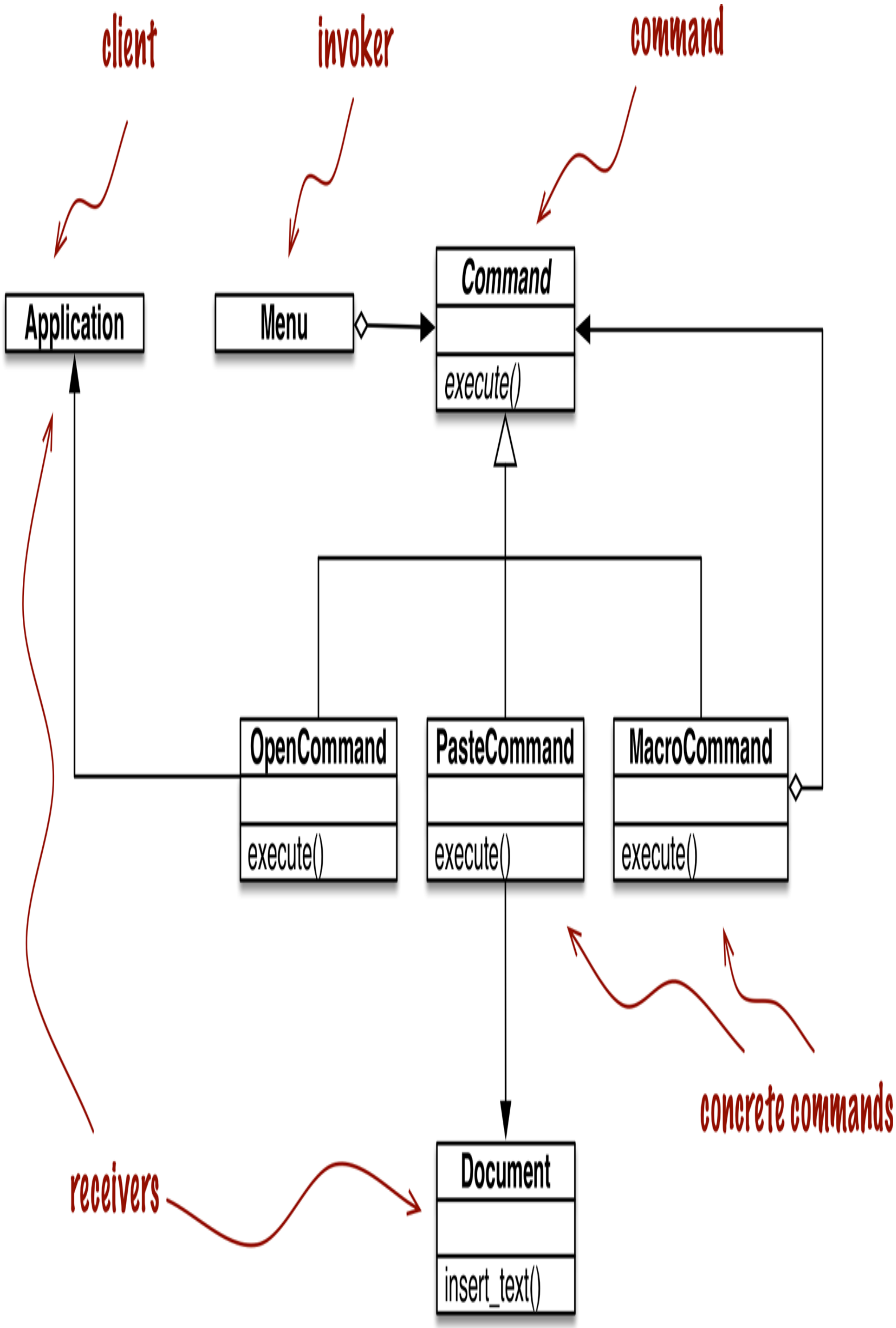

client
invoker
command
Application
Menu
Command
execute()
OpenCommand
execute()
PasteCommand
execute()
MacroCommand
execute()
concrete commands
receivers
Document
insert_text()

Figure 10-2. UML class diagram for menu-driven text editor implemented with the Command design pattern. Each command may have a different receiver: the object that implements the action. For PasteCommand, the receiver is the Document. For OpenCommand, the receiver is the application.

The goal of Command is to decouple an object that invokes an operation (the Invoker) from the provider object that implements it (the Receiver). In the example from *Design Patterns*, each invoker is a menu item in a graphical application, and the receivers are the document being edited or the application itself.

The idea is to put a `Command` object between the two, implementing an interface with a single method, `execute`, which calls some method in the Receiver to perform the desired operation. That way the Invoker does not need to know the interface of the Receiver, and different receivers can be adapted through different `Command` subclasses. The Invoker is configured with a concrete command and calls its `execute` method to operate it. Note in Figure 10-2 that `MacroCommand` may store a sequence of commands; its `execute()` method calls the same method in each command stored.

Quoting from Gamma et al., "Commands are an object-oriented replacement for callbacks." The question is: do we need an object-oriented replacement for callbacks? Sometimes yes, but not always.

Instead of giving the Invoker a `Command` instance, we can simply give it a function. Instead of calling `command.execute()`, the Invoker can just call `command()`. The `MacroCommand` can be implemented with a class implementing `__call__`. Instances of `MacroCommand` would be callables, each holding a list of functions for future invocation, as implemented in Example 10-10.

Example 10-10. Each instance of MacroCommand has an internal list of commands

```
class MacroCommand:
    """A command that executes a list of commands"""

    def __init__(self, commands):
        self.commands = list(commands)  ❶

    def __call__(self):
```

```
        for command in self.commands:  ❷
            command()
```

❶ Building a list from the `commands` arguments ensures that it is iterable and keeps a local copy of the command references in each `MacroCommand` instance.

❷ When an instance of `MacroCommand` is invoked, each command in `self.commands` is called in sequence.

More advanced uses of the Command pattern—to support undo, for example—may require more than a simple callback function. Even then, Python provides a couple of alternatives that deserve consideration:

- A callable instance like `MacroCommand` in Example 10-10 can keep whatever state is necessary, and provide extra methods in addition to `__call__`.
- A closure can be used to hold the internal state of a function between calls.

This concludes our rethinking of the Command pattern with first-class functions. At a high level, the approach here was similar to the one we applied to Strategy: replacing with callables the instances of a participant class that implemented a single-method interface. After all, every Python callable implements a single-method interface and that method is named `__call__`.

Chapter Summary

As Peter Norvig pointed out a couple of years after the classic *Design Patterns* book appeared, “16 of 23 patterns have qualitatively simpler implementation in Lisp or Dylan than in C++ for at least some uses of each pattern” (slide 9 of Norvig’s “Design Patterns in Dynamic Languages” presentation). Python shares some of the dynamic features of the Lisp and Dylan languages, in particular first-class functions, our focus in this part of the book.

From the same talk quoted at the start of this chapter, in reflecting on the 20th anniversary of *Design Patterns: Elements of Reusable Object-Oriented Software*, Ralph Johnson has stated that one of the failings of the book is “Too much emphasis on patterns as end-points instead of steps in the design process.”[7] In this chapter, we used the Strategy pattern as a starting point: a working solution that we could simplify using first-class functions.

In many cases, functions or callable objects provide a more natural way of implementing callbacks in Python than mimicking the Strategy or the Command patterns as described by Gamma, Helm, Johnson & Vlissides. The refactoring of Strategy and the discussion of Command in this chapter are examples of a more general insight: sometimes you may encounter a design pattern or an API that requires that components implement an interface with a single method, and that method has a generic-sounding name such as “execute”, “run”, or “do_it”. Such patterns or APIs often can be implemented with less boilerplate code in Python using functions as first-class objects.

Further Reading

“Recipe 8.21. Implementing the Visitor Pattern,” in the *Python Cookbook, Third Edition* (O’Reilly), by David Beazley and Brian K. Jones, presents an elegant implementation of the Visitor pattern in which a `NodeVisitor` class handles methods as first-class objects.

On the general topic of design patterns, the choice of readings for the Python programmer is not as broad as what is available to other language communities.

Learning Python Design Patterns, by Gennadiy Zlobin (Packt), is the only book that I have seen entirely devoted to patterns in Python. But Zlobin's work is quite short (100 pages) and covers eight of the original 23 design patterns.

Expert Python Programming by Tarek Ziadé (Packt) is one of the best intermediate-level Python books in the market, and its final chapter, "Useful Design Patterns," presents several of the classic patterns from a Pythonic perspective.

Alex Martelli has given several talks about Python Design Patterns. There is a video of his EuroPython 2011 presentation and a set of slides on his personal website. I've found different slide decks and videos over the years, of varying lengths, so it is worthwhile to do a thorough search for his name with the words "Python Design Patterns." A publisher told me Martelli is working on a book about this subject. I will certainly get it when it comes out.

There are many books about design patterns in the context of Java, but among them the one I like most is *Head First Design Patterns*, *Second Edition* by Eric Freeman & Elisabeth Robson (O'Reilly). It explains 16 of the 23 classic patterns. If you like the wacky style of the *Head First* series and need an introduction to this topic, you will love that work. It is Java-centric, but the *Second Edition* was uptaded to reflect the addition of first-class functions in Java, making some of the examples closer to code we'd write in Python.

For a fresh look at patterns from the point of view of a dynamic language with duck typing and first-class functions, *Design Patterns in Ruby* by Russ Olsen (Addison-Wesley) has many insights that are also applicable to Python. In spite of their many syntactic differences, at the semantic level Python and Ruby are closer to each other than to Java or C++.

In Design Patterns in Dynamic Languages (slides), Peter Norvig shows how first-class functions (and other dynamic features) make several of the original design patterns either simpler or unnecessary.

The *Introduction* of the original *Design Patterns* book by Gamma et al. is worth the price of the book—more than the catalog of 23 patterns which includes recipes ranging from very important to rarely useful. The widely quoted design principles “Program to an interface, not an implementation” and “Favor object composition over class inheritance” both come from that *Introduction*.

The application of patterns to design originated with the architect Christopher Alexander, presented in the book *A Pattern Language* (Oxford University Press, 1977). Alexander’s idea is to create a standard vocabulary allowing teams to share common design decisions while designing buildings. M. J. Dominus wrote *“Design Patterns” Aren’t*: an intriguing slide deck and postscript text arguing that Alexander’s original vision of patterns is more profound, more human, and also applicable to software engineering.

SOAPBOX

Python has first-class functions and first-class types, features that Norvig claims affect 10 of the 23 patterns (slide 10 of Design Patterns in Dynamic Languages). In the Chapter 9, we saw that Python also has generic functions ("Single Dispatch Generic Functions"), a limited form of the CLOS multimethods that Gamma et al. suggest as a simpler way to implement the classic Visitor pattern. Norvig, on the other hand, says that multimethods simplify the Builder pattern (slide 10). Matching design patterns to language features is not an exact science.

In classrooms around the world, design patterns are frequently taught using Java examples. I've heard more than one student claim that they were led to believe that the original design patterns are useful in any implementation language. It turns out that the "classic" 23 patterns from the Gamma et al. book apply to "classic" Java very well in spite of being originally presented mostly in the context of C++—a few have Smalltalk examples in the book. But that does not mean every one of those patterns applies equally well in any language. The authors are explicit right at the beginning of their book that "some of our patterns are supported directly by the less common object-oriented languages" (recall full quote on first page of this chapter).

The Python bibliography about design patterns is very thin, compared to that of Java, C++, or Ruby. In "Further Reading" I mentioned *Learning Python Design Patterns* by Gennadiy Zlobin, which was published as recently as November 2013. In contrast, Russ Olsen's *Design Patterns in Ruby* was published in 2007 and has 384 pages—284 more than Zlobin's work.

Now that Python is becoming increasingly popular in academia, let's hope more will be written about design patterns in the context of this language. Also, Java 8 introduced method references and anonymous functions, and those highly anticipated features are likely to prompt fresh approaches to patterns in Java—recognizing that as languages evolve, so must our understanding of how to apply the classic design patterns.

The `__call__` of the wild

As we collaborated to put the final touches to this book, tech reviewer Leonardo Rochael wondered…

If functions have a `__call__` method, and methods are also callable, do `__call__` methods also have a `__call__` method?

I don't know if his discovery is useful, but it is a fun fact:

```
>>> def turtle():
...     return 'eggs'
...
>>> turtle()
'eggs'
>>> turtle.__call__()
'eggs'
>>> turtle.__call__.__call__()
'eggs'
>>> turtle.__call__.__call__.__call__()
'eggs'
>>> turtle.__call__.__call__.__call__.__call__()
'eggs'
>>> turtle.__call__.__call__.__call__.__call__.__call__()
'eggs'
>>>
turtle.__call__.__call__.__call__.__call__.__call__.__call__()
'eggs'
>>>
turtle.__call__.__call__.__call__.__call__.__call__.__call__._
_call__()
'eggs'
```

Turtles all the way down!

---

1 From a slide in the talk "Root Cause Analysis of Some Faults in Design Patterns," presented by Ralph Johnson at IME/CCSL, Universidade de São Paulo, Nov. 15, 2014.

2 Quoted from page 4 of *Design Patterns* (Addison-Wesley, 1995).

3 I had to reimplement `Order` with `@dataclass` due to a bug in Mypy. You may ignore this detail, because this class works with `NamedTuple` as well, just like in Example 10-1. If `Order` is a `NamedTuple`, Mypy 0.910 crashes when checking the type hint for `promotion`. I tried adding `# type ignore` to that specific line, but Mypy crashed anyway. Mypy handles the same type hint correctly if `Order` is built with `@dataclass`. Issue #9397 is unresolved as of July 19, 2021. Hopefully it will be fixed by the time you read this.

4 See page 323 of *Design Patterns*.

5 *idem*, p. 196

6 *flake8* and VS Code both complain that these names are imported but not used. By definition, static analysis tools cannot understand the dynamic nature of Python. If we heed every advice from such tools, we'll soon be writing grim and verbose Java-like code with Python syntax.

7 "Root Cause Analysis of Some Faults in Design Patterns", presented by Johnson at IME-USP, November 15, 2014.

Part IV. Classes and Protocols

Chapter 11. A Pythonic Object

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 11th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *For a library or framework to be Pythonic is to make it as easy and natural as possible for a Python programmer to pick up how to perform a task.*[1].
>
> —Martijn Faassen, creator of Python and JavaScript frameworks

Thanks to the Python Data Model, your user-defined types can behave as naturally as the built-in types. And this can be accomplished without inheritance, in the spirit of *duck typing*: you just implement the methods needed for your objects to behave as expected.

In previous chapters, we studied the behavior of many built-in objects. We will now build user-defined classes that behave as real Python objects. Your application classes probably don't need and should not implement as many special methods as the examples in this chapter. But if you are writing a library or a framework, the programmers who will use your classes may expect them to behave like the classes that Python provides. Fulfilling that expectation is one way of being "Pythonic."

This chapter starts where Chapter 1 ended, by showing how to implement several special methods that are commonly seen in Python objects of many different types.

In this chapter, we will see how to:

- Support the built-in functions that convert objects to other types (e.g., `repr()`, `bytes()`, `complex()`, etc).
- Implement an alternative constructor as a class method.
- Extend the format mini-language used by f-strings, the `format()` built-in, and the `str.format()` method.
- Provide read-only access to attributes.
- Make an object hashable for use in sets and as `dict` keys.
- Save memory with the use of `__slots__`.

We'll do all that as we develop a simple two-dimensional Euclidean vector type, `Vector2d`. This code will be the foundation of an N-dimensional vector class in Chapter 12.

The evolution of the example will be paused to discuss two conceptual topics:

- How and when to use the `@classmethod` and `@staticmethod` decorators.
- Private and protected attributes in Python: usage, conventions, and limitations.

What's new in this chapter

I added a new epigraph and a few words in the second paragraph of the chapter to address the concept of "Pythonic"—which was only discussed at the very end in the first edition.

“Formatted Displays” was updated to mention f-strings, introduced in Python 3.6. It’s a small change because f-strings support the same formatting mini-language as the `format()` built-in and the `str.format()` method, so any previously implemented `__format__` methods simply work with f-strings.

The rest of the chapter barely changed—the special methods are mostly the same since Python 3.0, and the core ideas appeared in Python 2.2.

Let’s get started with the object representation methods.

Object Representations

Every object-oriented language has at least one standard way of getting a string representation from any object. Python has two:

`repr()`

Return a string representing the object as the developer wants to see it. It’s what you get when the Python console or a debugger shows an object.

`str()`

Return a string representing the object as the user wants to see it. It’s what you get when you `print()` an object.

The special methods `__repr__` and `__str__` support `repr()` and `str()`, as we saw in Chapter 1.

There are two additional special methods to support alternative representations of objects: `__bytes__` and `__format__`. The `__bytes__` method is analogous to `__str__`: it’s called by `bytes()` to get the object represented as a byte sequence. Regarding `__format__`, it is used by f-strings, by the built-in function `format()`, and by the `str.format()` method. They call `obj.__format__(format_spec)` to get string displays of objects using special formatting codes. We’ll cover `__bytes__` in the next example, and `__format__` after that.

> **WARNING**
>
> If you’re coming from Python 2, remember that in Python 3 `__repr__`, `__str__`, and `__format__` must always return Unicode strings (type `str`). Only `__bytes__` is supposed to return a byte sequence (type `bytes`).

Vector Class Redux

In order to demonstrate the many methods used to generate object representations, we’ll use a `Vector2d` class similar to the one we saw in Chapter 1. We will build on it in this and future sections. Example 11-1 illustrates the basic behavior we expect from a `Vector2d` instance.

Example 11-1. Vector2d instances have several representations

```
    >>> v1 = Vector2d(3, 4)
    >>> print(v1.x, v1.y)  ❶
    3.0 4.0
    >>> x, y = v1  ❷
    >>> x, y
    (3.0, 4.0)
    >>> v1  ❸
    Vector2d(3.0, 4.0)
    >>> v1_clone = eval(repr(v1))  ❹
    >>> v1 == v1_clone  ❺
    True
    >>> print(v1)  ❻
    (3.0, 4.0)
    >>> octets = bytes(v1)  ❼
    >>> octets

b'd\\x00\\x00\\x00\\x00\\x00\\x00\\x08@\\x00\\x00\\x00\\x00\\x00\\x
00\\x10@'
    >>> abs(v1)  ❽
    5.0
    >>> bool(v1), bool(Vector2d(0, 0))  ❾
    (True, False)
```

❶ The components of a `Vector2d` can be accessed directly as attributes (no getter method calls).

❷ A `Vector2d` can be unpacked to a tuple of variables.

❸ The `repr` of a `Vector2d` emulates the source code for constructing the instance.

❹ Using `eval` here shows that the `repr` of a `Vector2d` is a faithful representation of its constructor call.[2]

❺ `Vector2d` supports comparison with `==`; this is useful for testing.

❻ `print` calls `str`, which for `Vector2d` produces an ordered pair display.

❼ `bytes` uses the `__bytes__` method to produce a binary representation.

❽ `abs` uses the `__abs__` method to return the magnitude of the `Vector2d`.

❾ `bool` uses the `__bool__` method to return `False` for a `Vector2d` of zero magnitude or `True` otherwise.

`Vector2d` from Example 11-1 is implemented in *vector2d_v0.py* (Example 11-2). The code is based on Example 1-2, except for the methods for the `+` and `*` operations, which we'll see later in Chapter 16. We'll add the method for `==` since it's useful for testing. At this point, `Vector2d` uses several special methods to provide operations that a Pythonista expects in a well-designed object.

Example 11-2. vector2d_v0.py: methods so far are all special methods

```
from array import array
import math
```

```
class Vector2d:
    typecode = 'd'  ❶

    def __init__(self, x, y):
        self.x = float(x)    ❷
        self.y = float(y)

    def __iter__(self):
        return (i for i in (self.x, self.y))  ❸

    def __repr__(self):
        class_name = type(self).__name__
        return '{}({!r}, {!r})'.format(class_name, *self)  ❹

    def __str__(self):
        return str(tuple(self))  ❺

    def __bytes__(self):
        return (bytes([ord(self.typecode)]) +  ❻
                bytes(array(self.typecode, self)))  ❼

    def __eq__(self, other):
        return tuple(self) == tuple(other)  ❽

    def __abs__(self):
        return math.hypot(self.x, self.y)  ❾

    def __bool__(self):
        return bool(abs(self))  ❿
```

❶ `typecode` is a class attribute we'll use when converting `Vector2d` instances to/from `bytes`.

❷ Converting `x` and `y` to `float` in `__init__` catches errors early, which is helpful in case `Vector2d` is called with unsuitable arguments.

❸ `__iter__` makes a `Vector2d` iterable; this is what makes unpacking work (e.g, `x, y = my_vector`). We implement it simply by using a generator expression to yield the components one after the other.[3]

❹

`__repr__` builds a string by interpolating the components with `{!r}` to get their `repr`; because `Vector2d` is iterable, `*self` feeds the `x` and `y` components to `format`.

❺ From an iterable `Vector2d`, it's easy to build a `tuple` for display as an ordered pair.

❻ To generate `bytes`, we convert the typecode to `bytes` and concatenate…

❼ …`bytes` converted from an `array` built by iterating over the instance.

❽ To quickly compare all components, build tuples out of the operands. This works for operands that are instances of `Vector2d`, but has issues. See the following warning.

❾ The magnitude is the length of the hypotenuse of the right triangle formed by the `x` and `y` components.

❿ `__bool__` uses `abs(self)` to compute the magnitude, then converts it to `bool`, so `0.0` becomes `False`, nonzero is `True`.

> **WARNING**
>
> Method `__eq__` in Example 11-2 works for `Vector2d` operands but also returns `True` when comparing `Vector2d` instances to other iterables holding the same numeric values (e.g., `Vector(3, 4) == [3, 4]`). This may be considered a feature or a bug. Further discussion needs to wait until Chapter 16, when we cover operator overloading.

We have a fairly complete set of basic methods, but we still need a way to rebuild a `Vector2d` from the binary representation produced by `bytes()`.

An Alternative Constructor

Since we can export a `Vector2d` as bytes, naturally we need a method that imports a `Vector2d` from a binary sequence. Looking at the standard library for inspiration, we find that `array.array` has a class method named `.frombytes` that suits our purpose—we saw it in "Arrays". We adopt its name and use its functionality in a class method for `Vector2d` in *vector2d_v1.py* (Example 11-3).

Example 11-3. Part of vector2d_v1.py: this snippet shows only the frombytes class method, added to the Vector2d definition in vector2d_v0.py (Example 11-2)

```
    @classmethod  ❶
    def frombytes(cls, octets):  ❷
        typecode = chr(octets[0])  ❸
        memv = memoryview(octets[1:]).cast(typecode)  ❹
        return cls(*memv)  ❺
```

❶ The `classmethod` decorator modifies a method so it can be called directly on a class.

❷ No `self` argument; instead, the class itself is passed as the first argument—conventionally named `cls`.

❸ Read the `typecode` from the first byte.

❹ Create a `memoryview` from the `octets` binary sequence and use the `typecode` to cast it.[4]

❺ Unpack the `memoryview` resulting from the cast into the pair of arguments needed for the constructor.

I just used a `classmethod` decorator and it is very Python-specific, so let's have a word about it.

`classmethod` Versus `staticmethod`

The `classmethod` decorator is not mentioned in the Python tutorial, and neither is `staticmethod`. Anyone who has learned OO in Java may wonder why Python has both of these decorators and not just one of them.

Let's start with `classmethod`. Example 11-3 shows its use: to define a method that operates on the class and not on instances. `classmethod` changes the way the method is called, so it receives the class itself as the first argument, instead of an instance. Its most common use is for alternative constructors, like `frombytes` in Example 11-3. Note how the last line of `frombytes` actually uses the `cls` argument by invoking it to build a new instance: `cls(*memv)`.

In contrast, the `staticmethod` decorator changes a method so that it receives no special first argument. In essence, a static method is just like a plain function that happens to live in a class body, instead of being defined at the module level. Example 11-4 contrasts the operation of `classmethod` and `staticmethod`.

Example 11-4. Comparing behaviors of classmethod and staticmethod

```
>>> class Demo:
...     @classmethod
...     def klassmeth(*args):
...         return args  ❶
...     @staticmethod
...     def statmeth(*args):
...         return args  ❷
...
>>> Demo.klassmeth()  ❸
(<class '__main__.Demo'>,)
>>> Demo.klassmeth('spam')
(<class '__main__.Demo'>, 'spam')
>>> Demo.statmeth()   ❹
()
>>> Demo.statmeth('spam')
('spam',)
```

❶ `klassmeth` just returns all positional arguments.

❷ `statmeth` does the same.

❸ No matter how you invoke it, `Demo.klassmeth` receives the `Demo` class as the first argument.

❹ `Demo.statmeth` behaves just like a plain old function.

> **NOTE**
>
> The `classmethod` decorator is clearly useful, but I've never seen a compelling use case for `staticmethod`. If you want to define a function that does not interact with the class, just define it in the module. Maybe the function is closely related even if it never touches the class, so you may want to place it nearby in the code. Even so, defining the function right before or after the class in the same module is close enough for all practical purposes.[5]

Now that we've seen what `classmethod` is good for (and that `staticmethod` is not very useful), let's go back to the issue of object representation and see how to support formatted output.

Formatted Displays

The f-strings, the `format()` built-in function, and the `str.format()` method delegate the actual formatting to each type by calling their `.__format__(format_spec)` method. The `format_spec` is a formatting specifier, which is either:

- The second argument in `format(my_obj, format_spec)`, or
- Whatever appears after the colon in a replacement field delimited with `{}` inside an f-string or the `fmt` in `fmt.str.format()`

For example:

```
>>> brl = 1 / 4.82  # BRL to USD currency conversion rate
>>> brl
0.20746887966804978
>>> format(brl, '0.4f')  ❶
'0.2075'
>>> '1 BRL = {rate:0.2f} USD'.format(rate=brl)  ❷
'1 BRL = 0.21 USD'
>>> f'1 USD = {1 / brl:0.2f} BRL'  ❸
'1 USD = 4.82 BRL'
```

❶ Formatting specifier is `'0.4f'`.

❷ Formatting specifier is `'0.2f'`. The `rate` part in the replacement field is not part of the formatting specifier. It determines which keyword argument of `.format()` goes into that replacement field.

❸ Again, the formatting specifier is `'0.2f'`. The `1 / brl` expression is not part of it.

The second and third callouts make an important point: a format string such as `'{0.mass:5.3e}'` actually uses two separate notations. The `'0.mass'` to the left of the colon is the `field_name` part of the replacement field syntax, and it can be an arbitrary expression in an f-string. The `'5.3e'` after the colon is the formatting specifier. The notation used in the formatting specifier is called the Format Specification Mini-Language.

TIP

If f-strings, `format()` and `str.format()` are new to you, classroom experience tells me it's best to study the `format()` built-in function first, which uses just the

Format Specification Mini-Language. After you get the gist of that, read Formatted string literals and Format String Syntax to learn about the `{:}` replacement field notation, used in f-strings and `str.format()` method (including the `!s`, `!r`, and `!a` conversion flags). F-strings don't make `str.format()` obsolete: most of the time f-strings solve the problem, but sometimes it's better to specify the formatting string elsewhere, and not where it will be rendered.

A few built-in types have their own presentation codes in the Format Specification Mini-Language. For example—among several other codes—the `int` type supports `b` and `x` for base 2 and base 16 output, respectively, while `float` implements `f` for a fixed-point display and `%` for a percentage display:

```
>>> format(42, 'b')
'101010'
>>> format(2 / 3, '.1%')
'66.7%'
```

The Format Specification Mini-Language is extensible because each class gets to interpret the `format_spec` argument as it likes. For instance, the classes in the `datetime` module use the same format codes in the `strftime()` functions and in their `__format__` methods. Here are a couple examples using the `format()` built-in and the `str.format()` method:

```
>>> from datetime import datetime
>>> now = datetime.now()
>>> format(now, '%H:%M:%S')
'18:49:05'
>>> "It's now {:%I:%M %p}".format(now)
"It's now 06:49 PM"
```

If a class has no `__format__`, the method inherited from `object` returns `str(my_object)`. Because `Vector2d` has a `__str__`, this works:

```
>>> v1 = Vector2d(3, 4)
>>> format(v1)
'(3.0, 4.0)'
```

However, if you pass a format specifier, `object.__format__` raises `TypeError`:

```
>>> format(v1, '.3f')
Traceback (most recent call last):
```

```
...
TypeError: non-empty format string passed to object.__format__
```

We will fix that by implementing our own format mini-language. The first step will be to assume the format specifier provided by the user is intended to format each `float` component of the vector. This is the result we want:

```
>>> v1 = Vector2d(3, 4)
>>> format(v1)
'(3.0, 4.0)'
>>> format(v1, '.2f')
'(3.00, 4.00)'
>>> format(v1, '.3e')
'(3.000e+00, 4.000e+00)'
```

Example 11-5 implements `__format__` to produce the displays just shown.

Example 11-5. Vector2d.format method, take #1

```
# inside the Vector2d class

def __format__(self, fmt_spec=''):
    components = (format(c, fmt_spec) for c in self)  ❶
    return '({}, {})'.format(*components)  ❷
```

❶ Use the `format` built-in to apply the `fmt_spec` to each vector component, building an iterable of formatted strings.

❷ Plug the formatted strings in the formula `'(x, y)'`.

Now let's add a custom formatting code to our mini-language: if the format specifier ends with a `'p'`, we'll display the vector in polar coordinates: `<r, θ>`, where `r` is the magnitude and θ (theta) is the angle in radians. The rest of the format specifier (whatever comes before the `'p'`) will be used as before.

TIP

When choosing the letter for the custom format code I avoided overlapping with codes used by other types. In Format Specification Mini-Language we see that integers use the codes `'bcdoxXn'`, floats use `'eEfFgGn%'`, and strings use `'s'`. So I picked `'p'` for polar coordinates. Because each class interprets these codes independently, reusing a code letter in a custom format for a new type is not an error, but may be confusing to users.

To generate polar coordinates we already have the `__abs__` method for the magnitude, and we'll code a simple `angle` method using the `math.atan2()` function to get the angle. This is the code:

```
    # inside the Vector2d class

    def angle(self):
        return math.atan2(self.y, self.x)
```

With that, we can enhance our `__format__` to produce polar coordinates. See Example 11-6.

Example 11-6. Vector2d.format method, take #2, now with polar coordinates

```
    def __format__(self, fmt_spec=''):
        if fmt_spec.endswith('p'):  ❶
            fmt_spec = fmt_spec[:-1]  ❷
            coords = (abs(self), self.angle())  ❸
            outer_fmt = '<{}, {}>'  ❹
        else:
            coords = self  ❺
            outer_fmt = '({}, {})'  ❻
        components = (format(c, fmt_spec) for c in coords)  ❼
        return outer_fmt.format(*components)  ❽
```

❶ Format ends with `'p'`: use polar coordinates.

❷ Remove `'p'` suffix from `fmt_spec`.

❸ Build `tuple` of polar coordinates: `(magnitude, angle)`.

❹ Configure outer format with angle brackets.

❺ Otherwise, use `x, y` components of `self` for rectangular coordinates.

❻ Configure outer format with parentheses.

❼ Generate iterable with components as formatted strings.

❽ Plug formatted strings into outer format.

With Example 11-6, we get results similar to these:

```
>>> format(Vector2d(1, 1), 'p')
'<1.4142135623730951, 0.7853981633974483>'
>>> format(Vector2d(1, 1), '.3ep')
'<1.414e+00, 7.854e-01>'
>>> format(Vector2d(1, 1), '0.5fp')
'<1.41421, 0.78540>'
```

As this section shows, it’s not hard to extend the format specification mini-language to support user-defined types.

Now let’s move to a subject that’s not just about appearances: we will make our `Vector2d` hashable, so we can build sets of vectors, or use them as `dict` keys.

A Hashable Vector2d

As defined, so far our `Vector2d` instances are unhashable, so we can’t put them in a `set`:

```
>>> v1 = Vector2d(3, 4)
>>> hash(v1)
Traceback (most recent call last):
  ...
TypeError: unhashable type: 'Vector2d'
>>> set([v1])
Traceback (most recent call last):
```

```
    ...
TypeError: unhashable type: 'Vector2d'
```

To make a `Vector2d` hashable, we must implement `__hash__` (`__eq__` is also required, and we already have it). We also need to make vector instances immutable, as we've seen in "What is Hashable".

Right now, anyone can do `v1.x = 7` and there is nothing in the code to suggest that changing a `Vector2d` is forbidden. This is the behavior we want:

```
>>> v1.x, v1.y
(3.0, 4.0)
>>> v1.x = 7
Traceback (most recent call last):
    ...
AttributeError: can't set attribute
```

We'll do that by making the `x` and `y` components read-only properties in Example 11-7.

Example 11-7. vector2d_v3.py: only the changes needed to make Vector2d immutable are shown here; see full listing in Example 11-11

```
class Vector2d:
    typecode = 'd'

    def __init__(self, x, y):
        self.__x = float(x)  ❶
        self.__y = float(y)

    @property  ❷
    def x(self):  ❸
        return self.__x  ❹

    @property  ❺
    def y(self):
        return self.__y

    def __iter__(self):
        return (i for i in (self.x, self.y))  ❻

    # remaining methods: same as previous Vector2d
```

❶ Use exactly two leading underscores (with zero or one trailing underscore) to make an attribute private.[6]

❷ The `@property` decorator marks the getter method of a property.

❸ The getter method is named after the public property it exposes: `x`.

❹ Just return `self.__x`.

❺ Repeat same formula for `y` property.

❻ Every method that just reads the `x`, `y` components can stay as they were, reading the public properties via `self.x` and `self.y` instead of the private attribute, so this listing omits the rest of the code for the class.

> **NOTE**
>
> `Vector.x` and `Vector.y` are examples of read-only properties. Read/write properties will be covered in Chapter 23, where we dive deeper into `@property`.

Now that our vectors are reasonably safe from accidental mutation, we can implement the `__hash__` method. It should return an `int` and ideally take into account the hashes of the object attributes that are also used in the `__eq__` method, because objects that compare equal should have the same hash. The `__hash__` special method documentation suggests using the bitwise XOR operator (`^`) to mix the hashes of the components, so that's what we do. The code for our `Vector2d.__hash__` method is really simple, as shown in Example 11-8.

Example 11-8. vector2d_v3.py: implementation of hash

```
    # inside class Vector2d:

    def __hash__(self):
        return hash(self.x) ^ hash(self.y)
```

With the addition of the `__hash__` method, we now have hashable vectors:

```
>>> v1 = Vector2d(3, 4)
>>> v2 = Vector2d(3.1, 4.2)
>>> hash(v1), hash(v2)
(7, 384307168202284039)
>>> set([v1, v2])
{Vector2d(3.1, 4.2), Vector2d(3.0, 4.0)}
```

> **TIP**
>
> It’s not strictly necessary to implement properties or otherwise protect the instance attributes to create a hashable type. Implementing `__hash__` and `__eq__` correctly is all it takes. But the value of a hashable object is never supposed to change, so this provided an excellent opportunity to talk about read-only properties.

If you are creating a type that has a sensible scalar numeric value, you may also implement the `__int__` and `__float__` methods, invoked by the `int()` and `float()` constructors—which are used for type coercion in some contexts. There’s also a `__complex__` method to support the `complex()` built-in constructor. Perhaps `Vector2d` should provide `__complex__`, but I’ll leave that as an exercise for you.

Supporting Positional Patterns

So far, `Vector2d` instances are compatible with keyword class patterns—covered in “Keyword Class Patterns”.

For example, all of these keyword patterns work as expected:

Example 11-9. Keyword patterns for `Vector2d` subjects—requires Python 3.10.

```
def keyword_pattern_demo(v: Vector2d) -> None:
    match v:
        case Vector2d(x=0, y=0):
            print(f'{v!r} is null')
        case Vector2d(x=0):
```

```
            print(f'{v!r} is vertical')
        case Vector2d(y=0):
            print(f'{v!r} is horizontal')
        case Vector2d(x=x, y=y) if x==y:
            print(f'{v!r} is diagonal')
        case _:
            print(f'{v!r} is awesome')
```

However, if you try to use a positional pattern like this:

```
        case Vector2d(_, 0):
            print(f'{v!r} is horizontal')
```

You get:

```
TypeError: Vector2d() accepts 0 positional sub-patterns (1 given)
```

To make `Vector2d` work with positional patterns, we need to add a class attribute named `__match_args__` , listing the instance attributes in the order they will be used for positional pattern matching:

```
class Vector2d:
    __match_args__ = ('x', 'y')

    # etc...
```

Now we can save a few keystrokes when writing patterns to match `Vector2d` subjects:

Example 11-10. Positional patterns for `Vector2d` subjects—requires Python 3.10.

```
def positional_pattern_demo(v: Vector2d) -> None:
    match v:
        case Vector2d(0, 0):
            print(f'{v!r} is null')
        case Vector2d(0):
            print(f'{v!r} is vertical')
        case Vector2d(_, 0):
            print(f'{v!r} is horizontal')
        case Vector2d(x, y) if x==y:
            print(f'{v!r} is diagonal')
```

```
        case _:
            print(f'{v!r} is awesome')
```

The `__match_args__` class attribute does not need to include all public instance attributes. In particular, if the class `__init__` has required and optional arguments that are assigned to instance attributes, it may be reasonable to name the required arguments in `__match_args__`, but not the optional ones.

Let's step back and review what we've coded so far in `Vector2d`.

Complete Listing of Vector2d, version 3

We have been working on `Vector2d` for a while, showing just snippets, so Example 11-11 is a consolidated, full listing of *vector2d_v3.py*, including the doctests I used when developing it.

Example 11-11. vector2d_v3.py: the full monty

```
"""
A two-dimensional vector class

    >>> v1 = Vector2d(3, 4)
    >>> print(v1.x, v1.y)
    3.0 4.0
    >>> x, y = v1
    >>> x, y
    (3.0, 4.0)
    >>> v1
    Vector2d(3.0, 4.0)
    >>> v1_clone = eval(repr(v1))
    >>> v1 == v1_clone
    True
    >>> print(v1)
    (3.0, 4.0)
    >>> octets = bytes(v1)
    >>> octets

b'd\\x00\\x00\\x00\\x00\\x00\\x00\\x08@\\x00\\x00\\x00\\x00\\x00\\x
00\\x10@'
    >>> abs(v1)
    5.0
    >>> bool(v1), bool(Vector2d(0, 0))
```

```
    (True, False)
```

Test of ``.frombytes()`` class method:

```
    >>> v1_clone = Vector2d.frombytes(bytes(v1))
    >>> v1_clone
    Vector2d(3.0, 4.0)
    >>> v1 == v1_clone
    True
```

Tests of ``format()`` with Cartesian coordinates:

```
    >>> format(v1)
    '(3.0, 4.0)'
    >>> format(v1, '.2f')
    '(3.00, 4.00)'
    >>> format(v1, '.3e')
    '(3.000e+00, 4.000e+00)'
```

Tests of the ``angle`` method::

```
    >>> Vector2d(0, 0).angle()
    0.0
    >>> Vector2d(1, 0).angle()
    0.0
    >>> epsilon = 10**-8
    >>> abs(Vector2d(0, 1).angle() - math.pi/2) < epsilon
    True
    >>> abs(Vector2d(1, 1).angle() - math.pi/4) < epsilon
    True
```

Tests of ``format()`` with polar coordinates:

```
    >>> format(Vector2d(1, 1), 'p')  # doctest:+ELLIPSIS
    '<1.414213..., 0.785398...>'
    >>> format(Vector2d(1, 1), '.3ep')
    '<1.414e+00, 7.854e-01>'
    >>> format(Vector2d(1, 1), '0.5fp')
    '<1.41421, 0.78540>'
```

Tests of `x` and `y` read-only properties:

```
    >>> v1.x, v1.y
```

```
    (3.0, 4.0)
    >>> v1.x = 123
    Traceback (most recent call last):
      ...
    AttributeError: can't set attribute 'x'


Tests of hashing:

    >>> v1 = Vector2d(3, 4)
    >>> v2 = Vector2d(3.1, 4.2)
    >>> hash(v1), hash(v2)
    (7, 384307168202284039)
    >>> len({v1, v2})
    2

"""

from array import array
import math

class Vector2d:
    __match_args__ = ('x', 'y')

    typecode = 'd'

    def __init__(self, x, y):
        self.__x = float(x)
        self.__y = float(y)

    @property
    def x(self):
        return self.__x

    @property
    def y(self):
        return self.__y

    def __iter__(self):
        return (i for i in (self.x, self.y))

    def __repr__(self):
        class_name = type(self).__name__
        return '{}({!r}, {!r})'.format(class_name, *self)

    def __str__(self):
        return str(tuple(self))
```

```
    def __bytes__(self):
        return (bytes([ord(self.typecode)]) +
                bytes(array(self.typecode, self)))

    def __eq__(self, other):
        return tuple(self) == tuple(other)

    def __hash__(self):
        return hash(self.x) ^ hash(self.y)

    def __abs__(self):
        return math.hypot(self.x, self.y)

    def __bool__(self):
        return bool(abs(self))

    def angle(self):
        return math.atan2(self.y, self.x)

    def __format__(self, fmt_spec=''):
        if fmt_spec.endswith('p'):
            fmt_spec = fmt_spec[:-1]
            coords = (abs(self), self.angle())
            outer_fmt = '<{}, {}>'
        else:
            coords = self
            outer_fmt = '({}, {})'
        components = (format(c, fmt_spec) for c in coords)
        return outer_fmt.format(*components)

    @classmethod
    def frombytes(cls, octets):
        typecode = chr(octets[0])
        memv = memoryview(octets[1:]).cast(typecode)
        return cls(*memv)
```

To recap, in this and the previous sections, we saw some essential special methods that you may want to implement to have a full-fledged object.

> **NOTE**
>
> You should only implement these special methods if your application needs them. End users don’t care if the objects that make up the application are “Pythonic” or not.
>
> On the other hand, if your classes are part of a library for other Python programmers to use, you can’t really guess what they will do with your objects, and they may expect more of the “Pythonic” behaviors we are describing.

As coded in Example 11-11, `Vector2d` is a didactic example with a laundry list of special methods related to object representation, not a template for every user-defined class.

In the next section, we’ll take a break from `Vector2d` to discuss the design and drawbacks of the private attribute mechanism in Python—the double-underscore prefix in `self.__x`.

Private and “Protected” Attributes in Python

In Python, there is no way to create private variables like there is with the `private` modifier in Java. What we have in Python is a simple mechanism to prevent accidental overwriting of a “private” attribute in a subclass.

Consider this scenario: someone wrote a class named `Dog` that uses a `mood` instance attribute internally, without exposing it. You need to subclass `Dog` as `Beagle`. If you create your own `mood` instance attribute without being aware of the name clash, you will clobber the `mood` attribute used by the methods inherited from `Dog`. This would be a pain to debug.

To prevent this, if you name an instance attribute in the form `__mood` (two leading underscores and zero or at most one trailing underscore), Python stores the name in the instance `__dict__` prefixed with a leading underscore and the class name, so in the `Dog` class, `__mood` becomes `_Dog__mood`, and in `Beagle` it’s `_Beagle__mood`. This language feature goes by the lovely name of *name mangling*.

Example 11-12 shows the result in the `Vector2d` class from Example 11-7.

Example 11-12. Private attribute names are "mangled" by prefixing the _ and the class name

```
>>> v1 = Vector2d(3, 4)
>>> v1.__dict__
{'_Vector2d__y': 4.0, '_Vector2d__x': 3.0}
>>> v1._Vector2d__x
3.0
```

Name mangling is about safety, not security: it's designed to prevent accidental access and not malicious prying. Figure 11-1 illustrates another safety device.

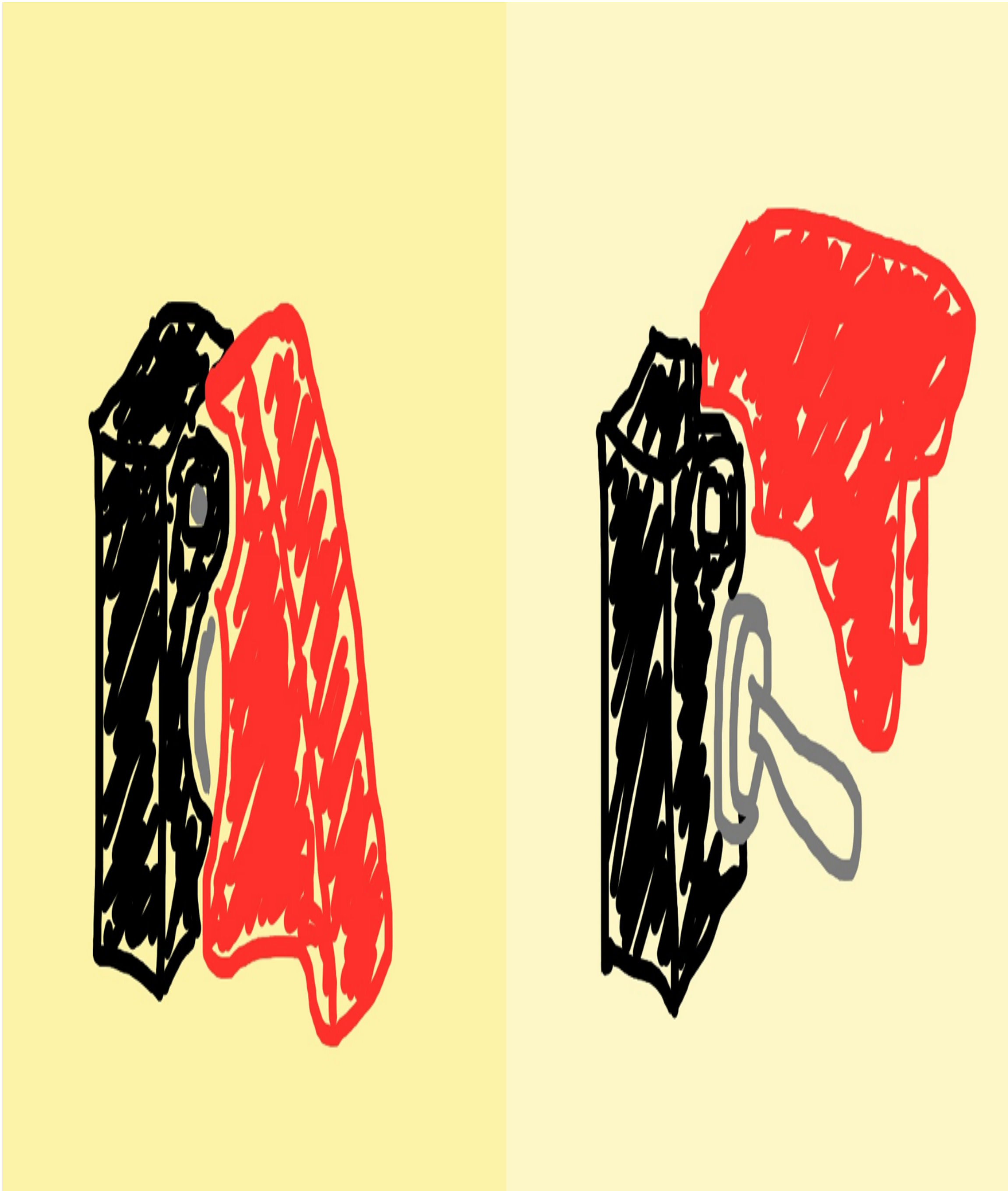


Figure 11-1. A cover on a switch is a safety device, not a security one: it prevents accidents, not sabotage.

Anyone who knows how private names are mangled can read the private attribute directly, as the last line of Example 11-12 shows—that's actually useful for debugging and serialization. They can also directly assign a value to a private component of a `Vector2d` by writing `v1._Vector2d__x`

`= 7`. But if you are doing that in production code, you can’t complain if something blows up.

The name mangling functionality is not loved by all Pythonistas, and neither is the skewed look of names written as `self.__x`. Some prefer to avoid this syntax and use just one underscore prefix to “protect” attributes by convention (e.g., `self._x`). Critics of the automatic double-underscore mangling suggest that concerns about accidental attribute clobbering should be addressed by naming conventions. Ian Bicking—creator of pip, virtualenv, and other projects—wrote:

> *Never, ever use two leading underscores. This is annoyingly private. If name clashes are a concern, use explicit name mangling instead (e.g., `_MyThing_blahblah`). This is essentially the same thing as double-underscore, only it’s transparent where double underscore obscures.*[7]

The single underscore prefix has no special meaning to the Python interpreter when used in attribute names, but it’s a very strong convention among Python programmers that you should not access such attributes from outside the class.[8] It’s easy to respect the privacy of an object that marks its attributes with a single `_`, just as it’s easy respect the convention that variables in `ALL_CAPS` should be treated as constants.

Attributes with a single `_` prefix are called “protected” in some corners of the Python documentation.[9] The practice of “protecting” attributes by convention with the form `self._x` is widespread, but calling that a “protected” attribute is not so common. Some even call that a “private” attribute.

To conclude: the `Vector2d` components are “private” and our `Vector2d` instances are “immutable”—with scare quotes—because there is no way to make them really private and immutable.[10]

We’ll now come back to our `Vector2d` class. In the next section, we cover a special attribute (not a method) that affects the internal storage of an object, with potentially huge impact on the use of memory but little effect on its public interface: `__slots__`.

Saving Memory with `__slots__`

By default, Python stores the attributes of each instance in a `dict` named `__dict__`. As we saw in "Practical Consequences of How dict Works", a `dict` has a signficant memory overhead—even with the optimizations mentioned in that section. But if you define a class attribute named `__slots__` holding sequence of attribute names, Python uses an alternative storage model for the instance attributes: the attributes named in `__slots__` are stored in a hidden array or references that uses less memory than a `dict`. Let's see how that works through simple examples.

Example 11-13. The `Pixel` class uses `slots.

```
>>> class Pixel:
...     __slots__ = ('x', 'y')  ❶
...
>>> p = Pixel()  ❷
>>> p.__dict__  ❸
Traceback (most recent call last):
  ...
AttributeError: 'Pixel' object has no attribute '__dict__'
>>> p.x = 10  ❹
>>> p.y = 20
>>> p.color = 'red'  ❺
Traceback (most recent call last):
  ...
AttributeError: 'Pixel' object has no attribute 'color'
```

❶ `__slots__` must be present when the class is created; adding or changing it later has no effect. The attribute names may be in a `tuple` or `list`, but I prefer a `tuple` to make it clear there's no point in changing it.

❷ Create an instance of `Pixel`, because we see the effects of `__slots__` on the instances.

❸ First effect: instances of `Pixel` have no `__dict__`.

❹ Set the `p.x` and `p.y` attributes normally.

❺ Second effect: trying to set an attribute not listed in `__slots__` raises `AttributeError`.

So far, so good. Now let's create a subclass of `Pixel` to see the counterintuitive side of `__slots__`:

Example 11-14. The `OpenPixel` is a subclass of `Pixel`.

```
>>> class OpenPixel(Pixel):  ❶
...     pass
...
>>> op = OpenPixel()
>>> op.__dict__  ❷
{}
>>> op.x = 8  ❸
>>> op.__dict__  ❹
{}
>>> op.x  ❺
8
>>> op.color = 'green'  ❻
>>> op.__dict__  ❼
{'color': 'green'}
```

❶ `OpenPixel` declares no attributes of its own.

❷ Surprise: instances of `OpenPixel` have a `__dict__`.

❸ If you set attribute `x` (named in the `__slots__` of the base class `Pixel`)…

❹ …it is not stored in the instance `__dict__`…

❺ …but it is stored in the hidden array of references in the instance.

❻ If you set an attribute not named in the `__slots__`…

❼ …it is stored in the instance `__dict__`.

Example 11-14 shows that the effect of `__slots__` is only partially inherited by a subclass. To make sure that instances of a subclass have no `__dict__`, you must declare `__slots__` again in the subclass.

If you declare `__slots__ = ()` (an empty tuple), then the instances of the subclass will have no `__dict__` and will only accept the attributes named in the `__slots__` of the base class.

If you want a subclass to have additional attributes, name them in `__slots__`:

Example 11-15. The `ColorPixel`, another subclass of `Pixel`.

```
>>> class ColorPixel(Pixel):
...    __slots__ = ('color',)  ❶
>>> cp = ColorPixel()
>>> cp.__dict__  ❷
Traceback (most recent call last):
  ...
AttributeError: 'ColorPixel' object has no attribute '__dict__'
>>> cp.x = 2
>>> cp.color = 'blue'  ❸
>>> cp.flavor = 'banana'
Traceback (most recent call last):
  ...
AttributeError: 'ColorPixel' object has no attribute 'flavor'
```

❶ Essentially, `__slots__` of the superclasses are added to the `__slots__` of the current class. Don’t forget that single item tuples must have a trailing comma.

❷ `ColorPixel` instances have no `__dict__`.

❸ You can set the attributes declared in the `__slots__` of this class and superclasses, but no other.

It’s possible to “save memory and eat it too”: if you add the `'__dict__'` name to the `__slots__` list, your instances will keep attributes named in `__slots__` in the per-instance array of references, but will also support dynamically created attributes, which will be stored in the usual `__dict__`. This is necessary if you want to use the `@cached_property` decorator, (covered in "Step 5: Caching Properties with functools").

Of course, having `'__dict__'` in `__slots__` may entirely defeat its purpose, depending on the number of static and dynamic attributes in each instance and how they are used. Careless optimization is worse than premature optimization: you add complexity but may not get any benefit.

Another special per-instance attribute that you may want to keep is `__weakref__`, necessary for an object to support weak references (mentioned briefly in "del and Garbage Collection"). That attribute exists by default in instances of user-defined classes. However, if the class defines `__slots__`, and you need the instances to be targets of weak references, then you need to include `'__weakref__'` among the attributes named in `__slots__`.

Now let's see the effect of adding `__slots__` to `Vector2d`.

Simple Measure of __slot__ Savings

Example 11-16 shows the implementation of `__slots__ in `Vector2d`.

Example 11-16. vector2d_v3_slots.py: the slots attribute is the only addition to Vector2d

```
class Vector2d:
    __match_args__ = ('x', 'y')  ❶
    __slots__ = ('__x', '__y')  ❷

    typecode = 'd'
    # methods are the same as previous version
```

❶ `__match_args__` lists the public attribute names for positional pattern matching.

❷ In contrast, `__slots__` lists the names of the instance attributes, which in this case are private attributes.

To measure the memory savings, I wrote the *mem_test.py* script. It takes the name of a module with a `Vector2d` class variant as command-line argument, and uses a list comprehension to build a `list` with 10,000,000 instances of `Vector2d`. In the first run shown in Example 11-17, I use `vector2d_v3.Vector2d` (from Example 11-7); in the second run, I used the version with `__slots__` from Example 11-16.

Example 11-17. mem_test.py creates 10 million `Vector2d` instances using the class defined in the named module.

```
$ time python3 mem_test.py vector2d_v3
Selected Vector2d type: vector2d_v3.Vector2d
Creating 10,000,000 Vector2d instances
Initial RAM usage:      6,983,680
  Final RAM usage:  1,666,535,424

real    0m11.990s
user    0m10.861s
sys     0m0.978s
(.py310b4) TW-LR-MBP:11-pythonic-obj luciano$ time python3
mem_test.py vector2d_v3_slots
Selected Vector2d type: vector2d_v3_slots.Vector2d
Creating 10,000,000 Vector2d instances
Initial RAM usage:      6,995,968
  Final RAM usage:    577,839,104

real    0m8.381s
user    0m8.006s
sys     0m0.352s
```

As Example 11-17 reveals, the RAM footprint of the script grows to 1.55 GiB when instance `__dict__` is used in each of the 10 million `Vector2d` instances, but that is reduced to 551 MiB when `Vector2d` has a `__slots__` attribute. The `__slots__` version is also faster. The *mem_test.py* script in this test basically deals with loading a module, checking memory usage, and formatting results. You can find its source code in the fluentpython/example-code-2e repository.

> **TIP**
>
> If you are handling millions of objects with numeric data, you should really be using NumPy arrays (see "NumPy"), which are not only memory-efficient but have highly optimized functions for numeric processing, many of which operate on the entire array at once. I designed the `Vector2d` class just to provide context when discussing special methods, because I try to avoid vague `foo` and `bar` examples when I can.

Summarizing The Issues with __slots__

The `__slots__` class attribute may provide significant memory savings if properly used, but there are a few caveats:

- You must remember to redeclare `__slots__` in each subclass to prevent their instances to have `__dict__`.
- Instances will only be able to have the attributes listed in `__slots__`, unless you include `'__dict__'` in `__slots__` (but doing so may negate the memory savings).
- Classes using `__slots__` cannot use the `@cached_property` decorator, unless they explicitly name `'__dict__'` in `__slots__`.
- Instances cannot be targets of weak references unless you add `'__weakref__'` in `__slots__`.

The last topic in this chapter has to do with overriding a class attribute in instances and subclasses.

Overriding Class Attributes

A distinctive feature of Python is how class attributes can be used as default values for instance attributes. In `Vector2d` there is the `typecode` class attribute. It's used twice in the `__bytes__` method, but we read it as `self.typecode` by design. Because `Vector2d` instances are created without a `typecode` attribute of their own, `self.typecode` will get the `Vector2d.typecode` class attribute by default.

But if you write to an instance attribute that does not exist, you create a new instance attribute—e.g., a `typecode` instance attribute—and the class attribute by the same name is untouched. However, from then on, whenever the code handling that instance reads `self.typecode`, the instance `typecode` will be retrieved, effectively shadowing the class attribute by the same name. This opens the possibility of customizing an individual instance with a different `typecode`.

The default `Vector2d.typecode` is `'d'`, meaning each vector component will be represented as an 8-byte double precision float when exporting to `bytes`. If we set the `typecode` of a `Vector2d` instance to `'f'` prior to exporting, each component will be exported as a 4-byte single precision float. Example 11-18 demonstrates.

> **NOTE**
>
> We are discussing adding a custom instance attribute, therefore Example 11-18 uses the `Vector2d` implementation without `__slots__` as listed in Example 11-11.

Example 11-18. Customizing an instance by setting the typecode attribute that was formerly inherited from the class

```
>>> from vector2d_v3 import Vector2d
>>> v1 = Vector2d(1.1, 2.2)
>>> dumpd = bytes(v1)
>>> dumpd
b'd\x9a\x99\x99\x99\x99\x99\xf1?\x9a\x99\x99\x99\x99\x99\x01@'
>>> len(dumpd)  ❶
17
>>> v1.typecode = 'f'  ❷
>>> dumpf = bytes(v1)
>>> dumpf
b'f\xcd\xcc\x8c?\xcd\xcc\x0c@'
>>> len(dumpf)  ❸
9
```

```
>>> Vector2d.typecode  ❹
'd'
```

❶ Default `bytes` representation is 17 bytes long.

❷ Set `typecode` to `'f'` in the `v1` instance.

❸ Now the `bytes` dump is 9 bytes long.

❹ `Vector2d.typecode` is unchanged; only the `v1` instance uses `typecode` `'f'`.

Now it should be clear why the `bytes` export of a `Vector2d` is prefixed by the `typecode`: we wanted to support different export formats.

If you want to change a class attribute you must set it on the class directly, not through an instance. You could change the default `typecode` for all instances (that don't have their own `typecode`) by doing this:

```
>>> Vector2d.typecode = 'f'
```

However, there is an idiomatic Python way of achieving a more permanent effect, and being more explicit about the change. Because class attributes are public, they are inherited by subclasses, so it's common practice to subclass just to customize a class data attribute. The Django class-based views use this technique extensively. Example 11-19 shows how.

Example 11-19. The ShortVector2d is a subclass of Vector2d, which only overwrites the default typecode

```
>>> from vector2d_v3 import Vector2d
>>> class ShortVector2d(Vector2d):  ❶
...     typecode = 'f'
...
>>> sv = ShortVector2d(1/11, 1/27)  ❷
>>> sv
ShortVector2d(0.09090909090909091, 0.037037037037037035)  ❸
>>> len(bytes(sv))  ❹
9
```

❶ Create `ShortVector2d` as a `Vector2d` subclass just to overwrite the `typecode` class attribute.

❷ Build `ShortVector2d` instance `sv` for demonstration.

❸ Inspect the `repr` of `sv`.

❹ Check that the length of the exported bytes is 9, not 17 as before.

This example also explains why I did not hardcode the `class_name` in `Vector2d.__repr__`, but instead got it from `type(self).__name__`, like this:

```
    # inside class Vector2d:

    def __repr__(self):
        class_name = type(self).__name__
        return '{}({!r}, {!r})'.format(class_name, *self)
```

If I had hardcoded the `class_name`, subclasses of `Vector2d` like `ShortVector2d` would have to overwrite `__repr__` just to change the `class_name`. By reading the name from the `type` of the instance, I made `__repr__` safer to inherit.

This ends our coverage of building a simple class that leverages the data model to play well with the rest of Python—offering different object representations, providing a custom formatting code, exposing read-only attributes, and supporting `hash()` to integrate with sets and mappings.

Chapter Summary

The aim of this chapter was to demonstrate the use of special methods and conventions in the construction of a well-behaved Pythonic class.

Is *vector2d_v3.py* (Example 11-11) more Pythonic than *vector2d_v0.py* (Example 11-2)? The `Vector2d` class in *vector2d_v3.py* certainly exhibits more Python features. But whether the first or the last `Vector2d` implementation is suitable depends on the context where it would be used. Tim Peter's Zen of Python says:

> *Simple is better than complex.*

An object should be as simple as the requirements dictate—and not a parade of language features. If the code is for an application, then it should focus on what is needed to support the end users, not more. If the code is for a library for other programmers to use, then it's reasonable to implement special methods supporting behaviors that Pythonistas expect. For example, `__eq__` may not be necessary to support a business requirement, but it makes it makes the class easier to test.

My goal in expanding the `Vector2d` code was to provide context for discussing Python special methods and coding conventions. The examples in this chapter have demonstrated several of the special methods we first saw in Table 1-1 (Chapter 1):

- String/bytes representation methods: `__repr__`, `__str__`, `__format__`, and `__bytes__`.
- Methods for reducing an object to a number: `__abs__`, `__bool__`, `__hash__`.
- The `__eq__` operator, to support testing and hashing (along with `__hash__`).

While supporting conversion to `bytes` we also implemented an alternative constructor, `Vector2d.frombytes()`, which provided the context for discussing the decorators `@classmethod` (very handy) and

`@staticmethod` (not so useful, module-level functions are simpler). The `frombytes` method was inspired by its namesake in the `array.array` class.

We saw that the Format Specification Mini-Language is extensible by implementing a `__format__` method that parses a `format_spec` provided to the `format(obj, format_spec)` built-in or within replacement fields `'{:«format_spec»}'` in f-strings or strings used with the `str.format()` method.

In preparation to make `Vector2d` instances hashable, we made an effort to make them immutable, at least preventing accidental changes by coding the `x` and `y` attributes as private, and exposing them as read-only properties. We then implemented `__hash__` using the recommended technique of xor-ing the hashes of the instance attributes.

We then discussed the memory savings and the caveats of declaring a `__slots__` attribute in `Vector2d`. Because using `__slots__` has side effects, it really makes sense only when handling a very large number of instances—think millions of instances, not just thousands. In many such cases, using pandas may be the best option.

The last topic we covered was the overriding of a class attribute accessed via the instances (e.g., `self.typecode`). We did that first by creating an instance attribute, and then by subclassing and overwriting at the class level.

Throughout the chapter, I mentioned how design choices in the examples were informed by studying the API of standard Python objects. If this chapter can be summarized in one sentence, this is it:

> *To build Pythonic objects, observe how real Python objects behave.*
>
> —Ancient Chinese proverb

Further Reading

This chapter covered several special methods of the data model, so naturally the primary references are the same as the ones provided in Chapter 1, which gave a high-level view of the same topic. For convenience, I'll repeat those four earlier recommendations here, and add a few other ones:

"Data Model" chapter of The Python Language Reference

> Most of the methods we used in this chapter are documented in "3.3.1. Basic customization".

Python in a Nutshell, 3rd Edition by Alex Martelli, Anna Ravenscroft, and Steve Holden covers the special methods in depth.

Python Cookbook, 3rd Edition, by David Beazley and Brian K. Jones

> Modern Python practices demonstrated through recipes. Chapter 8, "Classes and Objects" in particular has several solutions related to discussions in this chapter.

Python Essential Reference, 4th Edition, by David Beazley

> Covers the data model in detail. Even if only Python 2.6 and 3.0 is covered (in the fourth edition). The fundamental concepts are all the same and most of the Data Model APIs haven't changed at all since Python 2.2, when built-in types and user-defined classes were unified.

In 2015—the year when I finished *Fluent Python, First Edition*—Hynek Schlawack started the `attrs` package. From the `attrs` documentation:

> *`attrs` is the Python package that will bring back the **joy** of **writing classes** by relieving you from the drudgery of implementing object protocols (aka dunder methods).*

I mentioned `attrs` as a more powerful alternative to `@dataclass` in "Further Reading". The data class builders from Chapter 5 as well as `attrs` automatically equip your classes with several special methods. But knowing how to code those special methods yourself is still essential to understand what those packages do, to decide whether you really need them, and to override the methods they generate—when necessary.

In this chapter, we saw every special method related to object representation, except `__index__` and `__fspath__`. We'll discuss `__index__` in Chapter 12, "A Slice-Aware __getitem__". I will not cover `__fspath__`. To learn about it, see PEP 519—Adding a file system path protocol.

An early realization of the need for distinct string representations for objects appeared in Smalltalk. The 1996 article "How to Display an Object as a String: printString and displayString" by Bobby Woolf discusses the implementation of the `printString` and `displayString` methods in that language. From that article, I borrowed the pithy descriptions "the way the developer wants to see it" and "the way the user wants to see it" when defining `repr()` and `str()` in "Object Representations".

SOAPBOX

Properties Help Reduce Upfront Costs

In the initial versions of `Vector2d`, the `x` and `y` attributes were public, as are all Python instance and class attributes by default. Naturally, users of vectors need to access its components. Although our vectors are iterable and can be unpacked into a pair of variables, it's also desirable to write `my_vector.x` and `my_vector.y` to get each component.

When we felt the need to avoid accidental updates to the `x` and `y` attributes, we implemented properties, but nothing changed elsewhere in the code and in the public interface of `Vector2d`, as verified by the doctests. We are still able to access `my_vector.x` and `my_vector.y`.

This shows that we can always start our classes in the simplest possible way, with public attributes, because when (or if) we later need to impose more control with getters and setters, these can be implemented through properties without changing any of the code that already interacts with our objects through the names (e.g., `x` and `y`) that were initially simple public attributes.

This approach is the opposite of that encouraged by the Java language: a Java programmer cannot start with simple public attributes and only later, if needed, implement properties, because they don't exist in the language. Therefore, writing getters and setters is the norm in Java—even when those methods do nothing useful—because the API cannot evolve from simple public attributes to getters and setters without breaking all code that uses those attributes.

In addition, as Martelli, Ravenscroft & Holden point out in *Python in a Nutshell, 3rd Edition*, typing getter/setter calls everywhere is goofy. You have to write stuff like:

```
>>> my_object.set_foo(my_object.get_foo() + 1)
```

Just to do this:

```
>>> my_object.foo += 1
```

Ward Cunningham, inventor of the wiki and an Extreme Programming pioneer, recommends asking “What’s the simplest thing that could possibly work?” The idea is to focus on the goal.[11] Implementing setters and getters up front is a distraction from the goal. In Python, we can simply use public attributes knowing we can change them to properties later, if the need arises.

Safety Versus Security in Private Attributes

> *Perl doesn’t have an infatuation with enforced privacy. It would prefer that you stayed out of its living room because you weren’t invited, not because it has a shotgun.*
>
> —Larry Wall, Creator of Perl

Python and Perl are polar opposites in many regards, but Guido and Larry seem to agree on object privacy.

Having taught Python to many Java programmers over the years, I’ve found a lot of them put too much faith in the privacy guarantees that Java offers. As it turns out, the Java `private` and `protected` modifiers normally provide protection against accidents only (i.e., safety). They only offer security against malicious intent if the application is specially configured and deployed on top of a Java SecurityManager, and that seldom happens in practice, even in security conscious corporate settings.

To prove my point, I like to show this Java class (Example 11-20).

Example 11-20. Confidential.java: a Java class with a private field named secret

```
public class Confidential {

    private String secret = "";

    public Confidential(String text) {
```

```
        this.secret = text.toUpperCase();
    }
}
```

In Example 11-20, I store the `text` in the `secret` field after converting it to uppercase, just to make it obvious that whatever is in that field will be in all caps.

The actual demonstration consists of running *expose.py* with Jython. That script uses introspection (“reflection” in Java parlance) to get the value of a private field. The code is in Example 11-21.

Example 11-21. expose.py: Jython code to read the content of a private field in another class

```
#!/usr/bin/env jython
# NOTE: Jython is still Python 2.7 in late2020

import Confidential

message = Confidential('top secret text')
secret_field = Confidential.getDeclaredField('secret')
secret_field.setAccessible(True)  # break the lock!
print 'message.secret =', secret_field.get(message)
```

If you run Example 11-21, this is what you get:

```
$ jython expose.py
message.secret = TOP SECRET TEXT
```

The string `'TOP SECRET TEXT'` was read from the `secret` private field of the `Confidential` class.

There is no black magic here: *expose.py* uses the Java reflection API to get a reference to the private field named `'secret'`, and then calls `'secret_field.setAccessible(True)'` to make it readable. The same thing can be done with Java code, of course (but it takes more than three times as many lines to do it; see the file `Expose.java` in the *Fluent Python, Second Edition* code repository).

The crucial call `.setAccessible(True)` will fail only if the Jython script or the Java main program (e.g., `Expose.class`) is running under the supervision of a SecurityManager. But in the real world, Java applications are rarely deployed with a SecurityManager—except for Java applets when they were still supported by browsers.

My point is: in Java too, access control modifiers are mostly about safety and not security, at least in practice. So relax and enjoy the power Python gives you. Use it responsibly.

---

1 From Faassen's blog post *What is Pythonic?*

2 I used `eval` to clone the object here just to make a point about `repr`; to clone an instance, the `copy.copy` function is safer and faster.

3 This line could also be written as `yield self.x; yield.self.y`. I have a lot more to say about the `__iter__` special method, generator expressions, and the `yield` keyword in Chapter 17.

4 We had a brief introduction to `memoryview`, explaining its `.cast` method in "Memory Views".

5 Leonardo Rochael, one of the technical reviewers of this book disagrees with my low opinion of `staticmethod`, and recommends the blog post "The Definitive Guide on How to Use Static, Class or Abstract Methods in Python" by Julien Danjou as a counter-argument. Danjou's post is very good; I do recommend it. But it wasn't enough to change my mind about `staticmethod`. You'll have to decide for yourself.

6 The pros and cons of private attributes are the subject of the upcoming "Private and "Protected" Attributes in Python".

7 From the Paste Style Guide.

8 In modules, a single _ in front of a top-level name does have an effect: if you write `from mymod import *` the names with a _ prefix are not imported from `mymod`. However, you can still write `from mymod import _privatefunc`. This is explained in the Python Tutorial, section 6.1. More on Modules.

9 One example is in the gettext module docs.

10 If this state of affairs depresses you, and makes you wish Python was more like Java in this regard, don't read my discussion of the relative strength of the Java `private` modifier in "Soapbox".

11 See "Simplest Thing that Could Possibly Work: A Conversation with Ward Cunningham, Part V".

Chapter 12. Writing Special Methods for Sequences

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 12th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Don’t check whether it is-a duck: check whether it quacks-like-a duck, walks-like-a duck, etc, etc, depending on exactly what subset of duck-like behavior you need to play your language-games with. (`comp.lang.python`, Jul. 26, 2000)*
>
> —Alex Martelli

In this chapter, we will create a class to represent a multidimensional `Vector` class—a significant step up from the two-dimensional `Vector2d` of Chapter 11. `Vector` will behave like a standard Python immutable flat sequence. Its elements will be floats, and it will support the following by the end of this chapter:

- Basic sequence protocol: `__len__` and `__getitem__`.
- Safe representation of instances with many items.

- Proper slicing support, producing new `Vector` instances.
- Aggregate hashing taking into account every contained element value.
- Custom formatting language extension.

We’ll also implement dynamic attribute access with `__getattr__` as a way of replacing the read-only properties we used in `Vector2d`—although this is not typical of sequence types.

The code-intensive presentation will be interrupted by a conceptual discussion about the idea of protocols as an informal interface. We’ll talk about how protocols and *duck typing* are related, and its practical implications when you create your own types.

What’s new in this chapter

There are no major changes in this chapter. There is a new, brief discussion of the `typing.Protocol` in a tip box near the end of “Protocols and Duck Typing”.

In “A Slice-Aware __getitem__”, the implementation of `__getitem__` in Example 12-6 is shorter and more robust than the example in the first edition, thanks to duck typing and `operator.index`. This change carried over to later implementations of `Vector` in this chapter and in Chapter 16.

Let’s get started.

Vector: A User-Defined Sequence Type

Our strategy to implement `Vector` will be to use composition, not inheritance. We’ll store the components in an `array` of floats, and will implement the methods needed for our `Vector` to behave like an immutable flat sequence.

But before we implement the sequence methods, let's make sure we have a baseline implementation of `Vector` that is compatible with our earlier `Vector2d` class—except where such compatibility would not make sense.

> **VECTOR APPLICATIONS BEYOND THREE DIMENSIONS**
>
> Who needs a vector with 1,000 dimensions? N-dimensional vectors (with large values of N) are widely used in information retrieval, where documents and text queries are represented as vectors, with one dimension per word. This is called the Vector space model. In this model, a key relevance metric is the cosine similarity (i.e., the cosine of the angle between a the vector representing the query and the vector representing the document). As the angle decreases, the cosine approaches the maximum value of 1, and so does the relevance of the document to the query.
>
> Having said that, the `Vector` class in this chapter is a didactic example and we'll not do much math here. Our goal is just to demonstrate some Python special methods in the context of a sequence type.
>
> NumPy and SciPy are the tools you need for real-world vector math. The PyPI package gensim, by Radim Řehůřek, implements vector space modeling for natural language processing and information retrieval, using NumPy and SciPy.

Vector Take #1: Vector2d Compatible

The first version of `Vector` should be as compatible as possible with our earlier `Vector2d` class.

However, by design, the `Vector` constructor is not compatible with the `Vector2d` constructor. We could make `Vector(3, 4)` and `Vector(3, 4, 5)` work, by taking arbitrary arguments with `*args` in `__init__`, but the best practice for a sequence constructor is to take the data as an iterable argument in the constructor, like all built-in sequence types do. Example 12-1 shows some ways of instantiating our new `Vector` objects.

Example 12-1. Tests of Vector.__init__ and Vector.__repr__

```
>>> Vector([3.1, 4.2])
Vector([3.1, 4.2])
>>> Vector((3, 4, 5))
Vector([3.0, 4.0, 5.0])
>>> Vector(range(10))
Vector([0.0, 1.0, 2.0, 3.0, 4.0, ...])
```

Apart from new constructor signature, I made sure every test I did with `Vector2d` (e.g., `Vector2d(3, 4)`) passed and produced the same result with a two-component `Vector([3, 4])`.

> **WARNING**
>
> When a `Vector` has more than six components, the string produced by `repr()` is abbreviated with `...` as seen in the last line of Example 12-1. This is crucial in any collection type that may contain a large number of items, because `repr` is used for debugging—and you don't want a single large object to span thousands of lines in your console or log. Use the `reprlib` module to produce limited-length representations, as in Example 12-2. The `reprlib` module was named `repr` in Python 2.7.

Example 12-2 lists the implementation of our first version of `Vector` (this example builds on the code shown in Examples 11-2 and 11-3).

Example 12-2. vector_v1.py: derived from vector2d_v1.py

```
from array import array
import reprlib
import math


class Vector:
    typecode = 'd'

    def __init__(self, components):
        self._components = array(self.typecode, components)  ❶

    def __iter__(self):
        return iter(self._components)  ❷
```

```
    def __repr__(self):
        components = reprlib.repr(self._components)  ❸
        components = components[components.find('['):-1]  ❹
        return f'Vector({components})'

    def __str__(self):
        return str(tuple(self))

    def __bytes__(self):
        return (bytes([ord(self.typecode)]) +
                bytes(self._components))  ❺

    def __eq__(self, other):
        return tuple(self) == tuple(other)

    def __abs__(self):
        return math.hypot(*self)  ❻

    def __bool__(self):
        return bool(abs(self))

    @classmethod
    def frombytes(cls, octets):
        typecode = chr(octets[0])
        memv = memoryview(octets[1:]).cast(typecode)
        return cls(memv)  ❼
```

❶ The `self._components` instance “protected” attribute will hold an `array` with the `Vector` components.

❷ To allow iteration, we return an iterator over `self._components`.[1]

❸ Use `reprlib.repr()` to get a limited-length representation of `self._components` (e.g., `array('d', [0.0, 1.0, 2.0, 3.0, 4.0, ...])`).

❹ Remove the `array('d',` prefix and the trailing `)` before plugging the string into a `Vector` constructor call.

❺ Build a `bytes` object directly from `self._components`.

❻ Since Python 3.8, `math.hypot` accepts n-dimensional points. I used this expression before: `math.sqrt(sum(x * x for x in self))`.

❼ The only change needed from the earlier `frombytes` is in the last line: we pass the `memoryview` directly to the constructor, without unpacking with `*` as we did before.

The way I used `reprlib.repr` deserves some elaboration. That function produces safe representations of large or recursive structures by limiting the length of the output string and marking the cut with `'...'`. I wanted the `repr` of a `Vector` to look like `Vector([3.0, 4.0, 5.0])` and not `Vector(array('d', [3.0, 4.0, 5.0]))`, because the fact that there is an `array` inside a `Vector` is an implementation detail. Because these constructor calls build identical `Vector` objects, I prefer the simpler syntax using a `list` argument.

When coding `__repr__`, I could have produced the simplified `components` display with this expression: `reprlib.repr(list(self._components))`. However, this would be wasteful, as I'd be copying every item from `self._components` to a `list` just to use the `list` `repr`. Instead, I decided to apply `reprlib.repr` to the `self._components` array directly, and then chop off the characters outside of the `[]`. That's what the second line of `__repr__` does in Example 12-2.

> **TIP**
>
> Because of its role in debugging, calling `repr()` on an object should never raise an exception. If something goes wrong inside your implementation of `__repr__`, you must deal with the issue and do your best to produce some serviceable output that gives the user a chance of identifying the target object.

Note that the `__str__`, `__eq__`, and `__bool__` methods are unchanged from `Vector2d`, and only one character was changed in `frombytes` (a `*` was removed in the last line). This is one of the benefits of making the original `Vector2d` iterable.

By the way, we could have subclassed `Vector` from `Vector2d`, but I chose not to do it for two reasons. First, the incompatible constructors really make subclassing not advisable. I could work around that with some clever parameter handling in `__init__`, but the second reason is more important: I want `Vector` to be a standalone example of a class implementing the sequence protocol. That's what we'll do next, after a discussion of the term *protocol*.

Protocols and Duck Typing

As early as Chapter 1, we saw that you don't need to inherit from any special class to create a fully functional sequence type in Python; you just need to implement the methods that fulfill the sequence protocol. But what kind of protocol are we talking about?

In the context of Object-Oriented programming, a protocol is an informal interface, defined only in documentation and not in code. For example, the sequence protocol in Python entails just the `__len__` and `__getitem__` methods. Any class `Spam` that implements those methods with the standard signature and semantics can be used anywhere a sequence is expected. Whether `Spam` is a subclass of this or that is irrelevant; all that matters is that it provides the necessary methods. We saw that in Example 1-1, reproduced here in Example 12-3.

Example 12-3. Code from Example 1-1, reproduced here for convenience

```
import collections

Card = collections.namedtuple('Card', ['rank', 'suit'])

class FrenchDeck:
    ranks = [str(n) for n in range(2, 11)] + list('JQKA')
    suits = 'spades diamonds clubs hearts'.split()
```

```python
    def __init__(self):
        self._cards = [Card(rank, suit) for suit in self.suits
                                        for rank in self.ranks]

    def __len__(self):
        return len(self._cards)

    def __getitem__(self, position):
        return self._cards[position]
```

The `FrenchDeck` class in Example 12-3 takes advantage of many Python facilities because it implements the sequence protocol, even if that is not declared anywhere in the code. An experienced Python coder will look at it and understand that it *is* a sequence, even if it subclasses `object`. We say it *is* a sequence because it *behaves* like one, and that is what matters.

This became known as *duck typing*, after Alex Martelli's post quoted at the beginning of this chapter.

Because protocols are informal and unenforced, you can often get away with implementing just part of a protocol, if you know the specific context where a class will be used. For example, to support iteration, only `__getitem__` is required; there is no need to provide `__len__`.

TIP

With PEP 544—Protocols: Structural subtyping (static duck typing), Python 3.8 supports *protocol classes*: `typing` constructs which we studied in "Static Protocols". This new use of the word protocol in Python has a related but different meaning. When I need to differentiate them, I write *static protocol* to refer to the protocols formalized in protocol classes, and *dynamic protocol* for the traditional sense. One key difference is that static protocol implementations must provide all methods defined in the protocol class. "Two kinds of protocols" in Chapter 13 has more details.

We'll now implement the sequence protocol in `Vector`, initially without proper support for slicing, but later adding that.

Vector Take #2: A Sliceable Sequence

As we saw with the `FrenchDeck` example, supporting the sequence protocol is really easy if you can delegate to a sequence attribute in your object, like our `self._components` array. These `__len__` and `__getitem__` one-liners are a good start:

```
class Vector:
    # many lines omitted
    # ...

    def __len__(self):
        return len(self._components)

    def __getitem__(self, index):
        return self._components[index]
```

With these additions, all of these operations now work:

```
>>> v1 = Vector([3, 4, 5])
>>> len(v1)
3
>>> v1[0], v1[-1]
(3.0, 5.0)
>>> v7 = Vector(range(7))
>>> v7[1:4]
array('d', [1.0, 2.0, 3.0])
```

As you can see, even slicing is supported—but not very well. It would be better if a slice of a `Vector` was also a `Vector` instance and not an `array`. The old `FrenchDeck` class has a similar problem: when you slice it, you get a `list`. In the case of `Vector`, a lot of functionality is lost when slicing produces plain arrays.

Consider the built-in sequence types: every one of them, when sliced, produces a new instance of its own type, and not of some other type.

To make `Vector` produce slices as `Vector` instances, we can't just delegate the slicing to `array`. We need to analyze the arguments we get in `__getitem__` and do the right thing.

Now, let’s see how Python turns the syntax `my_seq[1:3]` into arguments for `my_seq.__getitem__(...)`.

How Slicing Works

A demo is worth a thousand words, so take a look at Example 12-4.

Example 12-4. Checking out the behavior of __getitem__ and slices

```
>>> class MySeq:
...     def __getitem__(self, index):
...         return index  ❶
...
>>> s = MySeq()
>>> s[1]  ❷
1
>>> s[1:4]  ❸
slice(1, 4, None)
>>> s[1:4:2]  ❹
slice(1, 4, 2)
>>> s[1:4:2, 9]  ❺
(slice(1, 4, 2), 9)
>>> s[1:4:2, 7:9]  ❻
(slice(1, 4, 2), slice(7, 9, None))
```

❶ For this demonstration, `__getitem__` merely returns whatever is passed to it.

❷ A single index, nothing new.

❸ The notation `1:4` becomes `slice(1, 4, None)`.

❹ `slice(1, 4, 2)` means start at 1, stop at 4, step by 2.

❺ Surprise: the presence of commas inside the `[]` means `__getitem__` receives a tuple.

❻ The tuple may even hold several slice objects.

Now let’s take a closer look at `slice` itself in Example 12-5.

Example 12-5. Inspecting the attributes of the slice class

```
>>> slice  ❶
<class 'slice'>
>>> dir(slice) ❷
['__class__', '__delattr__', '__dir__', '__doc__', '__eq__',
 '__format__', '__ge__', '__getattribute__', '__gt__',
 '__hash__', '__init__', '__le__', '__lt__', '__ne__',
 '__new__', '__reduce__', '__reduce_ex__', '__repr__',
 '__setattr__', '__sizeof__', '__str__', '__subclasshook__',
 'indices', 'start', 'step', 'stop']
```

❶ `slice` is a built-in type (we saw it first in "Slice Objects").

❷ Inspecting a `slice` we find the data attributes `start`, `stop`, and `step`, and an `indices` method.

In Example 12-5, calling `dir(slice)` reveals an `indices` attribute, which turns out to be a very interesting but little-known method. Here is what `help(slice.indices)` reveals:

`S.indices(len) -> (start, stop, stride)`

> Assuming a sequence of length `len`, calculate the `start` and `stop` indices, and the `stride` length of the extended slice described by `S`. Out of bounds indices are clipped just like they are in a normal slice.

In other words, `indices` exposes the tricky logic that's implemented in the built-in sequences to gracefully handle missing or negative indices and slices that are longer than the original sequence. This method produces "normalized" tuples of nonnegative `start`, `stop`, and `stride` integers tailored to sequence of the given length.

Here are a couple of examples, considering a sequence of `len == 5`, e.g., `'ABCDE'`:

```
>>> slice(None, 10, 2).indices(5)  ❶
(0, 5, 2)
>>> slice(-3, None, None).indices(5)  ❷
(2, 5, 1)
```

❶ `'ABCDE'[:10:2]` is the same as `'ABCDE'[0:5:2]`

❷ `'ABCDE'[-3:]` is the same as `'ABCDE'[2:5:1]`

In our `Vector` code, we’ll not need the `slice.indices()` method because when we get a slice argument we’ll delegate its handling to the `_components` `array`. But if you can’t count on the services of an underlying sequence, this method can be a huge time saver.

Now that we know how to handle slices, let’s take a look at the improved `Vector.__getitem__` implementation.

A Slice-Aware __getitem__

Example 12-6 lists the two methods needed to make `Vector` behave as a sequence: `__len__` and `__getitem__` (the latter now implemented to handle slicing correctly).

Example 12-6. Part of vector_v2.py: __len__ and __getitem__ methods added to Vector class from vector_v1.py (see Example 12-2)

```
    def __len__(self):
        return len(self._components)

    def __getitem__(self, key):
        if isinstance(key, slice):  ❶
            cls = type(self)  ❷
            return cls(self._components[key])  ❸
        index = operator.index(key)  ❹
        return self._components[index]  ❺
```

❶ If the `key` argument is a `slice`…

❷ …get the class of the instance (i.e., `Vector`) and…

❸ …invoke the class to build another `Vector` instance from a slice of the `_components` array.

❹ If we can get an `index` from `key`…

❺ …return the specific item from `_components`.

The `operator.index()` function calls the `__index__` special method. The function and the special method were defined in PEP 357—Allowing Any Object to be Used for Slicing, proposed by Travis Oliphant to allow any of the numerous types of integers in NumPy to be used as indexes and slice arguments. The key difference between `operator.index()` and `int()` is that the former is intended for this specific purpose. For example, `int(3.14)` returns 3, but `operator.index(3.14)` raises `TypeError` because a `float` should not be used as an index.

> **NOTE**
>
> Excessive use of `isinstance` may be a sign of bad OO design, but handling slices in `__getitem__` is a justified use case. In the first edition, I also used an `isinstance` test on `key` to test if it was an integer. Using `operator.index` avoids this test, and raises `TypeError` with a very informative message if we can't get the `index` from `key`. See the last error message from Example 12-7 below.

Once the code in Example 12-6 is added to the `Vector` class, we have proper slicing behavior, as Example 12-7 demonstrates.

Example 12-7. Tests of enhanced Vector.getitem from Example 12-6

```
>>> v7 = Vector(range(7))
>>> v7[-1]  ❶
6.0
>>> v7[1:4]  ❷
Vector([1.0, 2.0, 3.0])
>>> v7[-1:]  ❸
Vector([6.0])
>>> v7[1,2]  ❹
Traceback (most recent call last):
  ...
TypeError: 'tuple' object cannot be interpreted as an integer
```

❶ An integer index retrieves just one component value as a `float`.

❷ A slice index creates a new `Vector`.

❸ A slice of `len == 1` also creates a `Vector`.

❹ `Vector` does not support multidimensional indexing, so a tuple of indices or slices raises an error.

Vector Take #3: Dynamic Attribute Access

In the evolution from `Vector2d` to `Vector`, we lost the ability to access vector components by name (e.g., `v.x`, `v.y`). We are now dealing with vectors that may have a large number of components. Still, it may be convenient to access the first few components with shortcut letters such as `x`, `y`, `z` instead of `v[0]`, `v[1]` and `v[2]`.

Here is the alternative syntax we want to provide for reading the first four components of a vector:

```
>>> v = Vector(range(10))
>>> v.x
0.0
>>> v.y, v.z, v.t
(1.0, 2.0, 3.0)
```

In `Vector2d`, we provided read-only access to `x` and `y` using the `@property` decorator (Example 11-7). We could write four properties in `Vector`, but it would be tedious. The `__getattr__` special method provides a better way.

The `__getattr__` method is invoked by the interpreter when attribute lookup fails. In simple terms, given the expression `my_obj.x`, Python checks if the `my_obj` instance has an attribute named `x`; if not, the search goes to the class (`my_obj.__class__`), and then up the inheritance graph.[2] If the `x` attribute is not found, then the `__getattr__` method defined in the class of `my_obj` is called with `self` and the name of the attribute as a string (e.g., `'x'`).

Example 12-8 lists our `__getattr__` method. Essentially it checks whether the attribute being sought is one of the letters `xyzt` and if so, returns the corresponding vector component.

Example 12-8. Part of vector_v3.py: `__getattr__` method added to `Vector` class.

```
    __match_args__ = ('x', 'y', 'z', 't')  ❶

    def __getattr__(self, name):
        cls = type(self)  ❷
        try:
            pos = cls.__match_args__.index(name)  ❸
        except ValueError:  ❹
            pos = -1
        if 0 <= pos < len(self._components):  ❺
            return self._components[pos]
        msg = f'{cls.__name__!r} object has no attribute {name!r}'
❻
        raise AttributeError(msg)
```

❶ Set `__match_args__` to allow pattern matching on the dynamic attributes supported by `__getattr__`.[3]

❷ Get the `Vector` class for later use.

❸ Try to get the position of `name` in `__match_args__`.

❹ `.index(name)` raises `ValueError` when `name` is not found; set `pos` to -1 (I'd rather use a method like `str.find` here, but `tuple` doesn't implement it.)

❺ If the `pos` is within range of the available components, return the component.

❻ If we get this far, raise `AttributeError` with a standard message text.

It’s not hard to implement `__getattr__`, but in this case it’s not enough. Consider the bizarre interaction in Example 12-9.

Example 12-9. Inappropriate behavior: assigning to v.x raises no error, but introduces an inconsistency

```
>>> v = Vector(range(5))
>>> v
Vector([0.0, 1.0, 2.0, 3.0, 4.0])
>>> v.x  ❶
0.0
>>> v.x = 10  ❷
>>> v.x  ❸
10
>>> v
Vector([0.0, 1.0, 2.0, 3.0, 4.0])  ❹
```

❶ Access element `v[0]` as `v.x`.

❷ Assign new value to `v.x`. This should raise an exception.

❸ Reading `v.x` shows the new value, `10`.

❹ However, the vector components did not change.

Can you explain what is happening? In particular, why the second time `v.x` returns `10` if that value is not in the vector components array? If you don’t know right off the bat, study the explanation of `__getattr__` given right before Example 12-8. It’s a bit subtle, but a very important foundation to understand a lot of what comes later in the book.

After you’ve given it some thought, proceed and we’ll explain exactly what happened.

The inconsistency in Example 12-9 was introduced because of the way `__getattr__` works: Python only calls that method as a fall back, when the object does not have the named attribute. However, after we assign `v.x = 10`, the `v` object now has an `x` attribute, so `__getattr__` will no longer be called to retrieve `v.x`: the interpreter will just return the value `10` that is bound to `v.x`. On the other hand, our implementation of `__getattr__` pays no attention to instance attributes other than `self._components`, from where it retrieves the values of the “virtual attributes” listed in `__match_args__`.

We need to customize the logic for setting attributes in our `Vector` class in order to avoid this inconsistency.

Recall that in the latest `Vector2d` examples from Chapter 11, trying to assign to the `.x` or `.y` instance attributes raised `AttributeError`. In `Vector` we want the same exception with any attempt at assigning to all single-letter lowercase attribute names, just to avoid confusion. To do that, we’ll implement `__setattr__` as listed in Example 12-10.

Example 12-10. Part of vector_v3.py: __setattr__ method in Vector class

```
    def __setattr__(self, name, value):
        cls = type(self)
        if len(name) == 1:  ❶
            if name in cls.__match_args__:  ❷
                error = 'readonly attribute {attr_name!r}'
            elif name.islower():  ❸
                error = "can't set attributes 'a' to 'z' in
{cls_name!r}"
            else:
                error = ''  ❹
            if error:  ❺
                msg = error.format(cls_name=cls.__name__,
attr_name=name)
                raise AttributeError(msg)
        super().__setattr__(name, value)  ❻
```

❶ Special handling for single-character attribute names.

❷ If `name` is one of `__match_args__`, set specific error message.

❸ If `name` is lowercase, set error message about all single-letter names.

❹ Otherwise, set blank error message.

❺ If there is a nonblank error message, raise `AttributeError`.

❻ Default case: call `__setattr__` on superclass for standard behavior.

> **TIP**
>
> The `super()` function provides a way to access methods of superclasses dynamically, a necessity in a dynamic language supporting multiple inheritance like Python. It's used to delegate some task from a method in a subclass to a suitable method in a superclass, as seen in Example 12-10. There is more about `super` in "Multiple Inheritance and Method Resolution Order".

While choosing the error message to display with `AttributeError`, my first check was the behavior of the built-in `complex` type, because they are immutable and have a pair of data attributes `real` and `imag`. Trying to change either of those in a `complex` instance raises `AttributeError` with the message `"can't set attribute"`. On the other hand, trying to set a read-only attribute protected by a property as we did in "A Hashable Vector2d" produces the message `"read-only attribute"`. I drew inspiration from both wordings to set the `error` string in `__setitem__`, but was more explicit about the forbidden attributes.

Note that we are not disallowing setting all attributes, only single-letter, lowercase ones, to avoid confusion with the supported read-only attributes `x`, `y`, `z`, and `t`.

> **WARNING**
>
> Knowing that declaring `__slots__` at the class level prevents setting new instance attributes, it's tempting to use that feature instead of implementing `__setattr__` as we did. However, because of all the caveats discussed in "Summarizing The Issues with __slots__", using `__slots__` just to prevent instance attribute creation is not recommended. `__slots__` should be used only to save memory, and only if that is a real issue.

Even without supporting writing to the `Vector` components, here is an important takeaway from this example: very often when you implement `__getattr__` you need to code `__setattr__` as well, to avoid inconsistent behavior in your objects.

If we wanted to allow changing components, we could implement `__setitem__` to enable `v[0] = 1.1` and/or `__setattr__` to make `v.x = 1.1` work. But `Vector` will remain immutable because we want to make it hashable in the coming section.

Vector Take #4: Hashing and a Faster ==

Once more we get to implement a `__hash__` method. Together with the existing `__eq__`, this will make `Vector` instances hashable.

The `__hash__` in Example 11-8 simply computed `hash(self.x) ^ hash(self.y)`. We now would like to apply the `^` (xor) operator to the hashes of every component, in succession, like this: `v[0] ^ v[1] ^ v[2]`…. That is what the `functools.reduce` function is for. Previously I said that `reduce` is not as popular as before,[4] but computing the hash of all vector components is a perfect job for it. Figure 12-1 depicts the general idea of the `reduce` function.

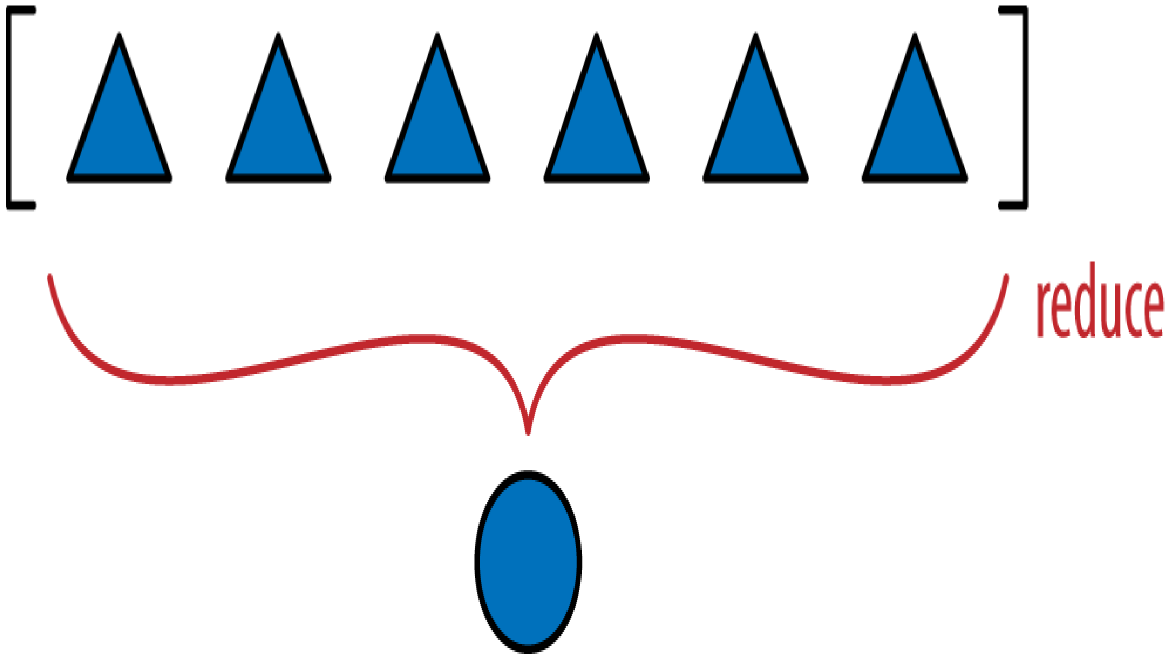


Figure 12-1. Reducing functions—reduce, sum, any, all—produce a single aggregate result from a sequence or from any finite iterable object.

So far we've seen that `functools.reduce()` can be replaced by `sum()`, but now let's properly explain how it works. The key idea is to reduce a series of values to a single value. The first argument to `reduce()` is a two-argument function, and the second argument is an iterable. Let's say we have a two-argument function `fn` and a list `lst`. When you call `reduce(fn, lst)`, `fn` will be applied to the first pair of elements—`fn(lst[0], lst[1])`—producing a first result, `r1`. Then `fn` is applied to `r1` and the next element—`fn(r1, lst[2])`—producing a second result, `r2`. Now `fn(r2, lst[3])` is called to produce `r3` … and so on until the last element, when a single result, `rN`, is returned.

Here is how you could use `reduce` to compute 5! (the factorial of 5):

```
>>> 2 * 3 * 4 * 5  # the result we want: 5! == 120
120
>>> import functools
>>> functools.reduce(lambda a,b: a*b, range(1, 6))
120
```

Back to our hashing problem, Example 12-11 shows the idea of computing the aggregate xor by doing it in three ways: with a `for` loop and two `reduce` calls.

Example 12-11. Three ways of calculating the accumulated xor of integers from 0 to 5

```
>>> n = 0
>>> for i in range(1, 6):  ❶
...     n ^= i
...
>>> n
1
>>> import functools
>>> functools.reduce(lambda a, b: a^b, range(6))  ❷
1
>>> import operator
>>> functools.reduce(operator.xor, range(6))  ❸
1
```

❶ Aggregate xor with a `for` loop and an accumulator variable.

❷ `functools.reduce` using an anonymous function.

❸ `functools.reduce` replacing custom `lambda` with `operator.xor`.

From the alternatives in Example 12-11, the last one is my favorite, and the `for` loop comes second. What is your preference?

As seen in "The operator Module", `operator` provides the functionality of all Python infix operators in function form, lessening the need for `lambda`.

To code `Vector.__hash__` in my preferred style, we need to import the `functools` and `operator` modules. Example 12-12 shows the relevant changes.

Example 12-12. Part of vector_v4.py: two imports and __hash__ method added to Vector class from vector_v3.py

```
from array import array
import reprlib
import math
import functools  ❶
import operator  ❷


class Vector:
    typecode = 'd'

    # many lines omitted in book listing...

    def __eq__(self, other):  ❸
        return tuple(self) == tuple(other)

    def __hash__(self):
        hashes = (hash(x) for x in self._components)  ❹
        return functools.reduce(operator.xor, hashes, 0)  ❺

    # more lines omitted...
```

❶ Import `functools` to use `reduce`.

❷ Import `operator` to use `xor`.

❸ No change to `__eq__`; I listed it here because it's good practice to keep `__eq__` and `__hash__` close in source code, because they need to work together.

❹ Create a generator expression to lazily compute the hash of each component.

❺ Feed `hashes` to `reduce` with the `xor` function to compute the aggregate hash code; the third argument, `0`, is the initializer (see next warning).

WARNING

When using `reduce`, it's good practice to provide the third argument, `reduce(function, iterable, initializer)`, to prevent this exception: `TypeError: reduce() of empty sequence with no initial value` (excellent message: explains the problem and how to fix it). The `initializer` is the value returned if the sequence is empty and is used as the first argument in the reducing loop, so it should be the identity value of the operation. As examples, for `+`, `|`, `^` the `initializer` should be `0`, but for `*`, `&` it should be `1`.

As implemented, the `__hash__` method in Example 12-12 is a perfect example of a map-reduce computation (Figure 12-2).

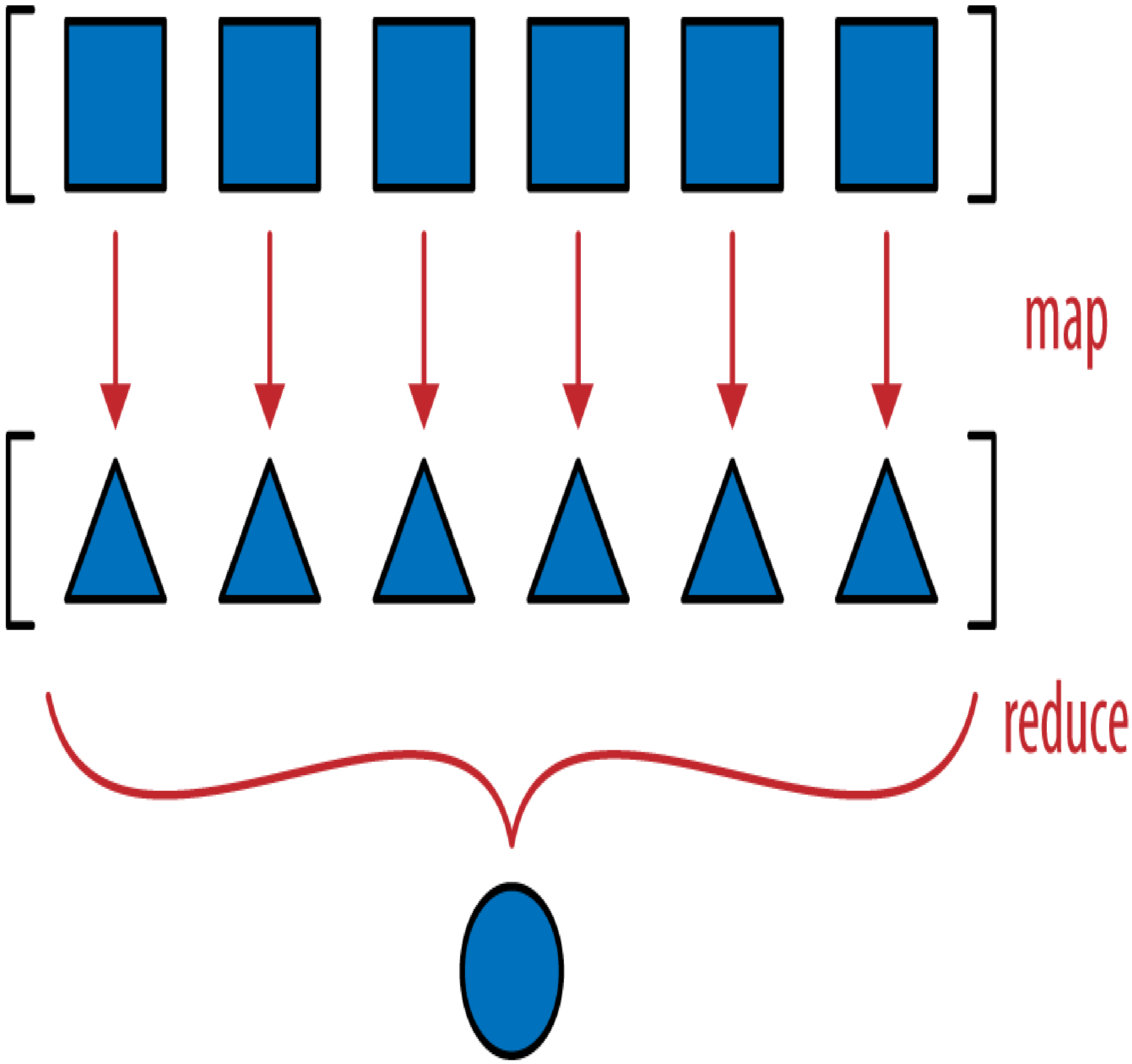


Figure 12-2. Map-reduce: apply function to each item to generate a new series (map), then compute aggregate (reduce)

The mapping step produces one hash for each component, and the reduce step aggregates all hashes with the `xor` operator. Using `map` instead of a *genexp* makes the mapping step even more visible:

```
def __hash__(self):
    hashes = map(hash, self._components)
    return functools.reduce(operator.xor, hashes)
```

> **TIP**
>
> The solution with `map` would be less efficient in Python 2, where the `map` function builds a new `list` with the results. But in Python 3, `map` is lazy: it creates a generator that yields the results on demand, thus saving memory—just like the generator expression we used in the `__hash__` method of Example 12-8.

While we are on the topic of reducing functions, we can replace our quick implementation of `__eq__` with another one that will be cheaper in terms of processing and memory, at least for large vectors. As introduced in Example 11-2, we have this very concise implementation of `__eq__`:

```
    def __eq__(self, other):
        return tuple(self) == tuple(other)
```

This works for `Vector2d` and for `Vector`—it even considers `Vector([1, 2])` equal to `(1, 2)`, which may be a problem, but we'll overlook that for now.[5] But for `Vector` instances that may have thousands of components, it's very inefficient. It builds two tuples copying the entire contents of the operands just to use the `__eq__` of the `tuple` type. For `Vector2d` (with only two components), it's a good shortcut, but not for the large multidimensional vectors. A better way of comparing one `Vector` to another `Vector` or iterable would be Example 12-13.

Example 12-13. The `Vector.__eq__` implementation using `zip` in a `for` loop for more efficient comparison

```
    def __eq__(self, other):
        if len(self) != len(other):  ❶
            return False
        for a, b in zip(self, other):  ❷
            if a != b:  ❸
                return False
        return True  ❹
```

❶ If the `len` of the objects are different, they are not equal.

❷

`zip` produces a generator of tuples made from the items in each iterable argument. See "The Awesome zip" if `zip` is new to you. The `len` comparison above is needed because `zip` stops producing values without warning as soon as one of the inputs is exhausted.

❸ As soon as two components are different, exit returning `False`.

❹ Otherwise, the objects are equal.

> **TIP**
>
> The `zip` function is named after the zipper fastener because the physical device works by interlocking pairs of teeth taken from both zipper sides, a good visual analogy for what `zip(left, right)` does. No relation with compressed files.

Example 12-13 is efficient, but the `all` function can produce the same aggregate computation of the `for` loop in one line: if all comparisons between corresponding components in the operands are `True`, the result is `True`. As soon as one comparison is `False`, `all` returns `False`. Example 12-14 shows how `__eq__` looks using `all`.

Example 12-14. The `Vector.__eq__` implementation using `zip` and `all`: same logic as Example 12-13

```
    def __eq__(self, other):
        return len(self) == len(other) and all(a == b for a, b in
zip(self, other))
```

Note that we first check that the operands have equal length, because `zip` will stop at the shortest operand.

Example 12-14 is the implementation we choose for `__eq__` in *vector_v4.py*.

THE AWESOME ZIP

Having a `for` loop that iterates over items without fiddling with index variables is great and prevents lots of bugs, but demands some special utility functions. One of them is the `zip` built-in, which makes it easy to iterate in parallel over two or more iterables by returning tuples that you can unpack into variables, one for each item in the parallel inputs. See Example 12-15.

Example 12-15. The zip built-in at work

```
>>> zip(range(3), 'ABC')  ❶
<zip object at 0x10063ae48>
>>> list(zip(range(3), 'ABC'))  ❷
[(0, 'A'), (1, 'B'), (2, 'C')]
>>> list(zip(range(3), 'ABC', [0.0, 1.1, 2.2, 3.3]))  ❸
[(0, 'A', 0.0), (1, 'B', 1.1), (2, 'C', 2.2)]
>>> from itertools import zip_longest  ❹
>>> list(zip_longest(range(3), 'ABC', [0.0, 1.1, 2.2, 3.3],
fillvalue=-1))
[(0, 'A', 0.0), (1, 'B', 1.1), (2, 'C', 2.2), (-1, -1, 3.3)]
```

❶ `zip` returns a generator that produces tuples on demand.

❷ Build a `list` just for display; usually we iterate over the generator.

❸ `zip` stops without warning when one of the iterables is exhausted.

❹ The `itertools.zip_longest` function behaves differently: it uses an optional `fillvalue` (`None` by default) to complete missing values so it can generate tuples until the last iterable is exhausted.

NEW `ZIP()` OPTION IN PYTHON 3.10.

I wrote in the *First Edition* that `zip` silently stopping at the shortest iterable was surprising—not a good trait for an API. Silently ignoring part of the input can cause subtle bugs. Instead, `zip` should raise `ValueError` if the iterables are not all of the same length, which is what happens when unpacking an iterable to a tuple of variables of different length—in line with Python's *fail fast* policy. PEP 618—Add Optional Length-Checking To zip added an optional `strict` argument to `zip` to make it behave in that way. It is implemented in Python 3.10.

The `zip` function can also be used to transpose a matrix represented as nested iterables. For example:

```
>>> a = [(1, 2, 3),
...      (4, 5, 6)]
>>> list(zip(*a))
[(1, 4), (2, 5), (3, 6)]
>>> b = [(1, 2),
...      (3, 4),
...      (5, 6)]
>>> list(zip(*b))
[(1, 3, 5), (2, 4, 6)]
```

If you want to grok `zip`, spend some time figuring out how these examples work.

The `enumerate` built-in is another generator function often used in `for` loops to avoid direct handling of index variables. If you are not familiar with `enumerate`, you should definitely check it out in the "Built-in functions" documentation. The `zip` and `enumerate` built-ins, along with several other generator functions in the standard library, are covered in "Generator Functions in the Standard Library".

We wrap up this chapter by bringing back the `__format__` method from `Vector2d` to `Vector`.

Vector Take #5: Formatting

The `__format__` method of `Vector` will resemble that of `Vector2d`, but instead of providing a custom display in polar coordinates, `Vector` will use spherical coordinates—also known as “hyperspherical” coordinates, because now we support *n* dimensions, and spheres are “hyperspheres” in 4D and beyond.[6] Accordingly, we’ll change the custom format suffix from `'p'` to `'h'`.

> **TIP**
>
> As we saw in “Formatted Displays”, when extending the Format Specification Mini-Language it’s best to avoid reusing format codes supported by built-in types. In particular, our extended mini-language also uses the float formatting codes `'eEfFgGn%'` in their original meaning, so we definitely must avoid these. Integers use `'bcdoxXn'` and strings use `'s'`. I picked `'p'` for `Vector2d` polar coordinates. Code `'h'` for hyperspherical coordinates is a good choice.

For example, given a `Vector` object in 4D space (`len(v) == 4`), the `'h'` code will produce a display like `<r, Φ₁, Φ₂, Φ₃>` where `r` is the magnitude (`abs(v)`) and the remaining numbers are the angular components Φ_1, Φ_2, Φ_3.

Here are some samples of the spherical coordinate format in 4D, taken from the doctests of *vector_v5.py* (see Example 12-16):

```
>>> format(Vector([-1, -1, -1, -1]), 'h')
'<2.0, 2.0943951023931957, 2.186276035465284,
3.9269908169872414>'
>>> format(Vector([2, 2, 2, 2]), '.3eh')
'<4.000e+00, 1.047e+00, 9.553e-01, 7.854e-01>'
>>> format(Vector([0, 1, 0, 0]), '0.5fh')
'<1.00000, 1.57080, 0.00000, 0.00000>'
```

Before we can implement the minor changes required in `__format__`, we need to code a pair of support methods: `angle(n)` to compute one of the angular coordinates (e.g., Φ_1), and `angles()` to return an iterable of all angular coordinates. I will not describe the math here; if you’re curious, Wikipedia’s "*n*-sphere” entry has the formulas I used to calculate the spherical coordinates from the Cartesian coordinates in the `Vector` components array.

Example 12-16 is a full listing of *vector_v5.py* consolidating all we've implemented since "Vector Take #1: Vector2d Compatible" and introducing custom formatting.

Example 12-16. vector_v5.py: doctests and all code for final Vector class; callouts highlight additions needed to support __format__

```
"""
A multidimensional ``Vector`` class, take 5

A ``Vector`` is built from an iterable of numbers::

    >>> Vector([3.1, 4.2])
    Vector([3.1, 4.2])
    >>> Vector((3, 4, 5))
    Vector([3.0, 4.0, 5.0])
    >>> Vector(range(10))
    Vector([0.0, 1.0, 2.0, 3.0, 4.0, ...])


Tests with two dimensions (same results as ``vector2d_v1.py``)::

    >>> v1 = Vector([3, 4])
    >>> x, y = v1
    >>> x, y
    (3.0, 4.0)
    >>> v1
    Vector([3.0, 4.0])
    >>> v1_clone = eval(repr(v1))
    >>> v1 == v1_clone
    True
    >>> print(v1)
    (3.0, 4.0)
    >>> octets = bytes(v1)
    >>> octets

b'd\\x00\\x00\\x00\\x00\\x00\\x00\\x08@\\x00\\x00\\x00\\x00\\x00\\x
00\\x10@'
    >>> abs(v1)
    5.0
    >>> bool(v1), bool(Vector([0, 0]))
    (True, False)
```

```
Test of ``.frombytes()`` class method:

    >>> v1_clone = Vector.frombytes(bytes(v1))
    >>> v1_clone
    Vector([3.0, 4.0])
    >>> v1 == v1_clone
    True


Tests with three dimensions::

    >>> v1 = Vector([3, 4, 5])
    >>> x, y, z = v1
    >>> x, y, z
    (3.0, 4.0, 5.0)
    >>> v1
    Vector([3.0, 4.0, 5.0])
    >>> v1_clone = eval(repr(v1))
    >>> v1 == v1_clone
    True
    >>> print(v1)
    (3.0, 4.0, 5.0)
    >>> abs(v1)  # doctest:+ELLIPSIS
    7.071067811...
    >>> bool(v1), bool(Vector([0, 0, 0]))
    (True, False)


Tests with many dimensions::

    >>> v7 = Vector(range(7))
    >>> v7
    Vector([0.0, 1.0, 2.0, 3.0, 4.0, ...])
    >>> abs(v7)  # doctest:+ELLIPSIS
    9.53939201...


Test of ``.__bytes__`` and ``.frombytes()`` methods::

    >>> v1 = Vector([3, 4, 5])
    >>> v1_clone = Vector.frombytes(bytes(v1))
    >>> v1_clone
    Vector([3.0, 4.0, 5.0])
    >>> v1 == v1_clone
    True
```

```
Tests of sequence behavior::

    >>> v1 = Vector([3, 4, 5])
    >>> len(v1)
    3
    >>> v1[0], v1[len(v1)-1], v1[-1]
    (3.0, 5.0, 5.0)


Test of slicing::

    >>> v7 = Vector(range(7))
    >>> v7[-1]
    6.0
    >>> v7[1:4]
    Vector([1.0, 2.0, 3.0])
    >>> v7[-1:]
    Vector([6.0])
    >>> v7[1,2]
    Traceback (most recent call last):
      ...
    TypeError: 'tuple' object cannot be interpreted as an integer


Tests of dynamic attribute access::

    >>> v7 = Vector(range(10))
    >>> v7.x
    0.0
    >>> v7.y, v7.z, v7.t
    (1.0, 2.0, 3.0)

Dynamic attribute lookup failures::

    >>> v7.k
    Traceback (most recent call last):
      ...
    AttributeError: 'Vector' object has no attribute 'k'
    >>> v3 = Vector(range(3))
    >>> v3.t
    Traceback (most recent call last):
      ...
    AttributeError: 'Vector' object has no attribute 't'
    >>> v3.spam
    Traceback (most recent call last):
      ...
    AttributeError: 'Vector' object has no attribute 'spam'
```

```
Tests of hashing::

    >>> v1 = Vector([3, 4])
    >>> v2 = Vector([3.1, 4.2])
    >>> v3 = Vector([3, 4, 5])
    >>> v6 = Vector(range(6))
    >>> hash(v1), hash(v3), hash(v6)
    (7, 2, 1)


Most hash codes of non-integers vary from a 32-bit to 64-bit
CPython build::

    >>> import sys
    >>> hash(v2) == (384307168202284039 if sys.maxsize > 2**32 else
357915986)
    True


Tests of ``format()`` with Cartesian coordinates in 2D::

    >>> v1 = Vector([3, 4])
    >>> format(v1)
    '(3.0, 4.0)'
    >>> format(v1, '.2f')
    '(3.00, 4.00)'
    >>> format(v1, '.3e')
    '(3.000e+00, 4.000e+00)'


Tests of ``format()`` with Cartesian coordinates in 3D and 7D::

    >>> v3 = Vector([3, 4, 5])
    >>> format(v3)
    '(3.0, 4.0, 5.0)'
    >>> format(Vector(range(7)))
    '(0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0)'


Tests of ``format()`` with spherical coordinates in 2D, 3D and 4D::

    >>> format(Vector([1, 1]), 'h')  # doctest:+ELLIPSIS
    '<1.414213..., 0.785398...>'
    >>> format(Vector([1, 1]), '.3eh')
    '<1.414e+00, 7.854e-01>'
    >>> format(Vector([1, 1]), '0.5fh')
    '<1.41421, 0.78540>'
```

```
    >>> format(Vector([1, 1, 1]), 'h')  # doctest:+ELLIPSIS
    '<1.73205..., 0.95531..., 0.78539...>'
    >>> format(Vector([2, 2, 2]), '.3eh')
    '<3.464e+00, 9.553e-01, 7.854e-01>'
    >>> format(Vector([0, 0, 0]), '0.5fh')
    '<0.00000, 0.00000, 0.00000>'
    >>> format(Vector([-1, -1, -1, -1]), 'h')  # doctest:+ELLIPSIS
    '<2.0, 2.09439..., 2.18627..., 3.92699...>'
    >>> format(Vector([2, 2, 2, 2]), '.3eh')
    '<4.000e+00, 1.047e+00, 9.553e-01, 7.854e-01>'
    >>> format(Vector([0, 1, 0, 0]), '0.5fh')
    '<1.00000, 1.57080, 0.00000, 0.00000>'
"""

from array import array
import reprlib
import math
import functools
import operator
import itertools  ❶


class Vector:
    typecode = 'd'

    def __init__(self, components):
        self._components = array(self.typecode, components)

    def __iter__(self):
        return iter(self._components)

    def __repr__(self):
        components = reprlib.repr(self._components)
        components = components[components.find('['):-1]
        return f'Vector({components})'

    def __str__(self):
        return str(tuple(self))

    def __bytes__(self):
        return (bytes([ord(self.typecode)]) +
                bytes(self._components))

    def __eq__(self, other):
        return (len(self) == len(other) and
                all(a == b for a, b in zip(self, other)))

    def __hash__(self):
```

```
        hashes = (hash(x) for x in self)
        return functools.reduce(operator.xor, hashes, 0)

    def __abs__(self):
        return math.hypot(*self)

    def __bool__(self):
        return bool(abs(self))

    def __len__(self):
        return len(self._components)

    def __getitem__(self, key):
        if isinstance(key, slice):
            cls = type(self)
            return cls(self._components[key])
        index = operator.index(key)
        return self._components[index]

    __match_args__ = ('x', 'y', 'z', 't')

    def __getattr__(self, name):
        cls = type(self)
        try:
            pos = cls.__match_args__.index(name)
        except ValueError:
            pos = -1
        if 0 <= pos < len(self._components):
            return self._components[pos]
        msg = f'{cls.__name__!r} object has no attribute {name!r}'
        raise AttributeError(msg)

    def angle(self, n):  ❷
        r = math.hypot(*self[n:])
        a = math.atan2(r, self[n-1])
        if (n == len(self) - 1) and (self[-1] < 0):
            return math.pi * 2 - a
        else:
            return a

    def angles(self):  ❸
        return (self.angle(n) for n in range(1, len(self)))

    def __format__(self, fmt_spec=''):
        if fmt_spec.endswith('h'):  # hyperspherical coordinates
            fmt_spec = fmt_spec[:-1]
            coords = itertools.chain([abs(self)],
                                     self.angles())  ❹
```

```
            outer_fmt = '<{}>'  ❺
        else:
            coords = self
            outer_fmt = '({})'  ❻
        components = (format(c, fmt_spec) for c in coords)  ❼
        return outer_fmt.format(', '.join(components))  ❽

    @classmethod
    def frombytes(cls, octets):
        typecode = chr(octets[0])
        memv = memoryview(octets[1:]).cast(typecode)
        return cls(memv)
```

❶ Import `itertools` to use `chain` function in `__format__`.

❷ Compute one of the angular coordinates, using formulas adapted from the *n*-sphere article.

❸ Create generator expression to compute all angular coordinates on demand.

❹ Use `itertools.chain` to produce *genexp* to iterate seamlessly over the magnitude and the angular coordinates.

❺ Configure spherical coordinate display with angular brackets.

❻ Configure Cartesian coordinate display with parentheses.

❼ Create generator expression to format each coordinate item on demand.

❽ Plug formatted components separated by commas inside brackets or parentheses.

NOTE

We are making heavy use of generator expressions in `__format__`, `angle`, and `angles` but our focus here is in providing `__format__` to bring `Vector` to the same implementation level as `Vector2d`. When we cover generators in Chapter 17 we'll use some of the code in `Vector` as examples, and then the generator tricks will be explained in detail.

This concludes our mission for this chapter. The `Vector` class will be enhanced with infix operators in Chapter 16, but our goal here was to explore techniques for coding special methods that are useful in a wide variety of collection classes.

Chapter Summary

The `Vector` example in this chapter was designed to be compatible with `Vector2d`, except for the use of a different constructor signature accepting a single iterable argument, just like the built-in sequence types do. The fact that `Vector` behaves as a sequence just by implementing `__getitem__` and `__len__` prompted a discussion of protocols, the informal interfaces used in duck-typed languages.

We then looked at how the `my_seq[a:b:c]` syntax works behind the scenes, by creating a `slice(a, b, c)` object and handing it to `__getitem__`. Armed with this knowledge, we made `Vector` respond correctly to slicing, by returning new `Vector` instances, just like a Pythonic sequence is expected to do.

The next step was to provide read-only access to the first few `Vector` components using notation such as `my_vec.x`. We did it by implementing `__getattr__`. Doing that opened the possibility of tempting the user to assign to those special components by writing `my_vec.x = 7`, revealing a potential bug. We fixed it by implementing `__setattr__` as well, to forbid assigning values to single-letter attributes. Very often, when you code a `__getattr__` you need to add `__setattr__` too, in order to avoid inconsistent behavior.

Implementing the `__hash__` function provided the perfect context for using `functools.reduce`, because we needed to apply the xor operator `^` in succession to the hashes of all `Vector` components to produce an aggregate hash code for the whole `Vector`. After applying `reduce` in `__hash__`, we used the `all` reducing built-in to create a more efficient `__eq__` method.

The last enhancement to `Vector` was to reimplement the `__format__` method from `Vector2d` by supporting spherical coordinates as an alternative to the default Cartesian coordinates. We used quite a bit of math and several generators to code `__format__` and its auxiliary functions, but these are implementation details—and we’ll come back to the generators in Chapter 17. The goal of that last section was to support a custom format, thus fulfilling the promise of a `Vector` that could do everything a `Vector2d` did, and more.

As we did in Chapter 11, here we often looked at how standard Python objects behave, to emulate them and provide a "Pythonic" look-and-feel to `Vector`.

In Chapter 16, we will implement several infix operators on `Vector`. The math will be much simpler than that in the `angle()` method here, but exploring how infix operators work in Python is a great lesson in OO design. But before we get to operator overloading, we'll step back from working on one class and look at organizing multiple classes with interfaces and inheritance, the subjects of Chapters 13 and 14.

Further Reading

Most special methods covered in the `Vector` example also appear in the `Vector2d` example from Chapter 11, so the references in "Further Reading" are all relevant here.

The powerful `reduce` higher-order function is also known as fold, accumulate, aggregate, compress, and inject. For more information, see Wikipedia's "Fold (higher-order function)" article, which presents applications of that higher-order function with emphasis on functional programming with recursive data structures. The article also includes a table listing fold-like functions in dozens of programming languages.

What's New in Python 2.5 has a short explanation of `__index__`, designed to support `__getitem__` methods, as we saw in "A Slice-Aware __getitem__". PEP 357—Allowing Any Object to be Used for Slicing details the need for it from the perspective of an implementor of a C-extension—Travis Oliphant, the primary creator of NumPy. Oliphant's many contributions to Python made it a leading scientific computing language, which then positioned it to lead the way in machine learning applications.

SOAPBOX

Protocols as Informal Interfaces

Protocols are not an invention of Python. The Smalltalk team, who also coined the expression “object oriented,” used “protocol” as a synonym for what we now call interfaces. Some Smalltalk programming environments allowed programmers to tag a group of methods as a protocol, but that was merely a documentation and navigation aid, and not enforced by the language. That’s why I believe “informal interface” is a reasonable short explanation for “protocol” when I speak to an audience that is more familiar with formal (and compiler enforced) interfaces.

Established protocols naturally evolve in any language that uses dynamic typing, that is, when type-checking is done at runtime because there is no static type information in method signatures and variables. Ruby is another important OO language that has dynamic typing and uses protocols.

In the Python documentation, you can often tell when a protocol is being discussed when you see language like “a file-like object.” This is a quick way of saying “something that behaves sufficiently like a file, by implementing the parts of the file interface that are relevant in the context.”

You may think that implementing only part of a protocol is sloppy, but it has the advantage of keeping things simple. Section 3.3 of the “Data Model” chapter suggests:

> *When implementing a class that emulates any built-in type, it is important that the emulation only be implemented to the degree that it makes sense for the object being modeled. For example, some sequences may work well with retrieval of individual elements, but extracting a slice may not make sense.*

When we don’t need to code nonsense methods just to fulfill some over-designed interface contract and keep the compiler happy, it becomes easier to follow the KISS principle.

On the other hand, if you want to use a type checker to verify your protocol implementations, then a stricter definition of protocol is required. That's what `typing.Protocol` provides.

I'll have more to say about protocols and interfaces in Chapter 13, where they are the main focus.

Origins of Duck Typing

I believe the Ruby community, more than any other, helped popularize the term "duck typing," as they preached to the Java masses. But the expression has been used in Python discussions before either Ruby or Python were "popular." According to Wikipedia, an early example of the duck analogy in object-oriented programming is a message to the Python-list by Alex Martelli from July 26, 2000: polymorphism (was Re: Type checking in python?). That's where the quote at the beginning of this chapter came from. If you are curious about the literary origins of the "duck typing" term, and the applications of this OO concept in many languages, check out Wikipedia's "Duck typing" entry.

A safe *format*, with Enhanced Usability

While implementing `__format__`, I did not take any precautions regarding `Vector` instances with a very large number of components, as we did in `__repr__` using `reprlib`. The reasoning is that `repr()` is for debugging and logging, so it must always generate some serviceable output, while `__format__` is used to display output to end users who presumably want to see the entire `Vector`. If you think this is dangerous, then it would be cool to implement a further extension to the format specifier mini-language.

Here is how I'd do it: by default, any formatted `Vector` would display a reasonable but limited number of components, say 30. If there are more elements than that, the default behavior would be similar to what the `reprlib` does: chop the excess and put `...` in its place. However, if the format specifier ended with the special `*` code, meaning "all," then the size limitation would be disabled. So a user who's unaware of the problem of very long displays will not be bitten by it by accident. But if the default limitation becomes a nuisance, then the presence of the `...` could lead the user to search the documentation and discover the `*` formatting code.

The Search for a Pythonic Sum

There's no single answer to "What is Pythonic?" just as there's no single answer to "What is beautiful?" Saying, as I often do, that it means using "idiomatic Python" is not 100% satisfactory, because what may be "idiomatic" for you may not be for me. One thing I know: "idiomatic" does not mean using the most obscure language features.

In the Python-list, there's a thread from April 2003 titled "Pythonic Way to Sum n-th List Element?". It's relevant to our discussion of `reduce` in this chapter.

The original poster, Guy Middleton, asked for an improvement on this solution, stating he did not like to use `lambda`:[7]

```
>>> my_list = [[1, 2, 3], [40, 50, 60], [9, 8, 7]]
>>> import functools
>>> functools.reduce(lambda a, b: a+b, [sub[1] for sub in
my_list])
60
```

That code uses lots of idioms: `lambda`, `reduce`, and a list comprehension. It would probably come last in a popularity contest, because it offends people who hate `lambda` and those who despise list comprehensions—pretty much both sides of a divide.

If you're going to use `lambda`, there's probably no reason to use a list comprehension—except for filtering, which is not the case here.

Here is a solution of my own that will please the `lambda` lovers:

```
>>> functools.reduce(lambda a, b: a + b[1], my_list, 0)
60
```

I did not take part in the original thread, and I wouldn't use that in real code, because I don't like `lambda` too much myself, but I wanted to show an example without a list comprehension.

The first answer came from Fernando Perez, creator of IPython, highlighting that NumPy supports *n*-dimensional arrays and *n*-dimensional slicing:

```
>>> import numpy as np
>>> my_array = np.array(my_list)
>>> np.sum(my_array[:, 1])
60
```

I think Perez's solution is cool, but Guy Middleton praised this next solution, by Paul Rubin and Skip Montanaro:

```
>>> import operator
>>> functools.reduce(operator.add, [sub[1] for sub in
my_list], 0)
60
```

Then Evan Simpson asked, "What's wrong with this?":

```
>>> total = 0
>>> for sub in my_list:
...     total += sub[1]
...
>>> total
60
```

Lots of people agreed that was quite Pythonic. Alex Martelli went as far as saying that's probably how Guido would code it.

I like Evan Simpson's code but I also like David Eppstein's comment on it:

> *If you want the sum of a list of items, you should write it in a way that looks like “the sum of a list of items”, not in a way that looks like “loop over these items, maintain another variable t, perform a sequence of additions”. Why do we have high level languages if not to express our intentions at a higher level and let the language worry about what low-level operations are needed to implement it?*

Then Alex Martelli comes back to suggest:

> *“The sum” is so frequently needed that I wouldn’t mind at all if Python singled it out as a built-in. But “reduce(operator.add, …” just isn’t a great way to express it, in my opinion (and yet as an old APL’er, and FP-liker, I should like it—but I don’t).*

Alex goes on to suggest a `sum()` function, which he contributed. It became a built-in in Python 2.3, released only three months after that conversation took place. So Alex’s preferred syntax became the norm:

```
>>> sum([sub[1] for sub in my_list])
60
```

By the end of the next year (November 2004), Python 2.4 was launched with generator expressions, providing what is now in my opinion the most Pythonic answer to Guy Middleton’s original question:

```
>>> sum(sub[1] for sub in my_list)
60
```

This is not only more readable than `reduce` but also avoids the trap of the empty sequence: `sum([])` is `0`, simple as that.

In the same conversation, Alex Martelli suggests the `reduce` built-in in Python 2 was more trouble than it was worth, because it encouraged coding idioms that were hard to explain. He was most convincing: the function was demoted to the `functools` module in Python 3.

Still, `functools.reduce` has its place. It solved the problem of our `Vector.__hash__` in a way that I would call Pythonic.

1 The `iter()` function is covered in Chapter 17, along with the `__iter__` method.

2 Attribute lookup is more complicated than this; we'll see the gory details in [Link to Come]. For now, this simplified explanation will do.

3 Although `__match_args__` exists to support pattern matching in Python 3.10, setting this attribute is harmless in previous versions of Python. In the *First Edition*, I named it `shortcut_names`. With the new name it does double duty: it supports positional patterns in `case` clauses, and it holds the names of the dynamic attributes supported by special logic in `__getattr__` and `__setattr__`.

4 The `sum`, `any`, and `all` cover the most common uses of `reduce`. See the discussion in "Modern Replacements for map, filter, and reduce".

5 We'll seriously consider the matter of `Vector([1, 2]) == (1, 2)` in "Operator Overloading 101".

6 The Wolfram Mathworld site has an article on Hypersphere; on Wikipedia, "hypersphere" redirects to the "*n*-sphere" entry.

7 I adapted the code for this presentation: in 2003, `reduce` was a built-in, but in Python 3 we need to import it; also, I replaced the names `x` and `y` with `my_list` and `sub`, for sub-list.

Chapter 13. Interfaces, Protocols, and ABCs

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 13th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Program to an interface, not an implementation.*[1]
>
> —Gamma, Helm, Johnson, Vlissides, First Principle of Object-Oriented Design

Object-oriented programming is all about interfaces. The best approach to understanding a type in Python is knowing the methods it provides—its interface—as discussed in "Types are defined by supported operations" (Chapter 8).

Depending on the programming language, we have one or more ways of defining and using interfaces. Since Python 3.8, we have four ways. They are depicted in the *Typing Map* (Figure 13-1). We can summarize them like this:

duck typing

Python’s default approach to typing from the beginning. We’ve been studying duck typing since Chapter 1.

goose typing

The approach supported by Abstract Base Classes (ABCs) since Python 2.6, which relies on runtime checks of objects against ABCs. *Goose typing* is a major subject in this chapter.

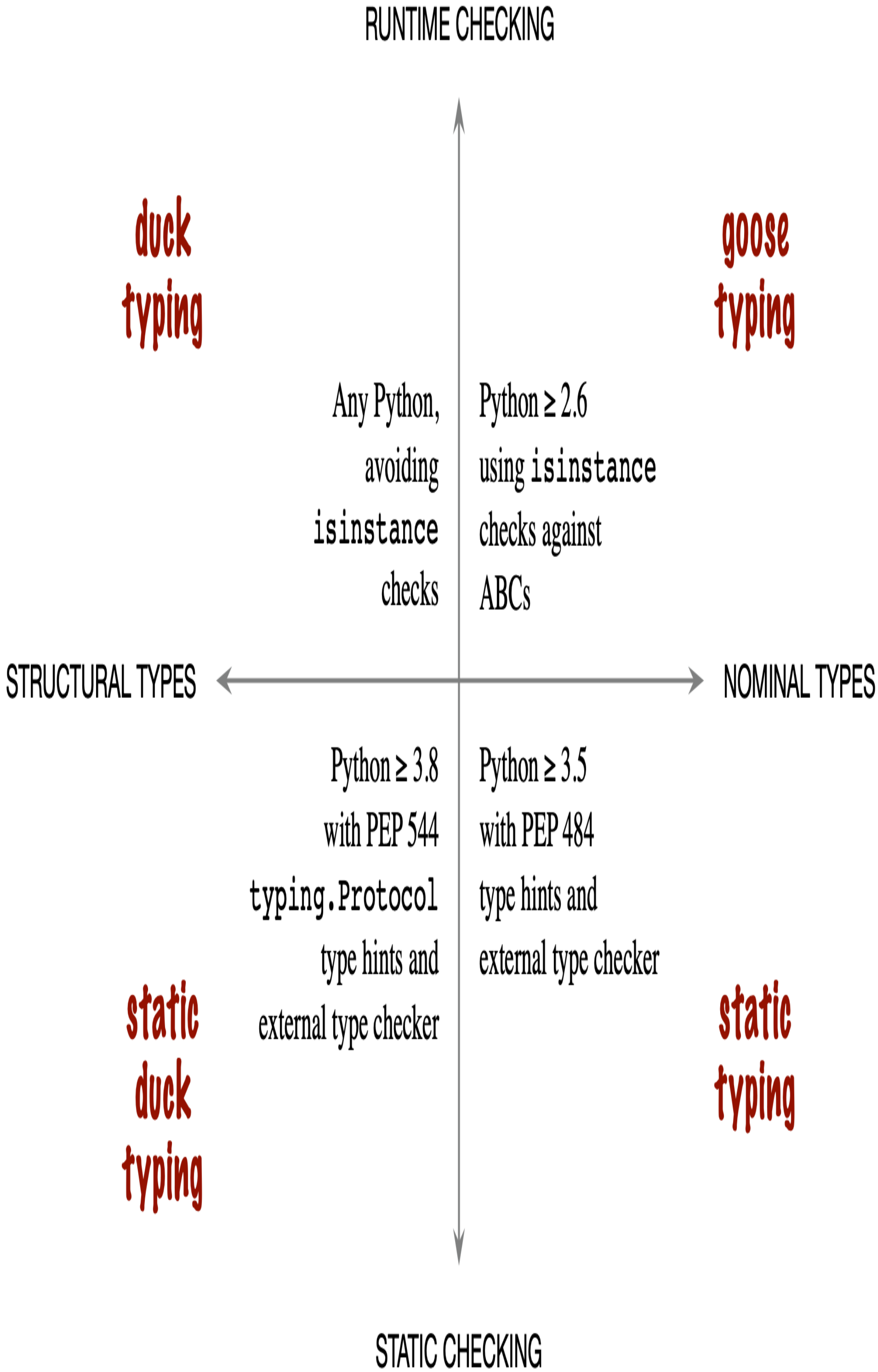
static typing

Traditional approach of statically-typed languages like C and Java; supported since Python 3.5 by the `typing` module, and enforced by external type checkers compliant with PEP 484—Type Hints. This is not the theme of this chapter. Most of Chapter 8 and the upcoming Chapter 15 are about static typing.

static duck typing

An approach made popular by the Go language; supported by subclasses of `typing.Protocol`—new in Python 3.8—also enforced by external type checkers. We first saw this in “Static Protocols” (Chapter 8).

The Typing Map



RUNTIME CHECKING
duck typing
goose typing
Any Python, avoiding isinstance checks
Python ≥ 2.6 using isinstance checks against ABCs
STRUCTURAL TYPES
NOMINAL TYPES
Python ≥ 3.8 with PEP 544 typing.Protocol type hints and external type checker
Python ≥ 3.5 with PEP 484 type hints and external type checker
static duck typing
static typing
STATIC CHECKING

Figure 13-1. The top half describes runtime type checking approaches using just the Python interpreter; the bottom requires an external static type checker such as MyPy or an IDE like PyCharm. The left quadrants cover typing based on the object's structure— i.e. the methods provided by the object, regardless of the name of its class or superclasses; the right quadrants depend on objects having explicitly named types: the name of the object's class, or the name of its superclasses.

These four typing approaches are complementary: they have different pros and cons. It doesn't make sense to dismiss any of them.

Each of these four approaches rely on interfaces to work, but static typing can be done—poorly—using only concrete types instead of interface abstractions like protocols and Abstract Base Classes. This chapter is about duck typing, goose typing and static duck typing—typing disciplines that revolve around interfaces.

This chapter is split in four top sections, addressing three of the four quadrants in the *Typing Map* (Figure 13-1):

- "Two kinds of protocols" compares the two forms of structural typing with protocols—i.e. the left-hand side of the *Typing Map*.
- "Programming ducks" dives deeper into Python's usual duck typing, including how to make it safer while preserving its major strength: flexibility.
- "Goose typing" explains the use of ABCs for stricter runtime type checking. This is the longest section, not because it's more important, but because there are more sections about *duck typing*, *static duck typing*, and *static typing* elsewhere in the book.
- "Static protocols" covers usage, implementation and design of `typing.Protocol` subclasses—useful for static and runtime type checking.

What's new in this chapter

This chapter was heavily edited and is about 24% longer than the corresponding *Chapter 11* in *Fluent Python, First Edition*. Although some sections and many paragraphs are the same, there's a lot of new content. These are the highlights:

- The chapter introduction and the *Typing Map* (Figure 13-1) are new. That's the key to most new content in this chapter—and all other chapters related to typing in Python ≥ 3.8.
- "Two kinds of protocols" explains the similarities and differences between dynamic and static protocols.
- "Defensive programming and "fail fast"" mostly reproduces content from the *First Edition*, but was updated and now has a section title to highlight its importance.
- "Static protocols" is all new. It builds on the initial presentation in "Static Protocols" (Chapter 8).
- I updated the UML class diagrams of `collections.abc` in Figure 13-2, Figure 13-3, and Figure 13-4 to include the `Collection` ABC added in Python 3.6.

Fluent Python, First Edition had a section encouraging use of the `numbers` ABCs for goose typing. In "The numbers ABCs and numeric protocols", I explain why you should use numeric static protocols from the `typing` module instead, if you plan to use static type checkers as well as runtime checks in the style of goose typing.

Two kinds of protocols

The word *protocol* has different meanings in computer science depending on context. A network protocol such as HTTP specifies commands that a client can send to a server, such as `GET`, `PUT`, and `HEAD`. We saw in "Protocols and Duck Typing" that an object protocol specifies methods which an object must provide to fulfill a role. The `FrenchDeck` example in Chapter 1 was demonstrated one object protocol, the sequence protocol: the methods that allow a Python object to behave as a sequence.

Implementing a full protocol may require several methods, but often it is OK to implement only part of it. Consider this `Vowels` class:

Example 13-1. Partial sequence protocol implementation with __getitem__.

```
>>> class Vowels:
...     def __getitem__(self, i):
...         return 'AEIOU'[i]
...
>>> v = Vowels()
>>> v[0]
'A'
>>> v[-1]
'U'
>>> for c in v: print(c)
...
A
E
I
O
U
>>> 'E' in v
True
>>> 'Z' in v
False
```

Implementing `__getitem__` is enough to allow retrieving items by index, and also to support iteration and the `in` operator. The `__getitem__` special method is really the key to the sequence protocol. Take a look at this entry from the Python/C API Reference Manual, section Sequence Protocol:

`int PySequence_Check(PyObject *o)`

> Return `1` if the object provides sequence protocol, and `0` otherwise. Note that it returns `1` for Python classes with a `__getitem__()` method unless they are `dict` subclasses […]

We expect a sequence to also support `len()`, by implementing `__len__`. `Vowels` has no `__len__` method, but it still behaves as a sequence in some contexts. And that may be enough for our purposes. That is why I like to say that a protocol is an "informal interface". That is also how protocols are understood in Smalltalk, the first Object-Oriented programming environment to use that term.

Except in pages about network programming, most uses of the word “protocol” in the Python documentation refer to these informal interfaces.

Now, with the adoption of PEP 544—Protocols: Structural subtyping (static duck typing) in Python 3.8, the word “protocol” has another meaning in Python—closely related, but different. As we saw in “Static Protocols” (Chapter 8), PEP 544 allows us to create subclasses of `typing.Protocol` to define one or more methods that a class must implement (or inherit) to satisfy a static type checker.

When I need to be specific, I will adopt these terms:

dynamic protocol

The informal protocols Python always had. Dynamic protocols are implicit, defined by convention and described in the documentation. Python’s most important dynamic protocols are supported by the interpreter itself, and are documented in the “Data Model” chapter of *The Python Language Reference*.

static protocol

A protocol as defined by PEP 544—Protocols: Structural subtyping (static duck typing), since Python 3.8. A static protocol has an explicit definition: a `typing.Protocol` subclass.

There are two key differences between them:

1. An object may implement only part of a dynamic protocol and still be useful; but to fulfill a static protocol, the object must provide every method declared in the protocol class, even if your program doesn’t need them all.

2. Static protocols can be verified by static type checkers, but dynamic protocols can’t.

Both kinds of protocols share the essential characteristic that a class never needs to declare that it supports a protocol by name, i.e. by inheritance.

In addition to static protocols, Python provides another way of defining an explicit interface in code: an Abstract Base Class (ABC).

The rest of this chapter covers dynamic and static protocols, as well as ABCs.

Programming ducks

Let’s start our discussion of dynamic protocols with two of the most important in Python: the sequence and iterable protocols. The interpreter goes out of its way to handle objects that provide even a minimal implementation of those protocols, as the next section explains.

Python Digs Sequences

The philosophy of the Python Data Model is to cooperate with essential dynamic protocols as much as possible. When it comes to sequences, Python tries hard to work with even the simplest implementations.

Figure 13-2 shows how the `Sequence` interface is formalized as an ABC. The Python interpreter and built-in sequences like `list`, `str` etc. do not rely on that ABC at all. I am using it only to describe what a full-fledged `Sequence` is expected to support.

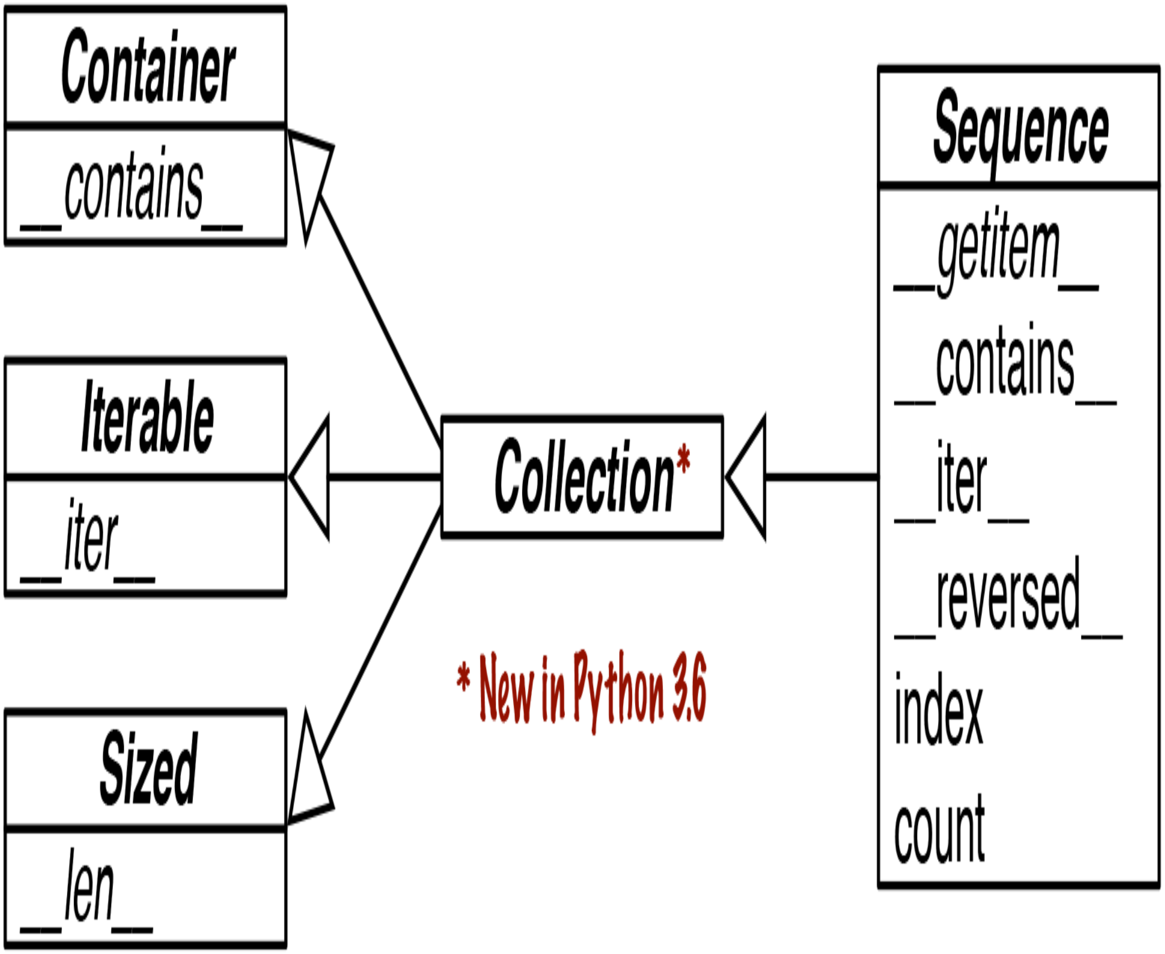


Figure 13-2. UML class diagram for the Sequence ABC and related abstract classes from collections.abc. Inheritance arrows point from subclass to its superclasses. Names in italic are abstract methods. Before Python 3.6, there was no `Collection` ABC—`Sequence` was a direct subclass of `Container`, `Iterable`, and `Sized`.

> **TIP**
>
> Most ABCs in the `collections.abc` module exist to formalize interfaces that are implemented by built-in objects and are implicitly supported by the interpreter—both of which predate the ABCs themselves. The ABCs are useful as starting points for new classes, and to support explicit type checking at runtime (a.k.a. *goose typing*) as well as type hints for static type checkers.

Studying Figure 13-2, we see that a correct subclass of `Sequence` must implement `__getitem__` and `__len__` (from `Sized`). All the other methods in `Sequence` are concrete, so subclasses can inherit their implementations—or provide better ones.

Now, recall the `Vowels` class in Example 13-1. It does not inherit from `abc.Sequence` and it only implements `__getitem__`.

There is no `__iter__` method, yet `Vowels` instances are iterable because—as a fallback—if Python finds a `__getitem__` method, it tries to iterate over the object by calling that method with integer indexes starting with `0`. Because Python is smart enough to iterate over `Vowels` instances, it can also make the `in` operator work even when the `__contains__` method is missing: it does a sequential scan to check if an item is present.

In summary, given the importance of sequence-like data structures, Python manages to make iteration and the `in` operator work by invoking `__getitem__` when `__iter__` and `__contains__` are unavailable.

The original `FrenchDeck` from Chapter 1 does not subclass `abc.Sequence` either, but it does implement both methods of the sequence protocol: `__getitem__` and `__len__`. See Example 13-2.

Example 13-2. A deck as a sequence of cards (same as Example 1-1)

```
import collections

Card = collections.namedtuple('Card', ['rank', 'suit'])

class FrenchDeck:
    ranks = [str(n) for n in range(2, 11)] + list('JQKA')
    suits = 'spades diamonds clubs hearts'.split()

    def __init__(self):
        self._cards = [Card(rank, suit) for suit in self.suits
                                        for rank in self.ranks]

    def __len__(self):
        return len(self._cards)

    def __getitem__(self, position):
        return self._cards[position]
```

Several of the examples in Chapter 1 work because of the special treatment Python gives to anything vaguely resembling a sequence. The iterable protocol in Python represents an extreme form of duck typing: the interpreter tries two different methods to iterate over objects.

To be clear: the behaviors I described in this section are implemented in the interpreter itself, mostly in C. They do not depend on methods from the `Sequence` ABC. For example, the concrete methods `__iter__` and `__contains__` in the `Sequence` class emulate the built-in behaviors of the Python interpreter. If you are curious, check source code of these methods in *Lib/_collections_abc.py*.

Now let's study another example emphasizing the dynamic nature of protocols—and why static type checkers have no chance of dealing with them.

Monkey-Patching: Implementing a Protocol at Runtime

> **NOTE**
>
> Monkey patching is dynamically changing a module, class, or function at runtime, to add features or fix bugs.[2] Because it does not change the source code like a regular patch, a monkey patch only affects the currently running instance of the program. The *gevent* networking library monkey patches parts of Python's standard library to allow lightweight concurrency without threads or `async/await`. Be aware that monkey patches depend on implementation details of the patched code, so they can easily break when libraries are updated.

The `FrenchDeck` class from Example 13-2 is missing an essential feature: it cannot be shuffled. Years ago when I first wrote the `FrenchDeck` example I did implement a `shuffle` method. Later I had a Pythonic insight: if a `FrenchDeck` acts like a sequence, then it doesn't need its own `shuffle` method because there is already `random.shuffle`, documented as "Shuffle the sequence *x* in place."

The standard `random.shuffle` function is used like this:

```
>>> from random import shuffle
>>> l = list(range(10))
```

```
>>> shuffle(l)
>>> l
[5, 2, 9, 7, 8, 3, 1, 4, 0, 6]
```

> **TIP**
>
> When you follow established protocols, you improve your chances of leveraging existing standard library and third-party code, thanks to duck typing.

However, if we try to shuffle a `FrenchDeck` instance, we get an exception, as in Example 13-3.

Example 13-3. random.shuffle cannot handle FrenchDeck

```
>>> from random import shuffle
>>> from frenchdeck import FrenchDeck
>>> deck = FrenchDeck()
>>> shuffle(deck)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File ".../random.py", line 265, in shuffle
    x[i], x[j] = x[j], x[i]
TypeError: 'FrenchDeck' object does not support item assignment
```

The error message is clear: “`'FrenchDeck'` object does not support item assignment.” The problem is that `shuffle` operates *in place*, by swapping items inside the collection, and `FrenchDeck` only implements the *immutable* sequence protocol. Mutable sequences must also provide a `__setitem__` method.

Because Python is dynamic, we can fix this at runtime, even at the interactive console. Example 13-4 shows how to do it.

Example 13-4. Monkey patching FrenchDeck to make it mutable and compatible with random.shuffle (continuing from Example 13-3)

```
>>> def set_card(deck, position, card):  ❶
...     deck._cards[position] = card
...
>>> FrenchDeck.__setitem__ = set_card  ❷
>>> shuffle(deck)  ❸
>>> deck[:5]
[Card(rank='3', suit='hearts'), Card(rank='4', suit='diamonds'),
```

```
Card(rank='4',
suit='clubs'), Card(rank='7', suit='hearts'), Card(rank='9',
suit='spades')]
```

❶ Create a function that takes `deck`, `position`, and `card` as arguments.

❷ Assign that function to an attribute named `__setitem__` in the `FrenchDeck` class.

❸ `deck` can now be shuffled because I added the necessary method of the mutable sequence protocol.

The signature of the `__setitem__` special method is defined in *The Python Language Reference* in "3.3.6. Emulating container types". Here I named the arguments `deck, position, card`—and not `self, key, value` as in the language reference—to show that every Python method starts life as a plain function, and naming the first argument `self` is merely a convention. This is OK in a console session, but in a Python source file it's much better to use `self`, `key`, and `value` as documented.

The trick is that `set_card` knows that the `deck` object has an attribute named `_cards`, and `_cards` must be a mutable sequence. The `set_card` function is then attached to the `FrenchDeck` class as the `__setitem__` special method. This is an example of *monkey patching*: changing a class or module at runtime, without touching the source code. Monkey patching is powerful, but the code that does the actual patching is very tightly coupled with the program to be patched, often handling private and undocumented attributes.

Besides being an example of monkey patching, Example 13-4 highlights the dynamic nature of protocols in dynamic duck typing: `random.shuffle` doesn't care about the class of the argument, it only needs the object to implement methods from the mutable sequence protocol. It doesn't even matter if the object was "born" with the necessary methods or if they were somehow acquired later.

Duck typing doesn't need to be wildly unsafe or hard to debug. The next section shows some useful code patterns to detect dynamic protocols without resorting to explicit checks.

Defensive programming and "fail fast"

Defensive programming is like defensive driving: a set of practices to enhance safety even when faced with careless programmers—or drivers.

Many bugs cannot be caught except at runtime—even in mainstream statically typed languages.[3] In a dynamically typed language, "fail fast" is excellent advice for safer and easier to maintain programs. Failing fast means raising runtime errors as soon as possible, for example, rejecting invalid arguments right a the beginning of a function body.

Here is one example: when you write code that accepts a sequence of items to process internally as a `list`, don't enforce a `list` argument by type checking. Instead, take the argument and immediately build a `list` from it. One example of this code pattern is the `__init__` method in Example 13-10, later in this chapter:

```
def __init__(self, iterable):
    self._balls = list(iterable)
```

That way you make your code more flexible, because the `list()` constructor handles any iterable that fits in memory. If the argument is not iterable, the call will fail fast with a very clear `TypeError` exception, right when the object is initialized. If you want to be more explict, you can wrap the `list()` call with `try/except` to customize the error message —but I'd use that extra code only on an external API, because the problem would be easy to see for maintainers of the codebase. Either way, the offending call will appear near the end of the traceback, making it straightforward to fix. If you don't catch the invalid argument in the class constructor, the program will blow up later, when some other method of the class needs to operate on `self._balls` and it is not a `list`. Then the root cause will be harder to find.

Of course, calling `list()` on the argument would be bad if the data shouldn't be copied, either because it's too large or because the function, by design, needs to change it in place for the benefit of the caller, like `random.shuffle` does. In that case, a runtime check like `isinstance(x, abc.MutableSequence)` would be the way to go.

If you are afraid to get an infinite generator—not a common issue—you can begin by calling `len()` on the argument. This would reject iterators, while safely dealing with tuples, arrays, and other existing or future classes that fully implement the `Sequence` interface. Calling `len()` is usually very cheap and an invalid argument will raise an error immediately.

On the other hand, if any iterable is acceptable, then call `iter(x)` as soon as possible to obtain an iterator, as we'll see in "Why Sequences Are Iterable: The `iter` Function". Again, if `x` is not iterable this will fail fast with an easy to debug exception.

In the cases I just described, a type hint could catch some problems earlier, but not all problems. Recall that the type `Any` is *consistent-with* every other type. Type inference may cause a variable to be tagged with the `Any` type. When that happens, the type checker is in the dark. In addition, type hints are not enforced at runtime. Fail fast is the last line of defense.

Defensive code leveraging duck types can also include logic to handle different types without using `isinstance()` or `hasattr()` tests.

One example is how we might emulate the handling of the `field_names` argument in `collections.namedtuple`: `field_names` accepts a single string with identifiers separated by spaces or commas, or a sequence of identifiers. Example 13-5 shows how I'd do it using duck typing.

Example 13-5. Duck typing to handle a string or an iterable of strings

```
try:  ❶
    field_names = field_names.replace(',', ' ').split()  ❷
except AttributeError:  ❸
    pass  ❹
field_names = tuple(field_names)  ❺
if not all(s.isidentifier() for s in field_names):  ❻
```

```
        raise ValueError('field_names must all be valid
identifiers')
```

❶ Assume it's a string (EAFP = it's easier to ask forgiveness than permission).

❷ Convert commas to spaces and split the result into a list of names.

❸ Sorry, `field_names` doesn't quack like a `str`: it has no `.replace`, or it returns something we can't `.split`.

❹ If `AttributeError` was raised, then `field_names` is not a `str` and we assume it was already an iterable of names.

❺ To make sure it's an iterable and to keep our own copy, create a tuple out of what we have. A `tuple` is more compact than `list`, and it also prevents my code from changing the names by mistake.

❻ Use `str.isidentifier` to ensure every name is a valid.

Example 13-5 shows one situation where duck typing is more expressive than static type hints. There is no way to spell a type hint that says "`field_names` must be a string of identifiers separated by spaces or commas". This is the relevant part of the `namedtuple` signature on typeshed: (see full source at stdlib/3/collections/*init*.pyi):

```
def namedtuple(
    typename: str,
    field_names: Union[str, Iterable[str]],
    *,
    # rest of signature omitted
```

As you can see, `field_names` is annotated as `Union[str, Iterable[str]]` which is OK as far as it goes, but is not enough to catch all possible problems.

After reviewing dynamic protocols, we move to a more explicit form of runtime type checking: goose typing.

Goose typing

> *An abstract class represents an interface.*[4]
>
> —Bjarne Stroustrup, Creator of C++

Python doesn't have an `interface` keyword. We use Abstract Base Classes (ABCs) to define explicit interfaces.

The *Python Glossary* entry for abstract base class has a good explanation of the value they bring to duck-typed languages:

abstract base class

> Abstract base classes complement duck-typing by providing a way to define interfaces when other techniques like `hasattr()` would be clumsy or subtly wrong (for example with magic methods). ABCs introduce virtual subclasses, which are classes that don't inherit from a class but are still recognized by `isinstance()` and `issubclass()`; see the `abc` module documentation.[5]

Goose typing is a runtime type checking approach that leverages ABCs. I will let Alex Martelli explain in "Waterfowl and ABCs".

> **NOTE**
>
> I am very grateful to my friends Alex Martelli and Anna Ravenscroft. I showed them the first outline of *Fluent Python* at OSCON 2013 and they encouraged me to submit it for publication with O'Reilly. Both later contributed with thorough tech reviews. Alex was already the most cited person in this book, and then he offered to write this essay. Take it away, Alex!

WATERFOWL AND ABCS

By Alex Martelli

I’ve been credited on Wikipedia for helping spread the helpful meme and sound-bite “*duck typing*” (i.e, ignoring an object’s actual type, focusing instead on ensuring that the object implements the method names, signatures, and semantics required for its intended use).

In Python, this mostly boils down to avoiding the use of `isinstance` to check the object’s type (not to mention the even worse approach of checking, for example, whether `type(foo) is bar`—which is rightly anathema as it inhibits even the simplest forms of inheritance!).

The overall *duck typing* approach remains quite useful in many contexts—and yet, in many others, an often preferable one has evolved over time. And herein lies a tale…

In recent generations, the taxonomy of genus and species (including but not limited to the family of waterfowl known as Anatidae) has mostly been driven by *phenetics*—an approach focused on similarities of morphology and behavior… chiefly, *observable* traits. The analogy to “duck typing” was strong.

However, parallel evolution can often produce similar traits, both morphological and behavioral ones, among species that are actually unrelated, but just happened to evolve in similar, though separate, ecological niches. Similar “accidental similarities” happen in programming, too—for example, consider the classic OOP example:

```
class Artist:
    def draw(self): ...

class Gunslinger:
    def draw(self): ...

class Lottery:
    def draw(self): ...
```

Clearly, the mere existence of a method named `draw`, callable without arguments, is far from sufficient to assure us that two objects `x` and `y` such that `x.draw()` and `y.draw()` can be called are in any way exchangeable or abstractly equivalent—nothing about the similarity of the semantics resulting from such calls can be inferred. Rather, we need a knowledgeable programmer to somehow positively *assert* that such an equivalence holds at some level!

In biology (and other disciplines) this issue has led to the emergence (and, on many facets, the dominance) of an approach that's an alternative to phenetics, known as *cladistics*—focusing taxonomical choices on characteristics that are inherited from common ancestors, rather than ones that are independently evolved. (Cheap and rapid DNA sequencing can make cladistics highly practical in many more cases, in recent years.)

For example, sheldgeese (once classified as being closer to other geese) and shelducks (once classified as being closer to other ducks) are now grouped together within the subfamily Tadornidae (implying they're closer to each other than to any other Anatidae, as they share a closer common ancestor). Furthermore, DNA analysis has shown, in particular, that the white-winged wood duck is not as close to the Muscovy duck (the latter being a shelduck) as similarity in looks and behavior had long suggested—so the wood duck was reclassified into its own genus, and entirely out of the subfamily!

Does this matter? It depends on the context! For such purposes as deciding how best to cook a waterfowl once you've bagged it, for example, specific observable traits (not all of them—plumage, for example, is de minimis in such a context), mostly texture and flavor (old-fashioned phenetics!), may be far more relevant than cladistics. But for other issues, such as susceptibility to different pathogens (whether you're trying to raise waterfowl in captivity, or preserve them in the wild), DNA closeness can matter much more…

So, by very loose analogy with these taxonomic revolutions in the world of waterfowls, I'm recommending supplementing (not entirely replacing—in certain contexts it shall still serve) good old *duck typing* with… *goose typing*!

What *goose typing* means is: `isinstance(obj, cls)` is now just fine… as long as `cls` is an abstract base class—in other words, `cls`'s metaclass is `abc.ABCMeta`.

You can find many useful existing abstract classes in `collections.abc` (and additional ones in the `numbers` module of *The Python Standard Library*).[6]

Among the many conceptual advantages of ABCs over concrete classes (e.g., Scott Meyer's "all non-leaf classes should be abstract"—see Item 33 in his book, *More Effective C++*), Python's ABCs add one major practical advantage: the `register` class method, which lets end-user code "declare" that a certain class becomes a "virtual" subclass of an ABC (for this purpose the registered class must meet the ABC's method name and signature requirements, and more importantly the underlying semantic contract—but it need not have been developed with any awareness of the ABC, and in particular need not inherit from it!). This goes a long way toward breaking the rigidity and strong coupling that make inheritance something to use with much more caution than typically practiced by most OOP programmers…

Sometimes you don't even need to register a class for an ABC to recognize it as a subclass!

That's the case for the ABCs whose essence boils down to a few special methods. For example:

```
>>> class Struggle:
...     def __len__(self): return 23
...
>>> from collections import abc
>>> isinstance(Struggle(), abc.Sized)
True
```

As you see, `abc.Sized` recognizes `Struggle` as "a subclass," with no need for registration, as implementing the special method named `__len__` is all it takes (it's supposed to be implemented with the proper syntax—callable without arguments—and semantics—returning a nonnegative integer denoting an object's "length"; any code that implements a specially named method, such as `__len__`, with arbitrary, non-compliant syntax and semantics has much worse problems anyway).

So, here's my valediction: whenever you're implementing a class embodying any of the concepts represented in the ABCs in `numbers`, `collections.abc`, or other framework you may be using, be sure (if needed) to subclass it from, or register it into, the corresponding ABC. At the start of your programs using some library or framework defining classes which have omitted to do that, perform the registrations yourself; then, when you must check for (most typically) an argument being, e.g, "a sequence," check whether:

```
isinstance(the_arg, collections.abc.Sequence)
```

And, *don't* define custom ABCs (or metaclasses) in production code… if you feel the urge to do so, I'd bet it's likely to be a case of "all problems look like a nail"-syndrome for somebody who just got a shiny new hammer—you (and future maintainers of your code) will be much happier sticking with straightforward and simple code, eschewing such depths. *Valē!*

To summarize, *goose typing* entails:

- Subclassing from ABCs to make it explict that you are implementing a previously defined interface.
- Runtime type checking using ABCs instead of concrete classes as the second argument for `isinstance` and `issubclass`.

Alex makes the point that inheriting from an ABC is more than implementing the required methods: it's also a clear declaration of intent by the developer. That intent can also be made explicit through registering a virtual subclass.

> **NOTE**
>
> Details of using `register` are covered in "A Virtual Subclass of an ABC", later in this chapter. For now, here is a brief example: given the `FrenchDeck` class, if I want it to pass a check like `issubclass(FrenchDeck, Sequence)`, I can make it a *virtual subclass* of the `Sequence` ABC with these lines:
>
> ```
> from collections.abc import Sequence
> Sequence.register(FrenchDeck)
> ```

The use of `isinstance` and `issubclass` becomes more acceptable if you are checking against ABCs instead of concrete classes. If used with concrete classes, type checks limit polymorphism—an essential feature of object oriented programming. But with ABCs these tests are more flexible. After all, if a component does not implement an ABC by subclassing—but does implement the required methods— it can always be registered after the fact so it passes those explicit type checks.

However, even with ABCs, you should beware that excessive use of `isinstance` checks may be a *code smell*—a symptom of bad OO design.

It's usually *not* OK to have a chain of `if/elif/elif` with `isinstance` checks performing different actions depending on the type of an object: you should be using polymorphism for that—i.e., design your classes so that the interpreter dispatches calls to the proper methods, instead of you hardcoding the dispatch logic in `if/elif/elif` blocks.

On the other hand, it's OK to perform an `isinstance` check against an ABC if you must enforce an API contract: "Dude, you have to implement this if you want to call me," as technical reviewer Lennart Regebro put it.

That’s particularly useful in systems that have a plug-in architecture. Outside of frameworks, duck typing is often simpler and more flexible than type checks.

Finally, in his essay, Alex reinforces more than once the need for restraint in the creation of ABCs. Excessive use of ABCs would impose ceremony in a language that became popular because it is practical and pragmatic. During the *Fluent Python* review process, Alex wrote in an e-mail:

> *ABCs are meant to encapsulate very general concepts, abstractions, introduced by a framework—things like “a sequence” and “an exact number.” [Readers] most likely don’t need to write any new ABCs, just use existing ones correctly, to get 99.9% of the benefits without serious risk of misdesign.*

Now let’s see goose typing in practice.

Subclassing an ABC

Following Martelli’s advice, we’ll leverage an existing ABC, `collections.MutableSequence`, before daring to invent our own. In Example 13-6, `FrenchDeck2` is explicitly declared a subclass of `collections.MutableSequence`.

Example 13-6. frenchdeck2.py: FrenchDeck2, a subclass of collections.MutableSequence

```
import collections
from collections.abc import MutableSequence

Card = collections.namedtuple('Card', ['rank', 'suit'])

class FrenchDeck2(MutableSequence):
    ranks = [str(n) for n in range(2, 11)] + list('JQKA')
    suits = 'spades diamonds clubs hearts'.split()

    def __init__(self):
        self._cards = [Card(rank, suit) for suit in self.suits
                                        for rank in self.ranks]

    def __len__(self):
        return len(self._cards)
```

```python
    def __getitem__(self, position):
        return self._cards[position]

    def __setitem__(self, position, value):  ❶
        self._cards[position] = value

    def __delitem__(self, position):  ❷
        del self._cards[position]

    def insert(self, position, value):  ❸
        self._cards.insert(position, value)
```

❶ `__setitem__` is all we need to enable shuffling…

❷ But subclassing `MutableSequence` forces us to implement `__delitem__`, an abstract method of that ABC.

❸ We are also required to implement `insert`, the third abstract method of `MutableSequence`.

Python does not check for the implementation of the abstract methods at import time (when the *frenchdeck2.py* module is loaded and compiled), but only at runtime when we actually try to instantiate `FrenchDeck2`. Then, if we fail to implement any of the abstract methods, we get a `TypeError` exception with a message such as `"Can't instantiate abstract class FrenchDeck2 with abstract methods __delitem__, insert"`. That's why we must implement `__delitem__` and `insert`, even if our `FrenchDeck2` examples do not need those behaviors: the `MutableSequence` ABC demands them.

As Figure 13-3 shows, not all methods of the `Sequence` and `MutableSequence` ABCs are abstract.

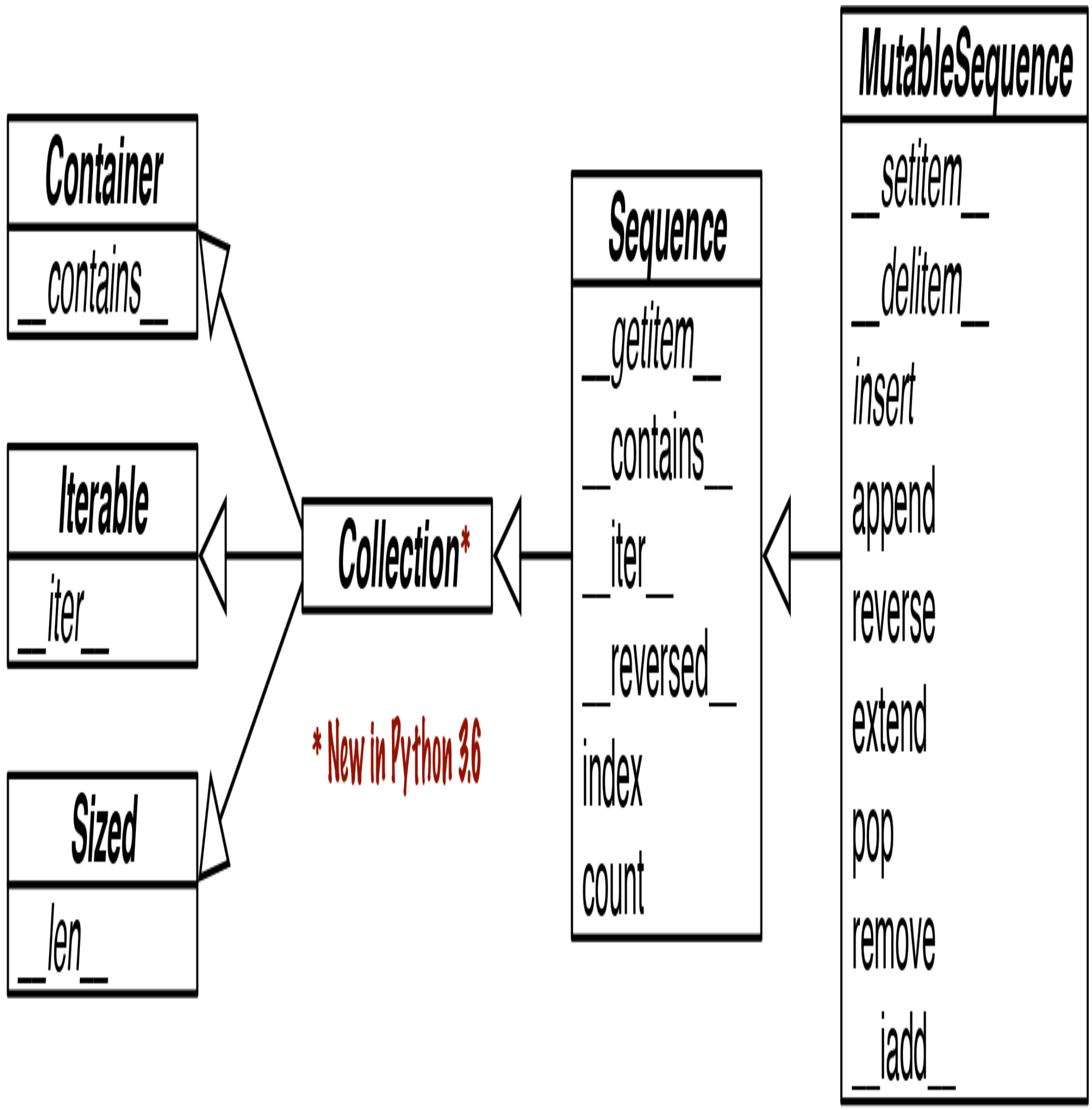


Figure 13-3. UML class diagram for the MutableSequence ABC and its superclasses from collections.abc (inheritance arrows point from subclasses to ancestors; names in italic are abstract classes and abstract methods)

To write `FrenchDeck2` as a subclass of `MutableSequence`, I had to pay the price of implementing `__delitem__` and `insert`, which my examples did not require. In return, `FrenchDeck2` inherits five concrete methods from `Sequence`: `__contains__`, `__iter__`, `__reversed__`, `index`, and `count`. From `MutableSequence`, it gets another six methods: `append`, `reverse`, `extend`, `pop`, `remove`, and `__iadd__`—which supports the `+=` operator for in-place concatenation.

The concrete methods in each `collections.abc` ABC are implemented in terms of the public interface of the class, so they work without any knowledge of the internal structure of instances.

> **TIP**
>
> As the coder of a concrete subclass, you may be able to override methods inherited from ABCs with more efficient implementations. For example, `__contains__` works by doing a sequential scan of the sequence, but if your concrete sequence keeps its items sorted, you can write a faster `__contains__` that does a binary search using `bisect` function (see [Link to Come]).

To use ABCs well, you need to know what's available. We'll review the collections ABCs next.

ABCs in the Standard Library

Since Python 2.6, the standard library provides several ABCs. Most are defined in the `collections.abc` module, but there are others. You can find ABCs in the `io` and `numbers` packages, for example. But the most widely used are in `collections.abc`.

> **TIP**
>
> There are two modules named `abc` in the standard library. Here we are talking about `collections.abc`. To reduce loading time, since Python 3.4 that module is implemented outside of the `collections` package—in *Lib/_collections_abc.py*—so it's imported separately from `collections`. The other `abc` module is just `abc` (i.e., *Lib/abc.py*) where the `abc.ABC` class is defined. Every ABC depends on the `abc` module, but we don't need to import it ourselves except to create a brand-new ABC.

Figure 13-4 is a summary UML class diagram (without attribute names) of 17 ABCs defined in `collections.abc`. The documentation of `collections.abc` has a nice table summarizing the ABCs, their relationships, and their abstract and concrete methods (called "mixin methods"). There is plenty of multiple inheritance going on in Figure 13-4. We'll devote most of Chapter 14 to multiple inheritance, but for now it's enough to say that it is usually not a problem when ABCs are concerned.[7]

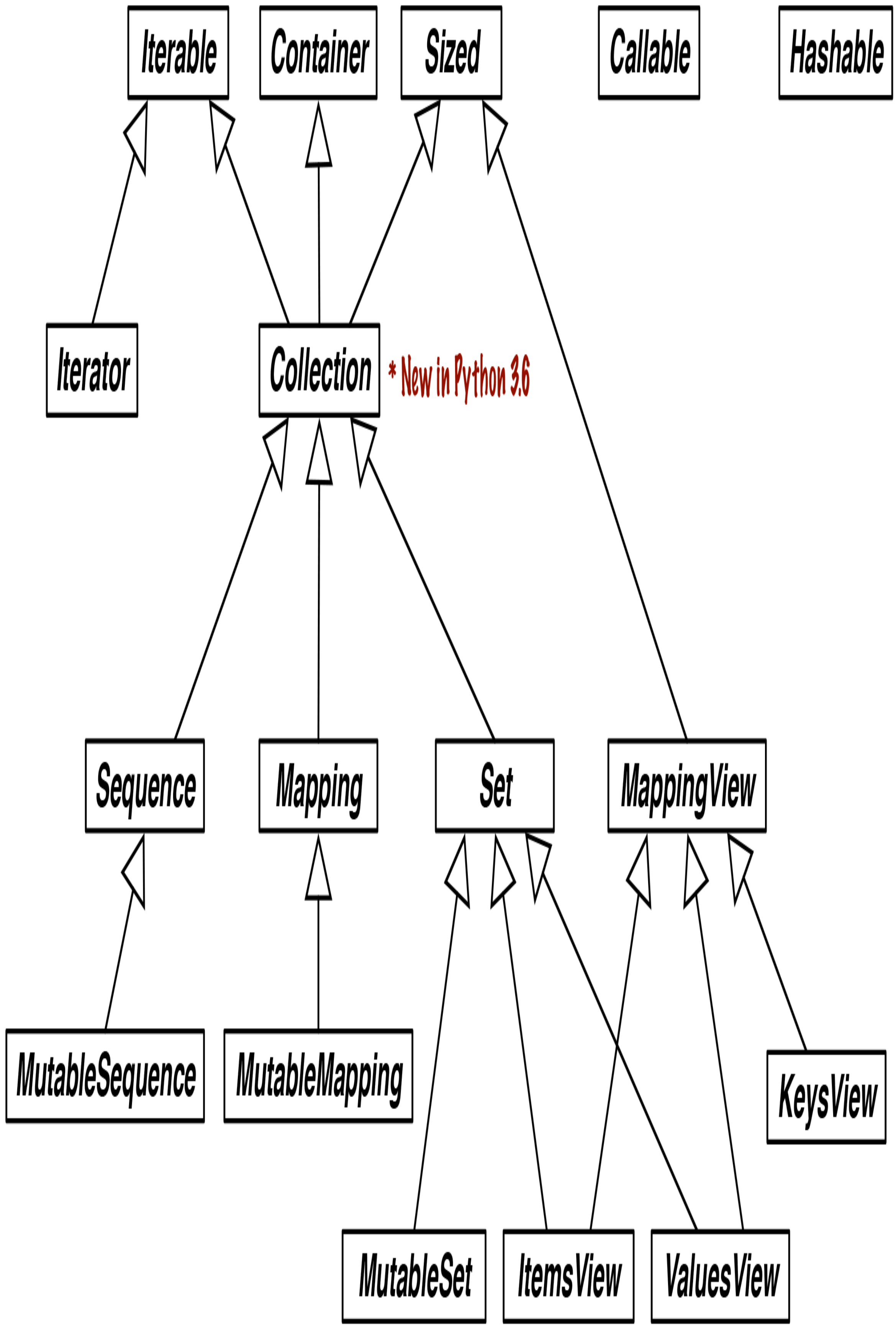

Iterable
Container
Sized
Callable
Hashable
Iterator
Collection
* New in Python 3.6
Sequence
Mapping
Set
MappingView
MutableSequence
MutableMapping
KeysView
MutableSet
ItemsView
ValuesView

Figure 13-4. UML class diagram for ABCs in collections.abc

Let’s review the clusters in Figure 13-4:

`Iterable`, `Container`, `Sized`

Every collection should either inherit from these ABCs or implement compatible protocols. `Iterable` supports iteration with `__iter__`, `Container` supports the `in` operator with `__contains__`, and `Sized` supports `len()` with `__len__`.

`Collection`

This ABC has no methods of its own, but was added in Python 3.6 to make it easier to subclass from `Iterable`, `Container`, and `Sized`.

`Sequence`, `Mapping`, `Set`

These are the main immutable collection types, and each has a mutable subclass. A detailed diagram for `MutableSequence` is in Figure 13-3; for `MutableMapping` and `MutableSet`, there are diagrams in Chapter 3 (Figures 3-1 and 3-2).

`MappingView`

In Python 3, the objects returned from the mapping methods `.items()`, `.keys()`, and `.values()` implement the interfaces defined in `ItemsView`, `KeysView`, and `ValuesView`, respectively. The first two also implement the rich interface of `Set`, with all the operators we saw in “Set Operations”.

`Iterator`

Note that iterator subclasses `Iterable`. We discuss this further in Chapter 17.

After looking at some existing ABCs, let’s practice goose typing by implementing an ABC from scratch and putting it to use. The goal here is not to encourage everyone to start creating ABCs left and right, but to learn how to read the source code of the ABCs you’ll find in the standard library and other packages.

`Callable`, *`Hashable`*

> These are not collections, but `collections.abc` was the first package to define ABCs in the standard library, and these two were deemed important enough to be included. They support type checking objects that must be callable or hashable.

For callable detection, the `callable(obj)` built-in function is more convenient than `insinstance(obj, Callable)`.

If `insinstance(obj, Hashable)` returns `False`, you can be certain that `obj` is not hashable. But if the return is `True`, it may be a false positive. The next box explains.

ISINSTANCE WITH HASHABLE AND ITERABLE CAN BE MISLEADING

It's easy to misinterpret the results of the `isinstance` and `issubclass` tests against the `Hashable` and `Iterable` ABCs.

If `isinstance(obj, Hashable)` returns `True`, that only means that the class of `obj` implements or inherits `__hash__`. But if `obj` is a `tuple` containing unhashable items, then `obj` is not hashable, despite the positive result of the `isinstance` check. Tech reviewer Jürgen Gmach pointed out that duck typing provides the most accurate way to determine if an instance is hashable: call `hash(obj)`. That call will raise `TypeError` if `obj` is not hashable.

On the other hand, even when `isinstance(obj, Iterable)` returns `False`, Python may still be able to iterate over `obj` using `__getitem__` with 0-based indices, as we saw in Chapter 1 and "Python Digs Sequences". The documentation for `collections.abc.Iterable` states:

> *The only reliable way to determine whether an object is iterable is to call `iter(obj)`.*

Defining and Using an ABC

TIP

This warning appeared in the *Interfaces* chapter of *Fluent Python, First Edition*:

> *ABCs, like descriptors and metaclasses, are tools for building frameworks. Therefore, only a small minority of Python developers can create ABCs without imposing unreasonable limitations and needless work on fellow programmers.*

Now ABCs have more potential use cases in type hints to support static typing. As discussed in "Abstract Base Classes", using ABCs instead of concrete types in function argument type hints gives more flexibility to the caller.

To justify creating an ABC, we need to come up with a context for using it as an extension point in a framework. So here is our context: imagine you need to display advertisements on a website or a mobile app in random order, but without repeating an ad before the full inventory of ads is shown. Now let's assume we are building an ad management framework called `ADAM`. One of its requirements is to support user-provided non-repeating random-picking classes.[8] To make it clear to `ADAM` users what is expected of a "non-repeating random-picking" component, we'll define an ABC.

In the literature about data structures, "stack" and "queue" describe abstract interfaces in terms of physical arrangements of objects. I will follow suit and use a real-world metaphor to name our ABC: bingo cages and lottery blowers are machines designed to pick items at random from a finite set, without repeating, until the set is exhausted.

The ABC will be named `Tombola`, after the Italian name of bingo and the tumbling container that mixes the numbers.

The `Tombola` ABC has four methods. The two abstract methods are:

`.load(…)`

put items into the container.

`.pick()`

remove one item at random from the container, returning it.

The concrete methods are:

`.loaded()`

return `True` if there is at least one item in the container.

`.inspect()`

return a `tuple` built from the items currently in the container, without changing its contents (the internal ordering is not preserved).

Figure 13-5 shows the `Tombola` ABC and three concrete implementations.

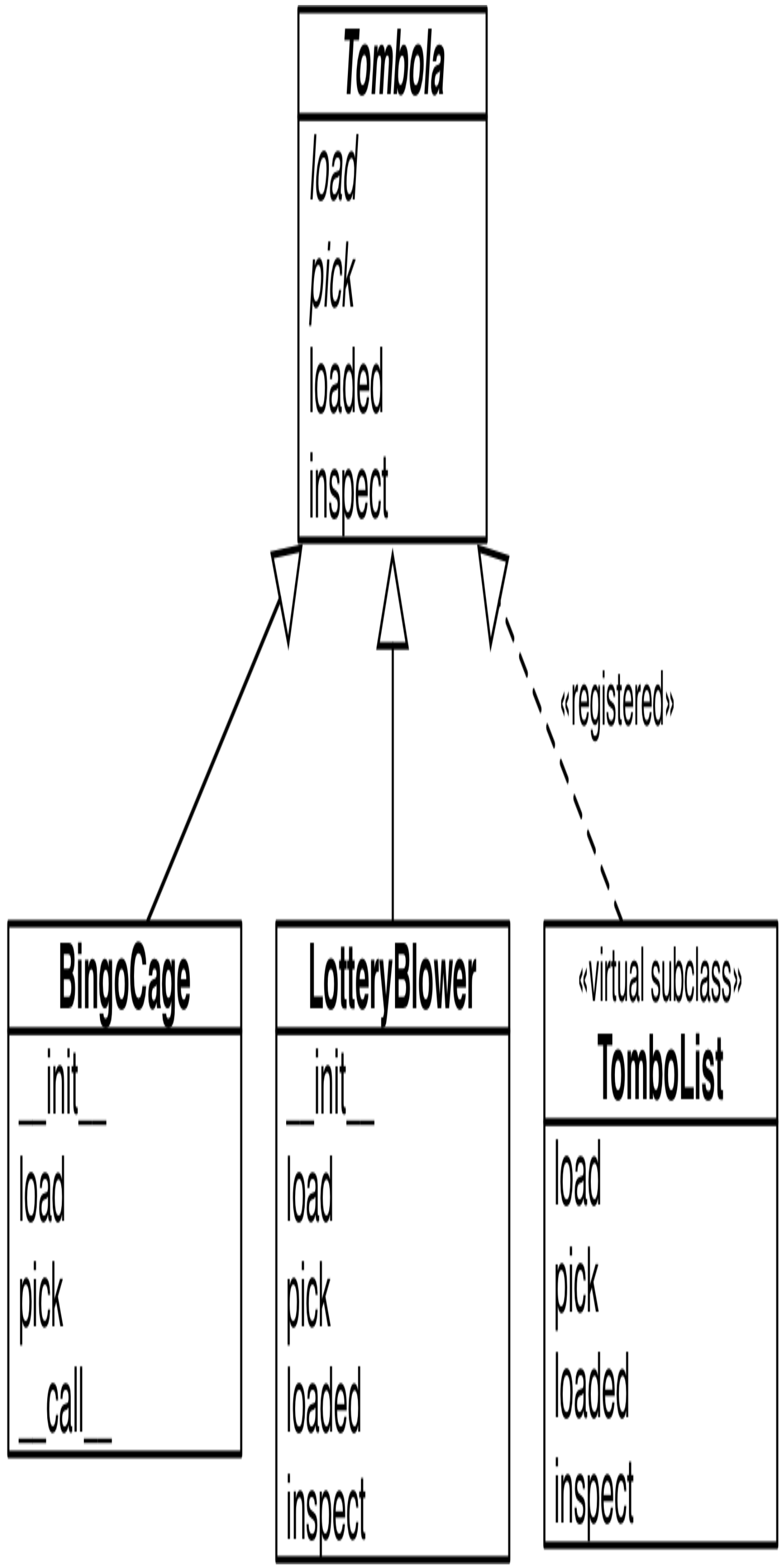

Tombola
load
pick
loaded
inspect
«registered»
BingoCage
__init__
load
pick
__call__
LotteryBlower
__init__
load
pick
loaded
inspect
«virtual subclass»
TomboList
load
pick
loaded
inspect

Figure 13-5. UML diagram for an ABC and three subclasses. The name of the Tombola ABC and its abstract methods are written in italics, per UML conventions. The dashed arrow is used for interface implementation—here I am using it to show that TomboList not only implements the Tombola interface, but is also registered as virtual subclass of Tombola—as we will see later in this chapter.[9]

Example 13-7 shows the definition of the `Tombola` ABC.

Example 13-7. tombola.py: Tombola is an ABC with two abstract methods and two concrete methods

```
import abc

class Tombola(abc.ABC):  ❶

    @abc.abstractmethod
    def load(self, iterable):  ❷
        """Add items from an iterable."""

    @abc.abstractmethod
    def pick(self):  ❸
        """Remove item at random, returning it.

        This method should raise `LookupError` when the instance is empty.
        """

    def loaded(self):  ❹
        """Return `True` if there's at least 1 item, `False` otherwise."""
        return bool(self.inspect())  ❺

    def inspect(self):
        """Return a sorted tuple with the items currently inside."""
        items = []
        while True:  ❻
            try:
                items.append(self.pick())
            except LookupError:
                break
        self.load(items)  ❼
        return tuple(items)
```

❶ To define an ABC, subclass `abc.ABC`.

❷

An abstract method is marked with the `@abstractmethod` decorator, and often its body is empty except for a docstring.[10]

❸ The docstring instructs implementers to raise `LookupError` if there are no items to pick.

❹ An ABC may include concrete methods.

❺ Concrete methods in an ABC must rely only on the interface defined by the ABC (i.e., other concrete or abstract methods or properties of the ABC).

❻ We can't know how concrete subclasses will store the items, but we can build the `inspect` result by emptying the `Tombola` with successive calls to `.pick()`…

❼ …then use `.load(…)` to put everything back.

> **TIP**
>
> An abstract method can actually have an implementation. Even if it does, subclasses will still be forced to override it, but they will be able to invoke the abstract method with `super()`, adding functionality to it instead of implementing from scratch. See the `abc` module documentation for details on `@abstractmethod` usage.

The code for the `.inspect()` method in Example 13-7 is silly but it shows that we can rely on `.pick()` and `.load(…)` to inspect what's inside the `Tombola` by picking all items and loading them back—without knowing how the items are actually stored. The point of this example is to highlight that it's OK to provide concrete methods in ABCs, as long as they only depend on other methods in the interface. Being aware of their internal data structures, concrete subclasses of `Tombola` may always override `.inspect()` with a smarter implementation, but they don't have to.

The `.loaded()` method in Example 13-7 has one line, but it’s expensive: it calls `.inspect()` to build the `tuple` just to apply `bool()` on it. This works, but a concrete subclass can do much better, as we’ll see.

Note that our roundabout implementation of `.inspect()` requires that we catch a `LookupError` thrown by `self.pick()`. The fact that `self.pick()` may raise `LookupError` is also part of its interface, but there is no way to make this explicit in Python, except in the documentation (see the docstring for the abstract `pick` method in Example 13-7.)

I chose the `LookupError` exception because of its place in the Python hierarchy of exceptions in relation to `IndexError` and `KeyError`, the most likely exceptions to be raised by the data structures used to implement a concrete `Tombola`. Therefore, implementations can raise `LookupError`, `IndexError`, `KeyError`, or a custom subclass of `LookupError` to comply. See Figure 13-6.

Figure 13-6. Part of the `Exception` class hierarchy.[11]

❶ `LookupError` is the exception we handle in `Tombola.inspect`;

❷ `IndexError` is the `LookupError` subclass raised when we try to get an item from a sequence with an index beyond the last position;

❸ `KeyError` is raised when we use a nonexistent key to get an item from a mapping.

We now have our very own `Tombola` ABC. To witness the interface checking performed by an ABC, let's try to fool `Tombola` with a defective implementation in Example 13-8.

Example 13-8. A fake Tombola doesn't go undetected

```
>>> from tombola import Tombola
>>> class Fake(Tombola):  ❶
...     def pick(self):
...         return 13
...
>>> Fake  ❷
<class '__main__.Fake'>
>>> f = Fake()  ❸
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: Can't instantiate abstract class Fake with abstract
method load
```

❶ Declare `Fake` as a subclass of `Tombola`.

❷ The class was created, no errors so far.

❸ `TypeError` is raised when we try to instantiate `Fake`. The message is very clear: `Fake` is considered abstract because it failed to implement `load`, one of the abstract methods declared in the `Tombola` ABC.

So we have our first ABC defined, and we put it to work validating a class. We'll soon subclass the `Tombola` ABC, but first we must cover some ABC coding rules.

ABC Syntax Details

The best way to declare an ABC is to subclass `abc.ABC` or any other ABC. `abc.ABC` is actually an instance of `abc.ABCMeta`—a special class factory, a.k.a. a "metaclass". We'll explain metaclasses in Chapter 25. For now, let's accept that metaclasses are used to build classes that are special in some way, and agree that an ABC is a special kind of class. For example, "regular" classes don't verify their subclasses for compliance to its interface, so this is a special behavior of ABCs.

Besides the `@abstractmethod`, the `abc` module defines the `@abstractclassmethod`, `@abstractstaticmethod`, and `@abstractproperty` decorators. However, these last three were deprecated in Python 3.3, when it became possible to stack decorators on top of `@abstractmethod`, making the others redundant. For example, the preferred way to declare an abstract class method is:

```
class MyABC(abc.ABC):
    @classmethod
    @abc.abstractmethod
    def an_abstract_classmethod(cls, ...):
        pass
```

> **WARNING**
>
> The order of stacked function decorators matters, and in the case of `@abstractmethod`, the documentation is explicit:
>
> > *When abstractmethod() is applied in combination with other method descriptors, it should be applied as the innermost decorator, …*[12]
>
> In other words, no other decorator may appear between `@abstractmethod` and the `def` statement.

Now that we got these ABC syntax issues covered, let's put `Tombola` to use by implementing two concrete descendants of it.

Subclassing an ABC

Given the `Tombola` ABC, we'll now develop two concrete subclasses that satisfy its interface. These classes were pictured in Figure 13-5, along with the virtual subclass to be discussed in the next section.

The `BingoCage` class in Example 13-9 is a variation of Example 7-8 using a better randomizer. This `BingoCage` implements the required abstract methods `load` and `pick`.

Example 13-9. bingo.py: BingoCage is a concrete subclass of Tombola

```
import random

from tombola import Tombola


class BingoCage(Tombola):  ❶

    def __init__(self, items):
        self._randomizer = random.SystemRandom()  ❷
        self._items = []
        self.load(items)  ❸

    def load(self, items):
        self._items.extend(items)
        self._randomizer.shuffle(self._items)  ❹

    def pick(self):  ❺
        try:
            return self._items.pop()
        except IndexError:
            raise LookupError('pick from empty BingoCage')

    def __call__(self):  ❻
        self.pick()
```

❶ This `BingoCage` class explicitly extends `Tombola`.

❷ Pretend we'll use this for online gaming. `random.SystemRandom` implements the `random` API on top of the `os.urandom(…)` function, which provides random bytes "suitable for cryptographic use" according to the `os` module docs.

❸ Delegate initial loading to the `.load(…)` method.

❹ Instead of the plain `random.shuffle()` function, we use the `.shuffle()` method of our `SystemRandom` instance.

❺ `pick` is implemented as in Example 7-8.

❻ `__call__` is also from Example 7-8. It's not needed to satisfy the `Tombola` interface, but there's no harm in adding extra methods.

`BingoCage` inherits the expensive `loaded` and the silly `inspect` methods from `Tombola`. Both could be overridden with much faster one-liners, as in Example 13-10. The point is: we can be lazy and just inherit the suboptimal concrete methods from an ABC. The methods inherited from `Tombola` are not as fast as they could be for `BingoCage`, but they do provide correct results for any `Tombola` subclass that correctly implements `pick` and `load`.

Example 13-10 shows a very different but equally valid implementation of the `Tombola` interface. Instead of shuffling the "balls" and popping the last, `LottoBlower` pops from a random position.

Example 13-10. lotto.py: LottoBlower is a concrete subclass that overrides the inspect and loaded methods from Tombola

```
import random

from tombola import Tombola


class LottoBlower(Tombola):

    def __init__(self, iterable):
        self._balls = list(iterable)  ❶

    def load(self, iterable):
        self._balls.extend(iterable)

    def pick(self):
        try:
            position = random.randrange(len(self._balls))  ❷
        except ValueError:
```

```
            raise LookupError('pick from empty LottoBlower')
        return self._balls.pop(position)  ❸

    def loaded(self):  ❹
        return bool(self._balls)

    def inspect(self):  ❺
        return tuple(self._balls)
```

❶ The initializer accepts any iterable: the argument is used to build a list.

❷ The `random.randrange(…)` function raises `ValueError` if the range is empty, so we catch that and throw `LookupError` instead, to be compatible with `Tombola`.

❸ Otherwise the randomly selected item is popped from `self._balls`.

❹ Override `loaded` to avoid calling `inspect` (as `Tombola.loaded` does in Example 13-7). We can make it faster by working with `self._balls` directly—no need to build a whole new `tuple`.

❺ Override `inspect` with one-liner.

Example 13-10 illustrates an idiom worth mentioning: in `__init__`, `self._balls` stores `list(iterable)` and not just a reference to `iterable` (i.e., we did not merely assign `self._balls = iterable`, aliasing the argument). As mentioned in "Defensive programming and "fail fast"", this makes our `LottoBlower` flexible because the `iterable` argument may be any iterable type. At the same time, we make sure to store its items in a `list` so we can `pop` items. And even if we always get lists as the `iterable` argument, `list(iterable)` produces a copy of the argument, which is a good practice considering we will be removing items from it and the client might not expect that the provided list will be changed.[13]

We now come to the crucial dynamic feature of goose typing: declaring virtual subclasses with the `register` method.

A Virtual Subclass of an ABC

An essential characteristic of goose typing—and one reason why it deserves a waterfowl name—is the ability to register a class as a *virtual subclass* of an ABC, even if it does not inherit from it. When doing so, we promise that the class faithfully implements the interface defined in the ABC—and Python will believe us without checking. If we lie, we'll be caught by the usual runtime exceptions.

This is done by calling a `register` class method on the ABC. The registered class then becomes a virtual subclass of the ABC, and will be recognized as such by `issubclass`, but it does not inherit any methods or attributes from the ABC.

> **WARNING**
>
> Virtual subclasses do not inherit from their registered ABCs, and are not checked for conformance to the ABC interface at any time, not even when they are instantiated. Also, static type checkers can't handle virtual subclasses at this time. For details, see Mypy issue 2922—ABCMeta.register support.

The `register` method is usually invoked as a plain function (see "Usage of register in Practice"), but it can also be used as a decorator. In Example 13-11, we use the decorator syntax and implement `TomboList`, a virtual subclass of `Tombola` depicted in Figure 13-7.

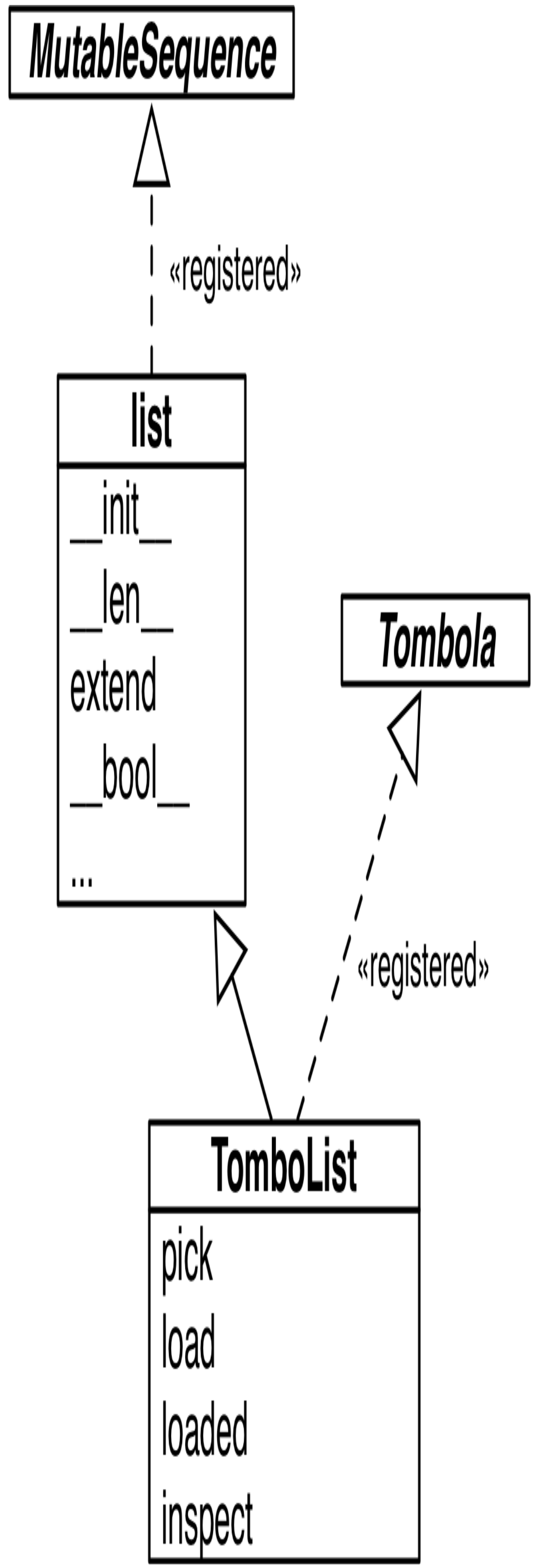

MutableSequence
«registered»
list
__init__
__len__
extend
__bool__
...
Tombola
«registered»
TomboList
pick
load
loaded
inspect

Figure 13-7. UML class diagram for the TomboList, a real subclass of list and a virtual subclass of Tombola

Example 13-11. tombolist.py: class TomboList is a virtual subclass of Tombola

```
from random import randrange

from tombola import Tombola

@Tombola.register  ❶
class TomboList(list):  ❷

    def pick(self):
        if self:  ❸
            position = randrange(len(self))
            return self.pop(position)  ❹
        else:
            raise LookupError('pop from empty TomboList')

    load = list.extend  ❺

    def loaded(self):
        return bool(self)  ❻

    def inspect(self):
        return tuple(self)

# Tombola.register(TomboList)  ❼
```

❶ `Tombolist` is registered as a virtual subclass of `Tombola`.

❷ `Tombolist` extends `list`.

❸ `Tombolist` inherits its boolean behavior from `list`, and that returns `True` if the list is not empty.

❹ Our `pick` calls `self.pop`, inherited from `list`, passing a random item index.

❺ `Tombolist.load` is the same as `list.extend`.

❻ `loaded` delegates to `bool`.[14]

7. It’s always possible to call `register` in this way, and it’s useful to do so when you need to register a class that you do not maintain, but which does fulfill the interface.

Note that because of the registration, the functions `issubclass` and `isinstance` act as if `TomboList` is a subclass of `Tombola`:

```
>>> from tombola import Tombola
>>> from tombolist import TomboList
>>> issubclass(TomboList, Tombola)
True
>>> t = TomboList(range(100))
>>> isinstance(t, Tombola)
True
```

However, inheritance is guided by a special class attribute named `__mro__`—the Method Resolution Order. It basically lists the class and its superclasses in the order Python uses to search for methods.[15] If you inspect the `__mro__` of `TomboList`, you’ll see that it lists only the “real” superclasses—`list` and `object`:

```
>>> TomboList.__mro__
(<class 'tombolist.TomboList'>, <class 'list'>, <class 'object'>)
```

`Tombola` is not in `Tombolist.__mro__`, so `Tombolist` does not inherit any methods from `Tombola`.

This concludes our `Tombola` ABC case study. In the next section, we’ll address how the `register` ABC function is used in the wild.

Usage of register in Practice

In Example 13-11, we used `Tombola.register` as a class decorator. Prior to Python 3.3, `register` could not be used like that—it had to be called as a plain function after the class definition, as suggested by the comment at the end of Example 13-11. However, even now, it’s more widely deployed as a function to register classes defined elsewhere. For example, in the source code for the `collections.abc` module, the built-in types `tuple`, `str`, `range`, and `memoryview` are registered as virtual subclasses of `Sequence` like this:

```
Sequence.register(tuple)
Sequence.register(str)
Sequence.register(range)
Sequence.register(memoryview)
```

Several other built-in types are registered to ABCs in *_collections_abc.py*. Those registrations happen only when that module is imported, which is OK because you'll have to import it anyway to get the ABCs. For example, you need to import `MutableMapping` from `collections.abc` to perform a check like `isinstance(my_dict, MutableMapping)`.

Subclassing an ABC or registering with an ABC are both explicit ways of making our classes pass `issubclass` checks—as well as `isinstance` checks, which also rely on `issubclass`. But some ABCs support structural typing as well. The next section explains.

Structural typing with ABCs

ABCs are mostly used with nominal typing. When a class `Sub` explicitly inherits from `AnABC`, or is registered with `AnABC`, the name of `AnABC` is linked to the `Sub` class—and that's how at runtime, `issubclass(AnABC, Sub)` returns `True`.

In contrast, structural typing is about looking at the structure of an object's public interface to determine its type: an object is *consistent-with* a type if it implements the methods defined in the type.[16] Dynamic and static duck typing are two approaches to structural typing.

It turns out that some ABCs also support structural typing. In his "Waterfowl and ABCs" essay, Alex shows that a class can be recognized as a subclass of an ABC even without registration. Here is his example again, with an added test using `issubclass`:

```
>>> class Struggle:
...     def __len__(self): return 23
...
>>> from collections import abc
>>> isinstance(Struggle(), abc.Sized)
True
>>> issubclass(Struggle, abc.Sized)
True
```

Class `Struggle` is considered a subclass of `abc.Sized` by the `issubclass` function (and, consequently, by `isinstance` as well) because `abc.Sized` implements a special class method named `__subclasshook__`.

The `__subclasshook__` for `Sized` checks whether the class argument has an attribute named `__len__`. If it does, then it is considered a virtual subclass of `Sized`. See Example 13-12.

Example 13-12. Definition of `Sized` from the source code of Lib/_collections_abc.py.

```
class Sized(metaclass=ABCMeta):

    __slots__ = ()

    @abstractmethod
    def __len__(self):
        return 0

    @classmethod
    def __subclasshook__(cls, C):
        if cls is Sized:
            if any("__len__" in B.__dict__ for B in C.__mro__):  ❶
                return True  ❷
        return NotImplemented  ❸
```

❶ If there is an attribute named `__len__` in the `__dict__` of any class listed in `C.__mro__` (i.e., `C` and its superclasses)…

❷ …return `True`, signaling that `C` is a virtual subclass of `Sized`.

❸ Otherwise return `NotImplemented` to let the subclass check proceed.

> **NOTE**
>
> If you are interested in the details of the subclass check, see the source code for the `ABCMeta.__subclasscheck__` method in Python 3.6: *Lib/abc.py*. Beware: it has lots of ifs and two recursive calls. In Python 3.7, Ivan Levkivskyi and INADA Naoki rewrote in C most of the logic for the `abc` module, for better performance. See Python issue #31333. The current implementation of `ABCMeta.__subclasscheck__` simply calls `_abc_subclasscheck`. The relevant C source code is in *cpython/Modules/_abc.c#L605*.

That's how `__subclasshook__` allows ABCs to support structural typing. You can formalize an interface with an ABC, you can make `isinstance` checks against that ABC, and still have a completely unrelated class pass an `issubclass` check because it implements a certain method (or because it does whatever it takes to convince a `__subclasshook__` to vouch for it).

Is it a good idea to implement `__subclasshook__` in our own ABCs? Probably not. All the implementations of `__subclasshook__` I've seen in the Python source code are in ABCs like `Sized` that declare just one special method, and they simply check for that special method name. Given their "special" status, you can be pretty sure that any method named `__len__` does what you expect. But even in the realm of special methods and fundamental ABCs, it can be risky to make such assumptions. For example, mappings implement `__len__`, `__getitem__`, and `__iter__`, but they are rightly not considered subtypes of `Sequence`, because you can't retrieve items using integer offsets or slices. That's why the `abc.Sequence` class does not implement `__subclasshook__`.

For ABCs that you and I may write, a `__subclasshook__` would be even less dependable. I am not ready to believe that any class named `Spam` that implements or inherits `load`, `pick`, `inspect`, and `loaded` is guaranteed to behave as a `Tombola`. It's better to let the programmer affirm it by subclassing `Spam` from `Tombola`, or registering it with `Tombola.register(Spam)`. Of course, your `__subclasshook__` could also check method signatures and other features, but I just don't think it's worthwhile.

Static protocols

> **NOTE**
>
> Static protocols were introduced in "Static Protocols" (Chapter 8). I considered delaying all coverage of protocols until the present Chapter 13, but decided that the initial presentation of type hints in functions had to include protocols because duck typing is an essential part of Python, and static type checking without protocols doesn't handle Pythonic APIs very well.

We will wrap up this chapter illustrating static protocols with two simple examples, and a discussion of numeric ABCs and protocols. Let's start by showing how a static protocol makes it possible to annotate and type check the `double()` function we first saw in "Types are defined by supported operations".

The typed double function

When introducing Python to programmers more used to statically typed languages, one of my favorite examples is this simple `double` function.

```
>>> def double(x):
...     return x * 2
...
>>> double(1.5)
3.0
>>> double('A')
'AA'
>>> double([10, 20, 30])
[10, 20, 30, 10, 20, 30]
>>> from fractions import Fraction
>>> double(Fraction(2, 5))
Fraction(4, 5)
```

Before static protocols were introduced, there was no practical way to add type hints to `double` without limiting its possible uses.[17]

Thanks to duck typing, `double` works even with types from the future, such as the enhanced `Vector` class that we'll see in "Overloading * for Scalar Multiplication" (Chapter 16).

```
>>> from vector_v7 import Vector
>>> double(Vector([11.0, 12.0, 13.0]))
Vector([22.0, 24.0, 26.0])
```

The initial implementation of type hints in Python was a nominal type system: the name of a type in an annotation had to match the name of the type of the actual arguments—or the name of one of its superclasses. Since it's impossible to name all types that implement a protocol by supporting the required operations, duck typing could not be described by type hints before Python 3.8.

Now, with `typing.Protocol` we can tell Mypy that `double` takes an argument `x` that supports `x * 2`. Here is how:

Example 13-13. `double_protocol.py`: definition of `double` using a `Protocol`.

```
from typing import TypeVar, Protocol

T = TypeVar('T')  ❶

class Repeatable(Protocol):
    def __mul__(self: T, repeat_count: int) -> T: ...  ❷

RT = TypeVar('RT', bound=Repeatable)  ❸

def double(x: RT) -> RT:  ❹
    return x * 2
```

❶ We'll use this `T` in the `__mul__` signature.

❷ `__mul__` is the essence of the `Repeatable` protocol. The `self` parameter is usually not annotated—its type is assumed to be the class.

Here we use `T` to make sure the result type is the same as the type of `self`. Also, note that `repeat_count` is limited to `int` in this protocol.

❸ The `RT` type variable is bounded by the `Repeatable` protocol: the type checker will require that the actual type implements `Repeatable`.

❹ Now the type checker is able to verify that the `x` parameter is an object that can be multiplied by an integer, and the return value has the same type as `x`.

This example shows why PEP 544 is titled "Protocols: Structural subtyping (static duck typing)". The nominal type of the actual argument `x` given to `double` is irrelevant as long as it quacks—that is, as long as it implements `__mul__`.

Runtime checkable static protocols

In the *Typing Map* (Figure 13-1), `typing.Protocol` appears in the static checking area—the bottom half of the diagram. However, when defining a `typing.Protocol` subclass, you can use the `@runtime_checkable` decorator to make that protocol support `isinstance/issubclass` checks at runtime. This works because `typing.Protocol` is an ABC, therefore it supports the `__subclasshook__` we saw in "Structural typing with ABCs".

As of Python 3.9, the `typing` module includes seven ready-to-use protocols that are runtime checkable. Here are two of them, quoted directly from the `typing` documentation:

`class typing.SupportsComplex`

An ABC with one abstract method `__complex__`.

`class typing.SupportsFloat`

> An ABC with one abstract method `__float__`.

These protocols are designed to check numeric types for “convertibility”: if an object `o` implements `__complex__`, then you should be able to get a `complex` by invoking `complex(o)`—because the `__complex__` special method exists to support the `complex()` built-in function.

This is the source code for the `typing.SupportsComplex` protocol:

Example 13-14.

```
@runtime_checkable
class SupportsComplex(Protocol):
    """An ABC with one abstract method __complex__."""
    __slots__ = ()

    @abstractmethod
    def __complex__(self) -> complex:
        pass
```

The key is the `__complex__` abstract method.[18] During static type checking, an object will be considered *consistent-with* the `SupportsComplex` protocol if it implements a `__complex__` method that takes only `self` and returns a `complex`.

Thanks to the `@runtime_checkable` class decorator applied to `SupportsComplex`, that protocol can also be used with `isinstance` checks:

Example 13-15. Using `SupportsComplex` at runtime.

```
>>> from typing import SupportsComplex
>>> import numpy as np
>>> c64 = np.complex64(3+4j)  ❶
>>> isinstance(c64, complex)   ❷
False
>>> isinstance(c64, SupportsComplex)  ❸
True
>>> c = complex(c64)  ❹
>>> c
(3+4j)
>>> isinstance(c, SupportsComplex) ❺
False
```

```
>>> complex(c)
(3+4j)
```

❶ `complex64` is one of five complex number types provided by NumPy.

❷ None of the NumPy complex types subclass the built-in `complex`.

❸ But NumPy's complex types implement `__complex__` so they comply with the `SupportsComplex` protocol.

❹ Therefore, you can create built-in `complex` objects from them.

❺ Sadly, the `complex` built-in type does not implement `__complex__` although `complex(c)` works fine if `c` is a `complex`.

As a result of that last point, if you want to test whether an object `c` is a `complex` or `SupportsComplex` you can provide a tuple of types as the second argument to `isinstance`, like this:

```
isinstance(c, (complex, SupportsComplex))
```

An alternative would be to use the `Complex` ABC, defined in the `numbers` module. The built-in `complex` type and the NumPy `complex64` and `complex128` types are all registered as virtual subclasses of `numbers.Complex`, therefore this works:

```
>>> import numbers
>>> isinstance(c, numbers.Complex)
True
>>> isinstance(c64, numbers.Complex)
True
```

I recommended using the `numbers` ABCs in *Fluent Python, First Edition* but now that's no longer good advice, because those ABCs are not recognized by the static type checkers, as we'll see in "The numbers ABCs and numeric protocols".

In this section I wanted to demonstrate that a runtime checkable protocol works with `isinstance`, but it turns out this is example not a particularly good use case of `isinstance`, as the sidebar “Duck typing is your friend” explains.

> **TIP**
>
> If you’re using an external type checker, there is one advantage of explict `isinstance` checks: when you write an `if` statement where the condition is `isinstance(o, MyType)`, then Mypy can infer that inside the `if` block the type of the `o` object is *consistent-with* `MyType`.

DUCK TYPING IS YOUR FRIEND

Very often at runtime, duck typing is the best approach for type checking: instead of calling `isinstance` or `hasattr`, just try the operations you need to do on the object, and handle exceptions as needed. Here is a concrete example.

Continuing the previous discussion—given an object `o` that I need to use as a complex number, this would be one approach:

```
if isinstance(o, (complex, SupportsComplex)):
    # do something that requires `o` to be convertible to
complex
else:
    raise TypeError('o must be convertible to complex')
```

The *goose typing* approach would be to use the `numbers.Complex` ABC:

```
if isinstance(o, numbers.Complex):
    # do something with `o`, an instance of `Complex`
else:
    raise TypeError('o must be an instance of Complex')
```

However, I prefer to leverage duck typing and do this, using the EAFP principle—it's easier to ask forgiveness than permission:

```
try:
    c = complex(o)
except TypeError as exc:
    raise TypeError('o must be convertible to complex') from
exc
```

And, if all you're going to do is raise a `TypeError` anyway, then I'd omit the `try/except/raise` statements and just write this:

```
c = complex(o)
```

In this last case, if `o` is not an acceptable type, Python will raise an exception with a very clear message: For example, this is what I get if `o` is a `tuple`:

```
TypeError: complex() first argument must be a string or a
number, not 'tuple'
```

I find the duck typing approach much better in this case.

Now that we've seen how to use static protocols at runtime with preexisting types like `complex` and `numpy.complex64`, let's see how to use them with a user-defined class.

Supporting a static protocol

Recall the `Vector2d` class we built in Chapter 11. Given that a `complex` number and a `Vector2d` instance both consist of a pair of floats, it makes sense to support conversion from `Vector2d` to `complex`.

Example 13-16 shows the implementation of the `__complex__` method to enhance the last version of `Vector2d` we saw in Example 11-11. For completeness, we can support the inverse operation with a `fromcomplex` class method to build a `Vector2d` from a `complex`.

Example 13-16. `vector2d_v4.py`: methods for converting to and from `complex`.

```
    def __complex__(self):
        return complex(self.x, self.y)

    @classmethod
    def fromcomplex(cls, datum):
        return cls(datum.real, datum.imag)  ❶
```

❶ This assumes that `datum` has `.real` and `.imag` attributes. We'll see a better implementation in Example 13-17.

Given the code above, and the `__abs__` method the `Vector2d` already had in Example 11-11, we get these features:

```
>>> from typing import SupportsComplex, SupportsAbs
>>> from vector2d_v4 import Vector2d
>>> v = Vector2d(3, 4)
>>> isinstance(v, SupportsComplex)
True
>>> isinstance(v, SupportsAbs)
True
>>> complex(v)
(3+4j)
>>> abs(v)
5.0
>>> Vector2d.fromcomplex(3+4j)
Vector2d(3.0, 4.0)
```

For runtime type checking, Example 13-16 is fine, but for better static coverage and error reporting with Mypy, the `__abs__`, `__complex__` and `fromcomplex` methods should get type hints as shown in Example 13-17.

Example 13-17. `vector2d_v5.py`: adding annotations to the methods under study.

```
    def __abs__(self) -> float:  ❶
        return math.hypot(self.x, self.y)

    def __complex__(self) -> complex:  ❷
        return complex(self.x, self.y)

    @classmethod
    def fromcomplex(cls, datum: SupportsComplex) -> Vector2d:  ❸
        c = complex(datum)  ❹
        return cls(c.real, c.imag)
```

❶ The `float` return annotation is needed, otherwise Mypy infers `Any`, and doesn’t check the body of the method.

❷ Even without the annotation, Mypy was able to infer that this returns a `complex`. The annotation prevents a warning, depending on your Mypy configuration.

❸ Here `SupportsComplex` ensures the `datum` is convertible.

❹ This explicit conversion is necessary, because the `SupportsComplex` type does not declare `.real` and `.imag` attributes, used in the next line. For example, `Vector2d` doesn't have those attributes, but implements `__complex__`.

The return type of `fromcomplex` can be `Vector2d` if `from __future__ import annotations` appears at the top of the module. That import causes type hints to be stored as strings, without being evaluated at import time—when functions definitions are evaluated. Without the `__future__` import of `annotations`, `Vector2d` is an invalid reference at this point (the class is not fully defined yet) and should be written as a string: `'Vector2d'`—as if it were a forward reference. This `__future__` import was introduced by PEP 563—Postponed Evaluation of Annotations, implemented in Python 3.7. That behavior was scheduled to become default in 3.10, but the change was delayed to a later version.[19] When that happens, the import will be redundant but harmless.

TYPE HINTS ARE IGNORED AT RUNTIME

Type hints are ignored at runtime, including for `isinstance` or `issubclass` checks against static protocols. For example, this means that any class with a `__float__` method is considered—at runtime—a virtual subclass of `SupportsFloat`, even if the `__float__` method exists only to raise a clearly worded exception[20]:

```
>>> from typing import SupportsFloat
>>> c = 3+4j
>>> isinstance(c, SupportsFloat)
True
>>> c.__float__
<method-wrapper '__float__' of complex object at
0x1065dc370>
>>> float(c)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: can't convert complex to float
```

Next, let's see how to create—and later, extend—a new static protocol.

Designing a static protocol

While studying goose typing, we saw the `Tombola` ABC in "Defining and Using an ABC". Here we'll see how to define a similar interface using a static protocol.

The `Tombola` ABC specifies two methods: `pick` and `load`. We could define a static protocol with these two methods as well, but I learned from the Go community that single-method protocols make static duck typing more useful and flexible. The Go standard library has several interfaces like `Reader`—an interface for I/O that requires just a `read` method. After a while, if you realize a more complete protocol is required, you can combine two or more protocols to define a new one.

Using a container that picks items at random may or may not require reloading the container, but it certainly needs a method to do the actual pick, so that's the method I will choose for the minimal `RandomPicker` protocol. The code for that protocol is in Example 13-18 and its use is demonstrated by tests in Example 13-19.

Example 13-18. `randompick.py`: definition of `RandomPicker`.

```
from typing import Protocol, runtime_checkable, Any

@runtime_checkable
class RandomPicker(Protocol):
    def pick(self) -> Any: ...
```

> **NOTE**
>
> The `pick` method returns `Any`. In "Implementing a generic static protocol" we will see how to make `RandomPicker` a generic type with a parameter to let users of the protocol to specify the return type of the `pick` method.

Example 13-19. `randompick_test.py`: `RandomPicker` in use.

```
import random
from typing import Any, Iterable, TYPE_CHECKING

from randompick import RandomPicker  ❶

class SimplePicker:  ❷
    def __init__(self, items: Iterable) -> None:
        self._items = list(items)
        random.shuffle(self._items)

    def pick(self) -> Any:  ❸
        return self._items.pop()

def test_isinstance() -> None:  ❹
    popper: RandomPicker = SimplePicker([1])  ❺
    assert isinstance(popper, RandomPicker)  ❻

def test_item_type() -> None:  ❼
    items = [1, 2]
    popper = SimplePicker(items)
    item = popper.pick()
    assert item in items
    if TYPE_CHECKING:
        reveal_type(item)  ❽
    assert isinstance(item, int)
```

❶ It’s not necessary to import the static protocol to define a class that implements it. Here I imported `RandomPicker` only to use it `test_isintance` below.

❷ `SimplePicker` implements `RandomPicker`—but it does not subclass it. This is static duck typing in action.

❸ `Any` is the default return type, so this annotation is not strictly necessary, but it does make it more clear that we are implementing the `RandomPicker` protocol as defined in Example 13-18.

❹ Don’t forget to add `-> None` hints to your tests, if you want Mypy to look at them.

❺ I added a type hint for the `popper` variable to show that Mypy understands that `SimplePicker` is *consistent-with*.

❻ This test proves that an instance of `SimplePicker` is also an instance of `RandomPicker`. This works because of the `@runtime_checkable` decorator applied to `RandomPicker`, and because `SimplePicker` has a `pick` method as required.

❼ This test invokes the `pick` method from a `SimplePicker`, verifies that it returns one of the items given to `SimplePicker`, and then does static and runtime checks on the returned item.

❽ This line generates a note in the output of Mypy.

As we saw in Example 8-22, `reveal_type` is a “magic” function recognized by Mypy—that’s why it is not imported and we can only call it inside `if` blocks protected by `typing.TYPE_CHECKING` which is only `True` in the eyes of a static type checker, but is `False` at runtime.

Both tests in Example 13-19 pass. Mypy does not see any errors in that code either, and shows the result of the `reveal_type` on the `item` returned by `pick`:

```
$ mypy randompick_test.py
randompick_test.py:24: note: Revealed type is 'Any'
```

Next, we'll see how to extend a protocol, adding a method.

Extending a protocol

As I mentioned at the start of the previous section, Go developers advocate to err on the side of minimalism when defining interfaces—their name for static protocols. Many of the most widely used Go interfaces have a single method.

When practice reveals that a protocol with more methods is useful, instead of adding methods to the original protocol it's better to derive a new protocol from it. Extending a static protocol in Python has a few caveats, as Example 13-20 shows.

Example 13-20. `randompickload.py`: extending `RandomPicker`.

```
from typing import Protocol, runtime_checkable
from randompick import RandomPicker

@runtime_checkable  ❶
class LoadableRandomPicker(RandomPicker, Protocol):  ❷
    def load(self, Iterable) -> None: ...  ❸
```

❶ If you want the derived protocol to be runtime checkable, you must apply the decorator again—its behavior is not inherited.[21]

❷ Every protocol must explicitly name `typing.Protocol` as one of its base classes—in addition to the protocol we are extending. This is different from the way inheritance works in Python.[22]

❸ Back to "regular" OOP: we only need to declare the method that is new in this derived protocol. The `pick` method declaration is inherited from `RandomPicker`.

This concludes the final example of defining and using a static protocol in this chapter. Naming is considered one of the hardest things in computer science, so let's talk about naming conventions for static protocols.

Protocol naming conventions

The page *Contributing to typeshed* recommends this naming convention for static protocols:

- Use plain names for protocols that represent a clear concept (e.g. `Iterator`, `Container`).
- Use `SupportsX` for protocols that provide callable methods (e.g. `SupportsInt`, `SupportsRead`, `SupportsReadSeek`).
- Use `HasX` for protocols that have readable and/or writable attributes or getter/setter methods (e.g. `HasItems`, `HasFileno`).

The Go standard library has a naming convention that is also useful: for single method protocols, if the method name is a verb, append "-er" or "-or" to make it a noun. Examples: `Formatter`, `Animator`, `Scanner`. For inspiration, see *Go (Golang) Standard Library Interfaces (Selected)* by Asuka Kenji.

To close this chapter, we'll go over numeric ABCs and their possible replacement with numeric protocols.

The numbers ABCs and numeric protocols

> **WARNING**
>
> As I review this in July 2021, the `numbers` package is not supported by PEP 484 or the Mypy type checker. Since 2017 there is an open issue in the Mypy project titled "int is not a Number?". This is not a Mypy bug; it reflects a shortcoming of the `numbers` package, which I explain below.

The `numbers` package defines the so-called *numeric tower* described in PEP 3141—A Type Hierarchy for Numbers. The tower is linear hierarchy of ABCs, where `Number` is the topmost ABC, `Complex` is its immediate subclass, and so on, down to `Integral`:

- `Number`
- `Complex`
- `Real`
- `Rational`
- `Integral`

So if you need to check for an integer, you can use `isinstance(x, numbers.Integral)` to accept `int`, `bool` (which subclasses `int`) or other integer types that are provided by external libraries that register their types as virtual subclasses of the `numbers` ABCs. For example, NumPy has 21 integer types—as well as several variations of floating point types registered as `numbers.Real`, and complex numbers with various bit widths registered as `numbers.Complex`.

> **TIP**
>
> Somewhat surprisingly, `decimal.Decimal` is not registered as a virtual subclass of `numbers.Real`. The reason is that, if you need the precision of `Decimal` in your program, then you want to be protected from accidental mixing of decimals with other less precise numeric types, particularly floating point numbers.

Sadly, the numeric tower was not designed for static type checking. The root ABC—`numbers.Number`—has no methods, so if you declare `x: Number` then type checkers will not let you do arithmetic or call any methods on `x`.

To be frank, we don't often need to implement type safe functions that can handle various types of floating point numbers, or integers of varying bit widths. When needed, a possible workaround is to use the numeric protocols provided by the `typing` module, which we discussed in "Runtime checkable static protocols".

Unfortunately, at runtime, the numeric protocols may let you down. As mentioned in "Type Hints Are Ignored at Runtime", Python's `complex` type implements `__float__`, but the method exists only to raise `TypeError` with an explicit message: "can't convert complex to float." It implements `__int__` as well, for the same reason. The presence of those methods make `isinstance` return misleading results. However, NumPy's complex types implement `__float__` and `__int__` methods that work, only issuing a warning when each of them is used for the first time:

```
>>> import numpy as np
>>> cd = np.cdouble(3+4j)
>>> cd
(3+4j)
>>> float(cd)
<stdin>:1: ComplexWarning: Casting complex values to real
discards the imaginary part
3.0
```

The opposite problem also happens: built-ins `complex`, `float` and `int`, and also `numpy.float16`, `numpy.uint8` don't have a `__complex__` method, so `isinstance(x, SupportsComplex)` returns `False` for them.[23]. The NumPy complex types, such as `np.complex64` do implement `__complex__` to convert to a built-in `complex`.

However, in practice, the `complex()` built-in constructor handles instances of all these types with no errors or warnings:

```
>>> import numpy as np
>>> from typing import SupportsComplex
>>> sample = [1+0j, np.complex64(1+0j), 1.0, np.float16(1.0), 1,
np.uint8(1)]
>>> [isinstance(x, SupportsComplex) for x in sample]
[False, True, False, False, False, False]
```

```
>>> [complex(x) for x in sample]
[(1+0j), (1+0j), (1+0j), (1+0j), (1+0j), (1+0j)]
```

This shows that `isinstance` checks against `SupportsComplex` suggest those conversions to `complex` would fail, but they all succeed. In the typing-sig mailing list, Guido pointed out that the built-in `complex` accepts a single argument, and that's why those conversions work.

On the other hand, Mypy accepts arguments of all those six types in a call to a `to_complex()` function defined like this:

```
def to_complex(n: SupportsComplex) -> complex:
    return complex(n)
```

As I write this, NumPy has no type hints, so its number types are all `Any`.[24] On the other hand, Mypy is somehow "aware" that the built-in `int` and `float` can be converted to `complex`, even though on typeshed only the built-in `complex` class has a `__complex__` method.[25]

In conclusion, although numeric types should not be hard to type check, the current situation is this: the type hints PEP-484 eschews the numeric tower and implicitly recommends that type checkers hard code the subtype relationships between built-in `complex`, `float` and `int`. Mypy does that, and also pragmatically accepts that `int` and `float` are *consistent-with* `SupportsComplex`, even though they don't implement `__complex__`.

> **TIP**
>
> I only found unexpected results when using `isinstance` checks with numeric `Supports*` protocols while experimenting with conversions to or from `complex`. If you don't use complex numbers, you can rely on those protocols instead of the `numbers` ABCs.

The main takeaways for this section are:

- The `numbers` ABCs are fine for goose typing, but unsuitable for static typing.
- The numeric static protocols `SupportsComplex`, `SupportsFloat`, etc. work well for static typing, but are unreliable for goose typing when complex numbers are involved.

We are now ready for a quick review of what we saw in this chapter.

Chapter Summary

The *Typing Map* (Figure 13-1) is the key to making sense of this chapter. After a brief introduction to the four approaches to typing, we contrasted dynamic and static protocols, which respectively support *duck typing* and *static duck typing*. Both kinds of protocols share the essential characteristic that a class is never required to explicitly declare support for any specific protocol. A class supports a protocol simply by implementing the necessary methods.

The next major section was "Programming ducks", where we explored the lengths to which the Python interpreter goes to make the sequence and iterable dynamic protocols work, including partial implementations of both. We then saw how a class can be made to implement a protocol at runtime through the addition of extra methods via monkey-patching. The duck typing section ended with hints for defensive programming, including detection of structural types without explicit `isinstance` or `hasattr` checks using `try/except` and failing fast.

After Alex Martelli introduced *goose typing* in "Waterfowl and ABCs", we saw how to subclass existing ABCs, surveyed important ABCs in the standard library, and created an ABC from scratch, which we then implemented by traditional subclassing and by registration. To close this section, we saw how the `__subclasshook__` special method enables ABCs to support structural typing by recognizing unrelated classes that provide methods fulfilling the interface defined in the ABC.

The last major section was "Static protocols", where we resumed coverage of *static duck typing* which started in Chapter 8, section "Static Protocols". We saw how the `@runtime_checkable` decorator also leverages `__subclasshook__` to support structural typing at runtime—even though the best use of static protocols is with static type checkers which can take into account type hints to make structural typing more reliable. Next we talked about the design and coding of a static protocol and how to extend it. The chapter ended with "The numbers ABCs and numeric protocols" which tells the sad story of the derelict state of the numeric tower and a few existing shortcomings of the proposed alternative: the numeric static protocols such as `SupportsFloat` and others added to the `typing` module in Python 3.8.

The main message of this chapter is that we have four complementary ways of programming with interfaces in modern Python, each with different advantages and drawbacks. You are likely to find suitable use cases for each typing scheme in any modern Python codebase of significant size. Rejecting any one of these approaches will make your work as a Python programmer harder than it needs to be.

Having said that, Python achieved widespread popularity while supporting only *duck typing*. Other popular languages such as JavaScript, PHP, and Ruby, as well as Lisp, Smalltalk, Erlang, and Clojure—not popular but very influential—are all languages that had and still have tremendous impact by leveraging the power and simplicity of *duck typing*.

Further Reading

Great books about Python have—almost by definition—great coverage of duck typing. Two of my favorite Python books had updates released after *Fluent Python, First Edition*: *The Quick Python Book 3rd Edition* (Manning, 2018), by Naomi Ceder; and *Python in a Nutshell, 3rd Edition* (O'Reilly, 2017) by Alex Martelli, Anna Ravenscroft, and Steve Holden.

For a discussion of the pros and cons of dynamic typing, see Guido van Rossum's interview to Bill Venners in "Contracts in Python: A Conversation with Guido van Rossum, Part IV".

The Mypy documentation is often the best source of information for anything related to static typing in Python, including static duck typing, addressed in their Protocols and structural subtyping chapter.

The remaining references are all about *goose typing*. Beazley and Jones's *Python Cookbook, 3rd Edition* (O'Reilly) has a section about defining an ABC (Recipe 8.12). The book was written before Python 3.4, so they don't use the now preferred syntax of declaring ABCs by subclassing from `abc.ABC` (instead, they use the `metaclass` keyword, which we'll only really need in Chapter 25). Apart from this small detail, the recipe covers the major ABC features very well.

The Python Standard Library by Example by Doug Hellmann (Addison-Wesley), has a chapter about the `abc` module. It's also available on the Web in Doug's excellent PyMOTW—Python Module of the Week. Hellmann also uses the old style of ABC declaration: `PluginBase(metaclass=abc.ABCMeta)` instead of the simpler `PluginBase(abc.ABC)` available since Python 3.4.

When using ABCs, multiple inheritance is not only common but practically inevitable, because each of the fundamental collection ABCs—`Sequence`, `Mapping`, and `Set`—extends `Collection`, which in turn extends multiple ABCs (see Figure 13-4). Therefore, Chapter 14 is an important follow-up to this one.

PEP 3119 — Introducing Abstract Base Classes gives the rationale for ABCs. PEP 3141 - A Type Hierarchy for Numbers presents the ABCs of the `numbers` module, but the discussion in the Mypy issue #3186—int is not a Number? includes some arguments about why the numeric tower is unsuitable for static type checking.

SOAPBOX

The MVP Journey of Python Static Typing

I work for Thoughtworks, a worldwide leader in agile software development. At Thoughtworks, we often recommend that our clients should aim to create and deploy MVPs: minimal viable products— "a simple version of a product that is given to users in order to validate the key business assumptions" as defined by my colleague Paulo Caroli in Lean Inception, a post in Martin Fowler's collective blog.

Guido van Rossum and the other core developers who designed and implemented static typing have followed an MVP strategy since 2006. First, PEP 3107—Function Annotations was implemented in Python 3.0 with very limited semantics: just syntax to attach annotations to function arguments and returns. This was done explicitly to allow for experimentation and collect feedback—key benefits of an MVP.

Eight years later, PEP 484—Type Hints was proposed and approved. Its implementation in Python 3.5 required no changes in the language or standard library—except the addition of the `typing` module, on which no other part of the standard library depended. PEP 484 supported only nominal types with generics—similar to Java—but with the actual static checking done by external tools. Important features—like variable annotations, generic built-in types, and static protocols—were missing. Despite those limitations, this typing MVP was valuable enough to attract investment and adoption by companies with very large Python codebases, like Dropbox, Google, and Facebook—as well as support from professional IDEs like PyCharm, Wing, and VS Code.

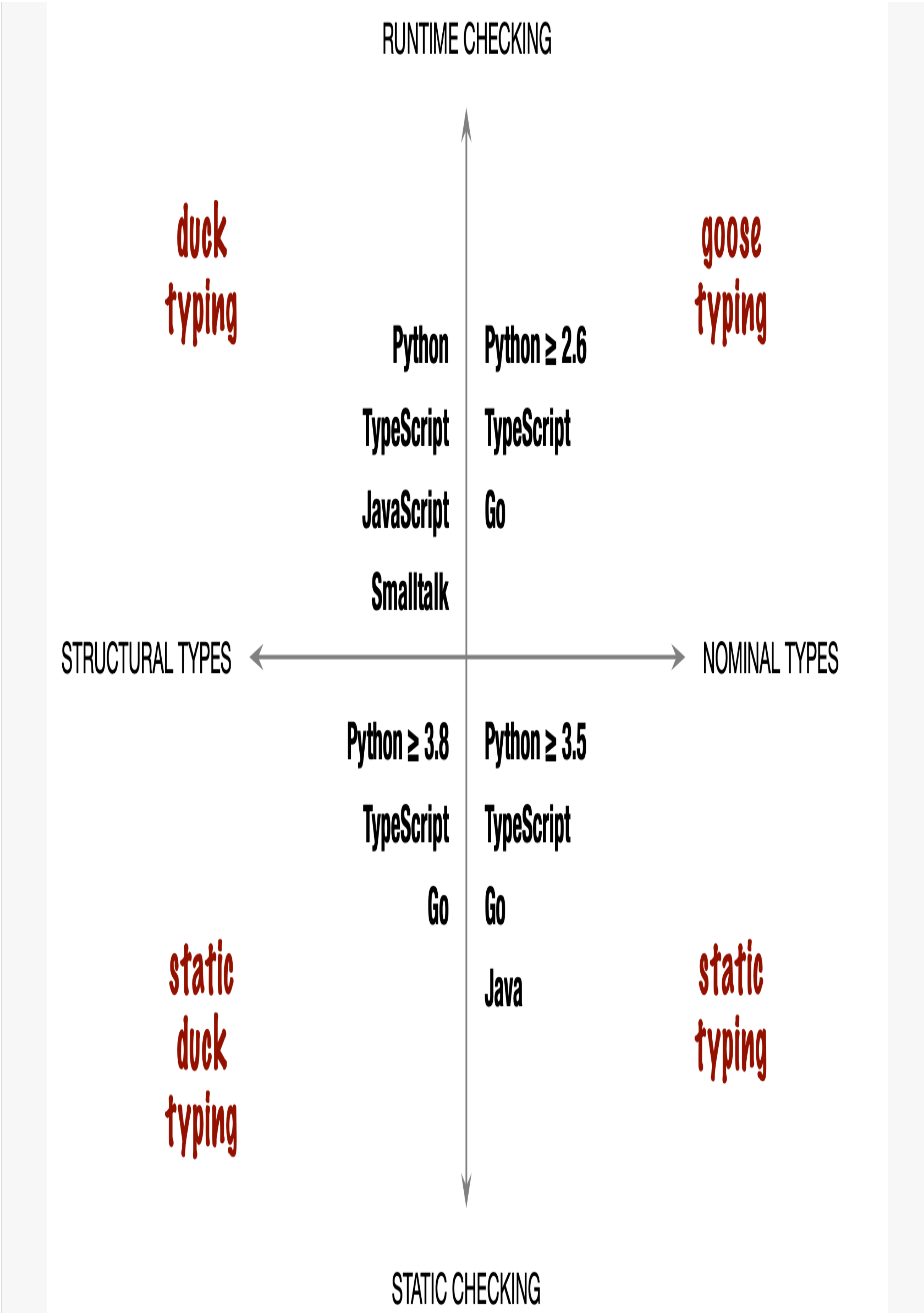
PEP 526—Syntax for Variable Annotations was the first evolutionary step that required changes to the interpreter, in Python 3.6. Further changes to the interpreter were made in Python 3.7 to support PEP 563—Postponed Evaluation of Annotations and PEP 560—Core support for typing module and generic types—which in turn allowed built-in and standard library collections to accept generic type hints out of the box in Python 3.9, thanks to PEP 585—Type Hinting Generics In Standard Collections.

During those years, some Python users—including me—were underwhelmed by the typing support. After I learned Go, the lack of static duck typing in Python's type hints was incomprehensible, in a language where duck typing had always been a core strength.

But that is the nature of MVPs: they may not satisfy all potential users, but they can be implemented with less effort, and guide further development with feedback from actual usage in the field.

If there is one thing we all learned from Python 3, is that incremental progress is safer than big-bang releases. I am glad we did not have to wait for Python 4—if it ever comes—to make Python more attractive to large enterprises, where the benefits of static typing outweigh the added complexity.

Typing Approaches in Popular Languages



RUNTIME CHECKING
duck typing
goose typing
Python
Python ≥ 2.6
TypeScript
TypeScript
JavaScript
Go
Smalltalk
STRUCTURAL TYPES
NOMINAL TYPES
Python ≥ 3.8
Python ≥ 3.5
TypeScript
TypeScript
Go
Go
Java
static duck typing
static typing
STATIC CHECKING

Figure 13-8. Four approaches to type checking and languages that support them.

Figure 13-8 is a variation of the *Typing Map* (Figure 13-1) with the names of a few popular languages that support each of the typing approaches.

TypeScript and Python ≥ 3.8 are the only languages in my small and arbitrary sample that support all four approaches.

Go is clearly a statically typed language in the Pascal tradition, but it pioneered *static duck typing*—at least among languages that are widely used today. I also put Go in the *goose typing* quadrant because of its type assertions, which allow checking and adapting to different types at runtime.

If I had to draw a similar diagram in the year 2000, only the *duck typing* and the *static typing* quadrants would have languages in them. I am not aware of languages that supported *static duck typing* or *goose typing* 20 years ago. The fact that each of the four quadrants have at least three popular languages suggests that a lot of people see value in each of the four approaches to typing.

Monkey Patching

Monkey patching has a bad reputation. If abused, it can lead to systems that are hard to understand and maintain. The patch is usually tightly coupled with its target, making it brittle. Another problem is that two libraries that apply monkey-patches may step on each other's toes, with the second library to run destroying patches of the first.

But monkey patching can also be useful, for example, to make a class implement a protocol at runtime. The adapter design pattern solves the same problem by implementing a whole new class.

It's easy to monkey-patch Python code, but there are limitations. Unlike Ruby and JavaScript, Python does not let you monkey-patch the built-in types. I actually consider this an advantage, because you can be certain that a `str` object will always have those same methods. This limitation reduces the chance that external libraries apply conflicting patches.

Metaphors and Idioms in Interfaces

A metaphor fosters understanding by making constraints and affordances clear. That's the value of the words "stack" and "queue" in describing those fundamental data structures: they make clear which operations ara allowed, i.e. how items can be added or removed. On the other hand, Alan Cooper writes in *About Face, 4E* (Wiley):

> *Strict adherence to metaphors ties interfaces unnecessarily tightly to the workings of the physical world.*

He's referring to user interfaces, but the admonition applies to APIs as well. But Cooper does grant that when a "truly appropriate" metaphor "falls on our lap," we can use it (he writes "falls on our lap" because it's so hard to find fitting metaphors that you should not spend time actively looking for them). I believe the bingo machine imagery I used in this chapter is appropriate and I stand by it.

About Face is by far the best book about UI design I've read—and I've read a few. Letting go of metaphors as a design paradigm, and replacing it with "idiomatic interfaces" was the most valuable thing I learned from Cooper's work.

In *About Face*, Cooper does not deal with APIs, but the more I think about his ideas, the more I see how they apply to Python. The fundamental protocols of the language are what Cooper calls "idioms." Once we learn what a "sequence" is we can apply that knowledge in different contexts. This is a main theme of *Fluent Python*: highlighting the fundamental idioms of the language, so your code is concise, effective, and readable—for a fluent Pythonista.

---

1 Design Patterns: Elements of Reusable Object-Oriented Software, Introduction, p. 18.

2 The *Monkey patch* article on Wikipedia has a funny example in Python.

3 That's why automated testing is necessary.

4 Bjarne Stroustrup, *The Design and Evolution of C++* (Addison-Wesley, 1994), p. 278.

5 Retrieved October 18, 2020.

6 You can also, of course, define your own ABCs—but I would discourage all but the most advanced Pythonistas from going that route, just as I would discourage them from defining their own custom metaclasses… and even for said “most advanced Pythonistas,” those of us sporting deep mastery of every fold and crease in the language, these are not tools for frequent use: such “deep metaprogramming,” if ever appropriate, is intended for authors of broad frameworks meant to be independently extended by vast numbers of separate development teams… less than 1% of “most advanced Pythonistas” may ever need that! — *A.M.*

7 Multiple inheritance was *considered harmful* and excluded from Java, except for interfaces: Java interfaces can extend multiple interfaces, and Java classes can implement multiple interfaces.

8 Perhaps the client needs to audit the randomizer; or the agency wants to provide a rigged one. You never know…

9 «registered» and «virtual subclass» are not standard UML terms. I am using them to represent a class relationship that is specific to Python.

10 Before ABCs existed, abstract methods would raise `NotImplementedError` to signal that subclasses were responsible for their implementation. In Smalltalk-80, abstract method bodies would invoke `subclassResponsibility`, a method inherited from `object` that would produce an error with the message “My subclass should have overridden one of my messages.”

11 The complete tree appears in section “5.4. Exception hierarchy” of *The Python Standard Library* documentation.

12 `@abc.abstractmethod` entry in the `abc` module documentation.

13 “Defensive Programming with Mutable Parameters” in Chapter 6 was devoted to the aliasing issue we just avoided here.

14 The same trick I used with `load()` doesn’t work with `loaded()`, because the `list` type does not implement `__bool__`, the method I’d have to bind to `loaded`. The `bool()` built-in doesn’t need `__bool__` to work because it can also use `__len__`. See “4.1. Truth Value Testing” in the “Built-in Types” chapter of the Python documentation.

15 There is a whole section explaining the `__mro__` class attribute in “Multiple Inheritance and Method Resolution Order”. Right now, this quick explanation will do.

16 The concept of type consistency was explained in “Subtype-of versus Consistent-with”.

17 OK, `double()` is not very useful, except as an example. But the Python standard library has many functions that could not be properly annotated before static protocols were added in Python 3.8. I helped fixing a couple of bugs in typeshed by adding type hints using protocols. For example, the pull request that fixed Should Mypy warn about potential invalid arguments to `max`? leveraged a `_SupportsLessThan` protocol, which I used to enhance the annotations for `max`, `min`, `sorted`, and `list.sort`.

18 The `__slots__` attribute is irrelevant to the current discussion—it’s an optimization we covered in “Saving Memory with `__slots__`”.

19 Read the Python Steering Council decision on *python-dev*.

20 Thanks to Guido van Rossum for telling me the reason why the `complex.__float__` method exists and to Ivan Levkivskyi for pointing out that inspecting type hints at runtime would have an unacceptable performance cost. Type checking is not just a matter of checking whether the type of `x` is `T`: it's about determining that the type of `x` is *consistent-with* `T`, which may be expensive.

21 For details and rationale, please see the section about @runtime_checkable in PEP 544—Protocols: Structural subtyping (static duck typing)

22 Again, please read Merging and extending protocols in PEP 544 for details and rationale.

23 I did not test all the other float and integer variants NumPy offers

24 The NumPy number types are all registered against the appropriate `numbers` ABCs, but Mypy ignores that fact.

25 That's a well-meaning lie on the part of typeshed: as of Python 3.9, the built-in `complex` type does not actually have a `__complex__` method.

Chapter 14. Inheritance: For Good or For Worse

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 14th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

—Alan Kay, The Early History of Smalltalk

This chapter is about inheritance and subclassing, with emphasis on two particulars that are very specific to Python:

- The pitfalls of subclassing from built-in types
- Multiple inheritance and the method resolution order

Many consider multiple inheritance more trouble than it's worth. The lack of it certainly did not hurt Java; it probably fueled its widespread adoption after many were traumatized by the excessive use of multiple inheritance in C++.

However, the amazing success and influence of Java means that a lot of programmers come to Python without having seen multiple inheritance in practice. This is why, instead of toy examples, our coverage of multiple inheritance will be illustrated by two important Python projects: the Tkinter GUI toolkit and the Django Web framework.

What's new in this chapter

This chapter has only minor changes. As the title suggests, the caveats of inheritance have always been one of the main themes here. But more and more software engineers consider it so problematic that I've added a couple of paragraphs about avoiding inheritance altogether to the end of "Chapter Summary" and "Further Reading".

We'll start with the issue of subclassing built-ins. The rest of the chapter will cover multiple inheritance with our case studies and discuss good and bad practices when building class hierarchies.

Subclassing Built-In Types Is Tricky

Before Python 2.2, it was not possible to subclass built-in types such as `list` or `dict`. Since then, it can be done but there is a major caveat: the code of the built-ins (written in C) does not call special methods overridden by user-defined classes.

A good short description of the problem is in the documentation for *PyPy*, in "Differences between PyPy and CPython", section Subclasses of built-in types:

> *Officially, CPython has no rule at all for when exactly overridden method of subclasses of built-in types get implicitly called or not. As an approximation, these methods are never called by other built-in methods of the same object. For example, an overridden `__getitem__()` in a subclass of `dict` will not be called by e.g. the built-in `get()` method.*

Example 14-1 illustrates the problem.

Example 14-1. Our __setitem__ override is ignored by the __init__ and __update__ methods of the built-in dict

```
>>> class DoppelDict(dict):
...     def __setitem__(self, key, value):
...         super().__setitem__(key, [value] * 2)  ❶
...
>>> dd = DoppelDict(one=1)  ❷
>>> dd
{'one': 1}
>>> dd['two'] = 2  ❸
>>> dd
{'one': 1, 'two': [2, 2]}
>>> dd.update(three=3)  ❹
>>> dd
{'three': 3, 'one': 1, 'two': [2, 2]}
```

❶ `DoppelDict.__setitem__` duplicates values when storing (for no good reason, just to have a visible effect). It works by delegating to the superclass.

❷ The `__init__` method inherited from `dict` clearly ignored that `__setitem__` was overridden: the value of `'one'` is not duplicated.

❸ The `[]` operator calls our `__setitem__` and works as expected: `'two'` maps to the duplicated value `[2, 2]`.

❹ The `update` method from `dict` does not use our version of `__setitem__` either: the value of `'three'` was not duplicated.

This built-in behavior is a violation of a basic rule of object-oriented programming: the search for methods should always start from the class of the target instance (`self`), even when the call happens inside a method implemented in a superclass. In this sad state of affairs, the `__missing__` method—which we saw in “The `__missing__` Method”—works as documented only because it’s handled as a special case.

The problem is not limited to calls within an instance—whether `self.get()` calls `self.__getitem__()`)—but also happens with overridden methods of other classes that should be called by the built-in methods. Example 14-2 is an example adapted from the PyPy documentation.

Example 14-2. The __getitem__ of AnswerDict is bypassed by dict.update

```
>>> class AnswerDict(dict):
...     def __getitem__(self, key):  ❶
...         return 42
...
>>> ad = AnswerDict(a='foo')  ❷
>>> ad['a']  ❸
42
>>> d = {}
>>> d.update(ad)  ❹
>>> d['a']  ❺
'foo'
>>> d
{'a': 'foo'}
```

❶ `AnswerDict.__getitem__` always returns `42`, no matter what the key.

❷ `ad` is an `AnswerDict` loaded with the key-value pair `('a', 'foo')`.

❸ `ad['a']` returns `42`, as expected.

❹ `d` is an instance of plain `dict`, which we update with `ad`.

❺ The `dict.update` method ignored our `AnswerDict.__getitem__`.

> **WARNING**
>
> Subclassing built-in types like `dict` or `list` or `str` directly is error-prone because the built-in methods mostly ignore user-defined overrides. Instead of subclassing the built-ins, derive your classes from the `collections` module using `UserDict`, `UserList`, and `UserString`, which are designed to be easily extended.

If you subclass `collections.UserDict` instead of `dict`, the issues exposed in Examples 14-1 and 14-2 are both fixed. See Example 14-3.

Example 14-3. DoppelDict2 and AnswerDict2 work as expected because they extend UserDict and not dict

```
>>> import collections
>>>
>>> class DoppelDict2(collections.UserDict):
...     def __setitem__(self, key, value):
...         super().__setitem__(key, [value] * 2)
...
>>> dd = DoppelDict2(one=1)
>>> dd
{'one': [1, 1]}
>>> dd['two'] = 2
>>> dd
{'two': [2, 2], 'one': [1, 1]}
>>> dd.update(three=3)
>>> dd
{'two': [2, 2], 'three': [3, 3], 'one': [1, 1]}
>>>
>>> class AnswerDict2(collections.UserDict):
...     def __getitem__(self, key):
...         return 42
...
>>> ad = AnswerDict2(a='foo')
>>> ad['a']
42
>>> d = {}
>>> d.update(ad)
>>> d['a']
42
>>> d
{'a': 42}
```

As an experiment to measure the extra work required to subclass a built-in, I rewrote the `StrKeyDict` class from Example 3-9. The original version inherited from `collections.UserDict`, and implemented just three methods: `__missing__`, `__contains__`, and `__setitem__`. The experimental `StrKeyDict` subclassed `dict` directly, and implemented the same three methods with minor tweaks due to the way the data was stored.

But in order to make it pass the same suite of tests, I had to implement `__init__`, `get`, and `update` because the versions inherited from `dict` refused to cooperate with the overridden `__missing__`, `__contains__`, and `__setitem__`. The `UserDict` subclass from Example 3-9 has 16 lines, while the experimental `dict` subclass ended up with 37 lines.[1]

To summarize: the problem described in this section applies only to method delegation within the C language implementation of the built-in types, and only affects user-defined classes derived directly from those types. If you subclass from a class coded in Python, such as `UserDict` or `MutableMapping`, you will not be troubled by this.[2]

Another matter related to inheritance, particularly of multiple inheritance, is: how does Python decide which attribute to use if superclasses from parallel branches define attributes with the same name? The answer is next.

Multiple Inheritance and Method Resolution Order

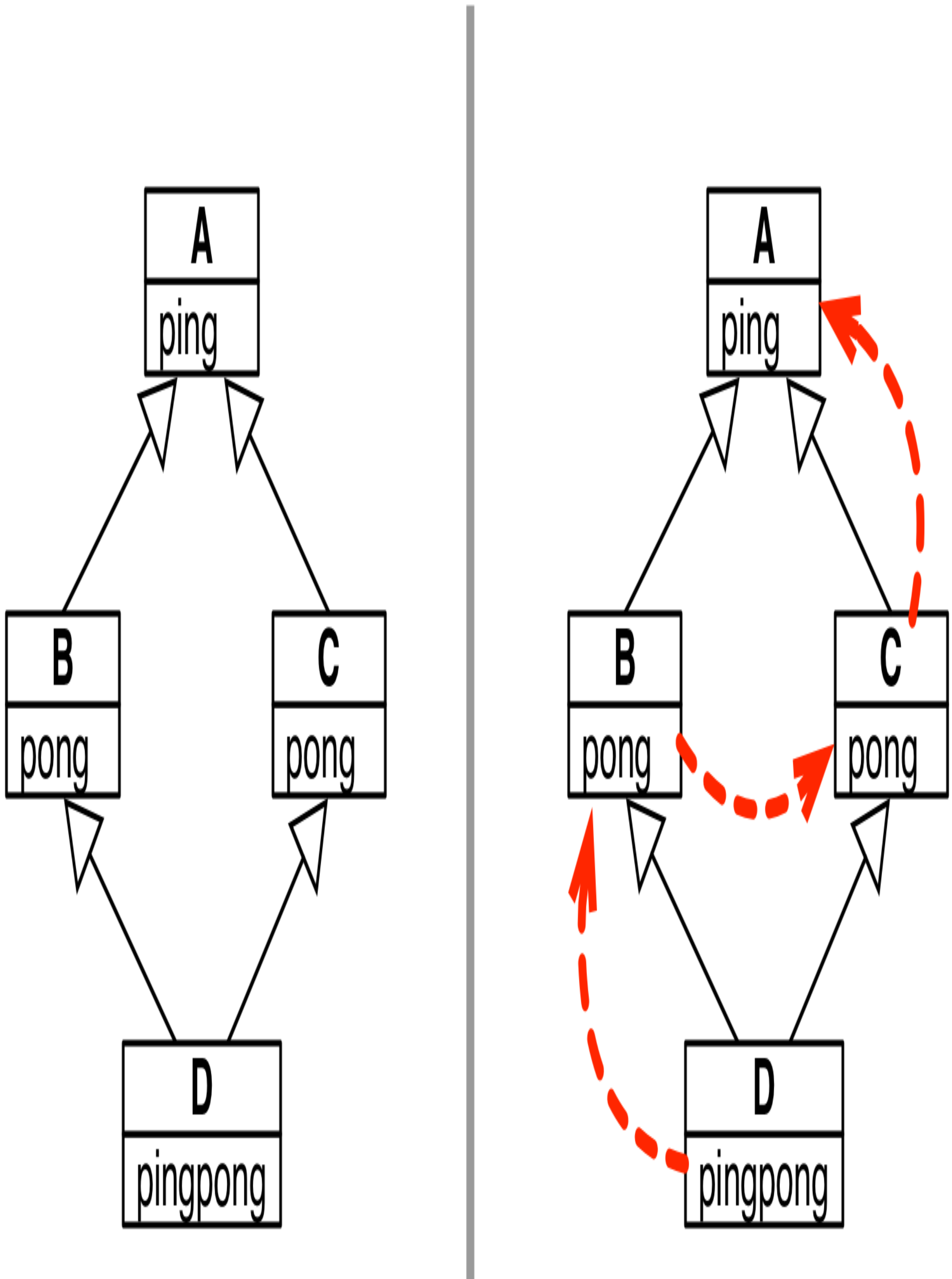

A
ping
B
pong
C
pong
D
pingpong
A
ping
B
pong
C
pong
D
pingpong

*Figure 14-1. **Left**: UML class diagram illustrating the "diamond problem." **Right**: Dashed arrows depict Python MRO (method resolution order) for Example 14-4.*

Any language implementing multiple inheritance needs to deal with potential naming conflicts when unrelated ancestor classes implement a method by the same name. This is called the "diamond problem," and is illustrated in Figure 14-1 and Example 14-4.

Example 14-4. diamond.py: classes A, B, C, and D form the graph in Figure 14-1

```
class A:
    def ping(self):
        print('ping:', self)


class B(A):
    def pong(self):
        print('pong:', self)


class C(A):
    def pong(self):
        print('PONG:', self)


class D(B, C):

    def ping(self):
        super().ping()
        print('post-ping:', self)

    def pingpong(self):
        self.ping()
        super().ping()
        self.pong()
        super().pong()
        C.pong(self)
```

Note that both classes `B` and `C` implement a `pong` method. The only difference is that `C.pong` outputs the word `PONG` in uppercase.

If you call `d.pong()` on an instance of `D`, which `pong` method actually runs? In C++, the programmer must qualify method calls with class names to resolve this ambiguity. This can be done in Python as well. Take a look at Example 14-5.

Example 14-5. Two ways of invoking method pong on an instance of class D

```
>>> from diamond import *
>>> d = D()
>>> d.pong()  ❶
pong: <diamond.D object at 0x10066c278>
>>> C.pong(d)  ❷
PONG: <diamond.D object at 0x10066c278>
```

❶ Simply calling `d.pong()` causes the `B` version to run.

❷ You can always call a method on a superclass directly, passing the instance as an explicit argument.

The ambiguity of a call like `d.pong()` is resolved because Python follows a specific order when traversing the inheritance graph. That order is called MRO: Method Resolution Order. Classes have an attribute called `__mro__` holding a tuple of references to the superclasses in MRO order, from the current class all the way to the `object` class. For the `D` class, this is the `__mro__` (see Figure 14-1):

```
>>> D.__mro__
(<class 'diamond.D'>, <class 'diamond.B'>, <class 'diamond.C'>,
<class 'diamond.A'>, <class 'object'>)
```

The recommended way to delegate method calls to superclasses is the `super()` built-in function, which became easier to use in Python 3, as method `pingpong` of class `D` in Example 14-4 illustrates.[3] However, it's also possible, and sometimes convenient, to bypass the MRO and invoke a method on a superclass directly. For example, the `D.ping` method could be written as:

```
    def ping(self):
        A.ping(self)  # instead of super().ping()
        print('post-ping:', self)
```

Note that when calling an instance method directly on a class, you must pass `self` explicitly, because you are accessing an *unbound method*.

However, it's safest and more future-proof to use `super()`, especially when calling methods on a framework, or any class hierarchies you do not control. Example 14-6 shows that `super()` follows the MRO when invoking a method.

Example 14-6. Using super() to call ping (source code in Example 14-4)

```
>>> from diamond import D
>>> d = D()
>>> d.ping()  ❶
ping: <diamond.D object at 0x10cc40630>  ❷
post-ping: <diamond.D object at 0x10cc40630>  ❸
```

❶ The `ping` of `D` makes two calls.

❷ The first call is `super().ping()`; the `super` delegates the `ping` call to class `A`; `A.ping` outputs this line.

❸ The second call is `print('post-ping:', self)`, which outputs this line.

Now let's see what happens when `pingpong` is called on an instance of `D`. See Example 14-7.

Example 14-7. The five calls made by pingpong (source code in Example 14-4)

```
>>> from diamond import D
>>> d = D()
>>> d.pingpong()
ping: <diamond.D object at 0x10bf235c0>  ❶
post-ping: <diamond.D object at 0x10bf235c0>
ping: <diamond.D object at 0x10bf235c0>  ❷
pong: <diamond.D object at 0x10bf235c0>  ❸
pong: <diamond.D object at 0x10bf235c0>  ❹
PONG: <diamond.D object at 0x10bf235c0>  ❺
```

❶

Call #1 is `self.ping()`, which runs the `ping` method of `D`, which outputs this line and the next one.

❷ Call #2 is `super().ping()`, which bypasses the `ping` in `D` and finds the `ping` method in `A`.

❸ Call #3 is `self.pong()`, which finds the `B` implementation of `pong`, according to the `__mro__`.

❹ Call #4 is `super().pong()`, which finds the same `B.pong` implementation, also following the `__mro__`.

❺ Call #5 is `C.pong(self)`, which finds the `C.pong` implementation, ignoring the `__mro__`.

The MRO takes into account not only the inheritance graph but also the order in which superclasses are listed in a subclass declaration. In other words, if in *diamond.py* (Example 14-4) the `D` class was declared as `class D(C, B):`, the `__mro__` of class `D` would be different: `C` would be searched before `B`.

I often check the `__mro__` of classes interactively when I am studying them. Example 14-8 has some examples using familiar classes.

Example 14-8. Inspecting the __mro__ attribute in several classes

```
>>> bool.__mro__  ❶
(<class 'bool'>, <class 'int'>, <class 'object'>)
>>> def print_mro(cls):  ❷
...     print(', '.join(c.__name__ for c in cls.__mro__))
...
>>> print_mro(bool)
bool, int, object
>>> from frenchdeck2 import FrenchDeck2
>>> print_mro(FrenchDeck2)  ❸
FrenchDeck2, MutableSequence, Sequence, Sized, Iterable, Container,
object
>>> import numbers
>>> print_mro(numbers.Integral)  ❹
Integral, Rational, Real, Complex, Number, object
```

```
>>> import io  ❺
>>> print_mro(io.BytesIO)
BytesIO, _BufferedIOBase, _IOBase, object
>>> print_mro(io.TextIOWrapper)
TextIOWrapper, _TextIOBase, _IOBase, object
```

❶ `bool` inherits methods and attributes from `int` and `object`.

❷ `print_mro` produces more compact displays of the MRO.

❸ The ancestors of `FrenchDeck2` include several ABCs from the `collections.abc` module.

❹ These are the numeric ABCs provided by the `numbers` module.

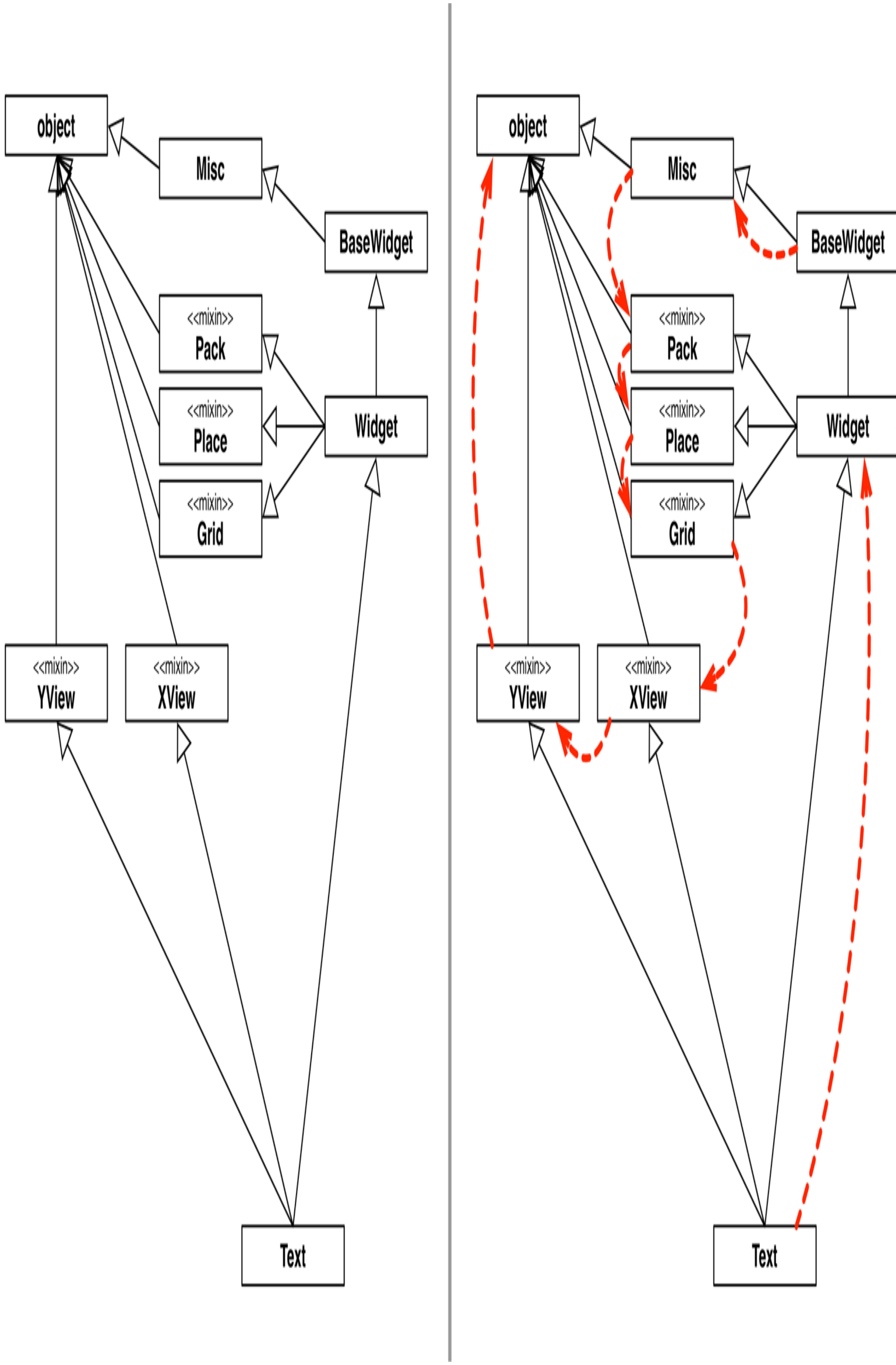
❺ The `io` module includes ABCs (those with the …`Base` suffix) and concrete classes like `BytesIO` and `TextIOWrapper`, which are the types of binary and text file objects returned by `open()`, depending on the mode argument.

> **NOTE**
>
> The MRO is computed using an algorithm called C3. The canonical paper on the Python MRO explaining C3 is Michele Simionato's "The Python 2.3 Method Resolution Order". If you are interested in the subtleties of the MRO, "Further Reading" has other pointers. But don't fret too much about this, the algorithm is sensible; as Simionato writes:
>
> *[…] unless you make strong use of multiple inheritance and you have non-trivial hierarchies, you don't need to understand the C3 algorithm, and you can easily skip this paper.*

To wrap up this discussion of the MRO, Figure 14-2 illustrates part of the complex multiple inheritance graph of the Tkinter GUI toolkit from the Python standard library. To study the picture, start at the `Text` class at the bottom. The `Text` class implements a full featured, multiline editable text widget. It has rich functionality of its own, but also inherits many methods from other classes. The left-hand side shows a plain UML class diagram. On the right, it's decorated with arrows showing the MRO, as listed here with the help of the `print_mro` convenience function defined in Example 14-8:

```
>>> import tkinter
>>> print_mro(tkinter.Text)
Text, Widget, BaseWidget, Misc, Pack, Place, Grid, XView, YView,
object
```

In the next section, we'll discuss the pros and cons of multiple inheritance, with examples from real frameworks that use it.



object
Misc
BaseWidget
<<mixin>>
Pack
<<mixin>>
Place
<<mixin>>
Grid
Widget
<<mixin>>
YView
<<mixin>>
XView
Text
object
Misc
BaseWidget
<<mixin>>
Pack
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Place
<<mixin>>
Grid
Widget
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YView
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XView
Text

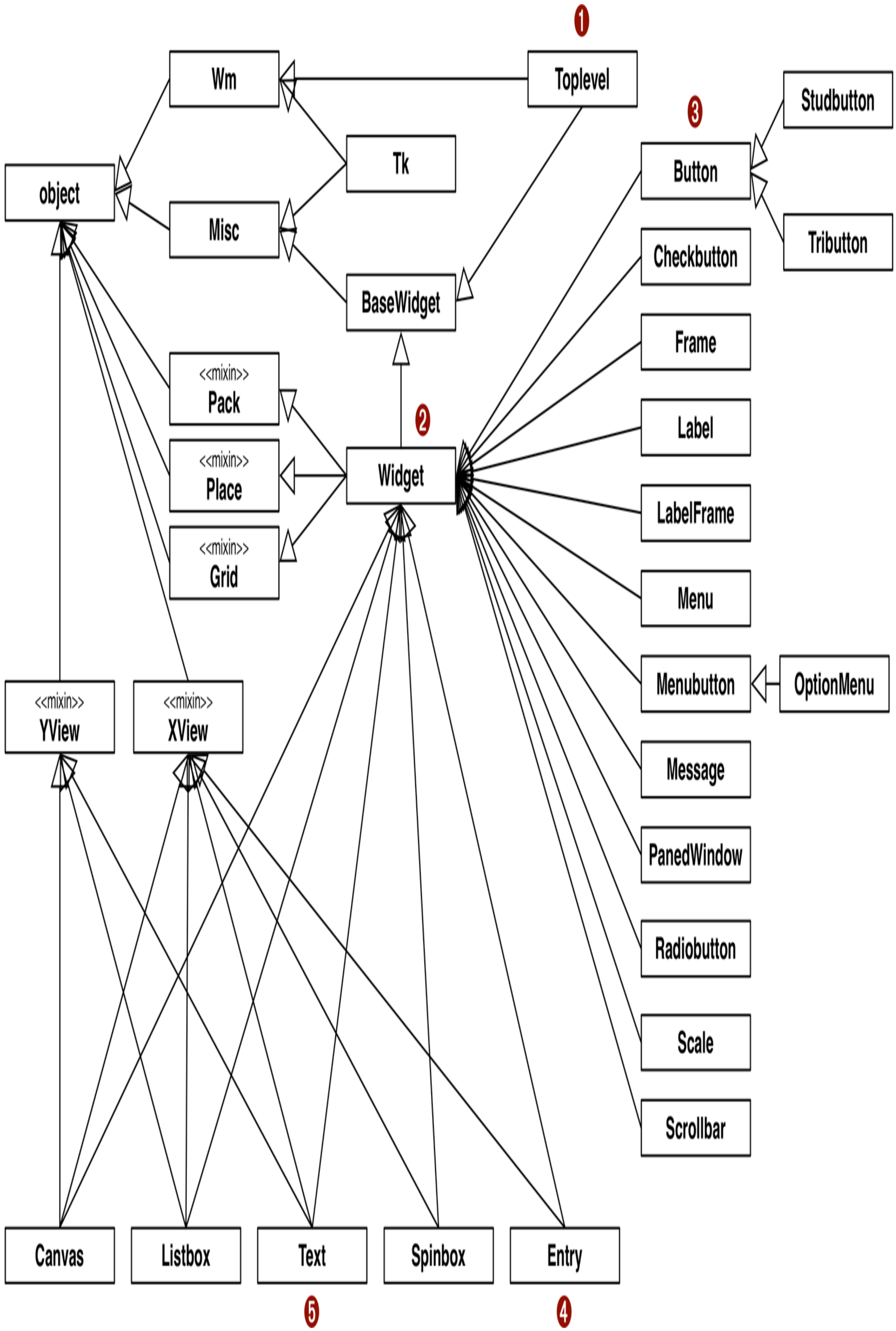
*Figure 14-2. **Left**: UML class diagram of the Tkinter Text widget class and its superclasses. **Right**: Dashed arrows depict Text.__mro__.*

Multiple Inheritance in the Real World

It is possible to put multiple inheritance to good use. The Adapter pattern in the *Design Patterns* book uses multiple inheritance, so it can't be completely wrong to do it (the remaining 22 patterns in the book use single inheritance only, so multiple inheritance is clearly not a cure-all).

In the Python standard library, the most visible use of multiple inheritance is the `collections.abc` package. That is not controversial: after all, even Java supports multiple inheritance of interfaces, and ABCs are interface declarations that may optionally provide concrete method implementations.[4]

An extreme example of multiple inheritance in the standard library is the Tkinter GUI toolkit (module `tkinter`: Python interface to Tcl/Tk). I used part of the Tkinter widget hierarchy to illustrate the MRO in Figure 14-2, but Figure 14-3 shows all the widget classes in the `tkinter` base package (there are more widgets in the `tkinter.ttk` sub-package).



1
Wm
Toplevel
object
Tk
Misc
BaseWidget
3
Studbutton
Button
Tributton
Checkbutton
Frame
<<mixin>>
Pack
2
Label
<<mixin>>
Place
Widget
LabelFrame
<<mixin>>
Grid
Menu
Menubutton
OptionMenu
<<mixin>>
YView
<<mixin>>
XView
Message
PanedWindow
Radiobutton
Scale
Scrollbar
Canvas
Listbox
Text
Spinbox
Entry
5
4

Figure 14-3. Summary UML diagram for the Tkinter GUI class hierarchy; classes tagged «mixin» are designed to provide concrete methods to other classes via multiple inheritance

Tkinter is 20 years old as I write this, and is not an example of current best practices. But it shows how multiple inheritance was used when coders did not appreciate its drawbacks. And it will serve as a counter-example when we cover some good practices in the next section.

Consider these classes from Figure 14-3:

❶ `Toplevel`: The class of a top-level window in a Tkinter application.

❷ `Widget`: The superclass of every visible object that can be placed on a window.

❸ `Button`: A plain button widget.

❹ `Entry`: A single-line editable text field.

❺ `Text`: A multiline editable text field.

Here are the MROs of those classes, displayed by the `print_mro` function from Example 14-8:

```
>>> import tkinter
>>> print_mro(tkinter.Toplevel)
Toplevel, BaseWidget, Misc, Wm, object
>>> print_mro(tkinter.Widget)
Widget, BaseWidget, Misc, Pack, Place, Grid, object
>>> print_mro(tkinter.Button)
Button, Widget, BaseWidget, Misc, Pack, Place, Grid, object
>>> print_mro(tkinter.Entry)
Entry, Widget, BaseWidget, Misc, Pack, Place, Grid, XView, object
>>> print_mro(tkinter.Text)
Text, Widget, BaseWidget, Misc, Pack, Place, Grid, XView, YView,
object
```

Things to note about how these classes relate to others:

- `Toplevel` is the only graphical class that does not inherit from `Widget`, because it is the top-level window and does not behave like a widget—for example, it cannot be attached to a window or frame. `Toplevel` inherits from `Wm`, which provides direct access functions of the host window manager, like setting the window title and configuring its borders.

- `Widget` inherits directly from `BaseWidget` and from `Pack`, `Place`, and `Grid`. These last three classes are geometry managers: they are responsible for arranging widgets inside a window or frame. Each encapsulates a different layout strategy and widget placement API.
- `Button`, like most widgets, descends only from `Widget`, but indirectly from `Misc`, which provides dozens of methods to every widget.
- `Entry` subclasses `Widget` and `XView`, the class that implements horizontal scrolling.
- `Text` subclasses from `Widget`, `XView`, and `YView`, which provides vertical scrolling functionality.

We’ll now discuss some good practices of multiple inheritance and see whether Tkinter goes along with them.

Coping with Multiple Inheritance

> *[…] we needed a better theory about inheritance entirely (and still do). For example, inheritance and instancing (which is a kind of inheritance) muddles both pragmatics (such as factoring code to save space) and semantics (used for way too many tasks such as: specialization, generalization, speciation, etc.).*
>
> —Alan Kay, The Early History of Smalltalk

As Alan Kay wrote, inheritance is used for different reasons, and multiple inheritance adds alternatives and complexity. It’s easy to create incomprehensible and brittle designs using multiple inheritance. Because we don’t have a comprehensive theory, here are a few tips to avoid spaghetti class graphs.

1. Distinguish Interface Inheritance from Implementation Inheritance

When dealing with multiple inheritance, it’s useful to keep straight the reasons why subclassing is done in the first place. The main reasons are:

- Inheritance of interface creates a subtype, implying an “is-a” relationship.
- Inheritance of implementation avoids code duplication by reuse.

In practice, both uses are often simultaneous, but whenever you can make the intent clear, do it. Inheritance for code reuse is an implementation detail, and it can often be replaced by composition and delegation. On the other hand, interface inheritance is the backbone of a framework.

2. Make Interfaces Explicit with ABCs

In modern Python, if a class is designed to define an interface, it should be an explicit ABC. In Python ≥ 3.4, this means: subclass `abc.ABC` or another ABC (see “ABC Syntax Details” if you need to support older Python versions).

3. Use Mixins for Code Reuse

If a class is designed to provide method implementations for reuse by multiple unrelated subclasses, without implying an “is-a” relationship, it should be an explicit *mixin class*. Conceptually, a mixin does not define a new type; it merely bundles methods for reuse. A mixin should never be instantiated, and concrete classes should not inherit only from a mixin. Each mixin should provide a single specific behavior, implementing few and very closely related methods.

4. Make Mixins Explicit by Naming

There is no formal way in Python to state that a class is a mixin, so it is highly recommended that they are named with a …`Mixin` suffix. Tkinter does not follow this advice, but if it did, `XView` would be `XViewMixin`, `Pack` would be `PackMixin`, and so on with all the classes where I put the «mixin» tag in Figure 14-3.

5. An ABC May Also Be a Mixin; The Reverse Is Not True

Because an ABC can implement concrete methods, it works as a mixin as well. An ABC also defines a type, which a mixin does not. And an ABC can be the sole base class of any other class, while a mixin should never be subclassed alone except by another, more specialized mixin—not a common arrangement in real code.

One restriction applies to ABCs and not to mixins: the concrete methods implemented in an ABC should only collaborate with methods of the same ABC and its superclasses. This implies that concrete methods in an ABC are always for convenience, because everything they do, a user of the class can also do by calling other methods of the ABC.

6. Don't Subclass from More Than One Concrete Class

Concrete classes should have zero or at most one concrete superclass.[5] In other words, all but one of the superclasses of a concrete class should be ABCs or mixins. For example, in the following code, if `Alpha` is a concrete class, then `Beta` and `Gamma` must be ABCs or mixins:

```
class MyConcreteClass(Alpha, Beta, Gamma):
    """This is a concrete class: it can be instantiated."""
    # ... more code ...
```

7. Provide Aggregate Classes to Users

If some combination of ABCs or mixins is particularly useful to client code, provide a class that brings them together in a sensible way. Grady Booch calls this an *aggregate class*.[6]

For example, here is the complete source code for `tkinter.Widget`:

```
class Widget(BaseWidget, Pack, Place, Grid):
    """Internal class.

    Base class for a widget which can be positioned with the
    geometry managers Pack, Place or Grid."""
    pass
```

The body of `Widget` is empty, but the class provides a useful service: it brings together four superclasses so that anyone who needs to create a new widget does not need to remember all those mixins, or wonder if they need to be declared in a certain order in a `class` statement. A better example of this is the Django `ListView` class, which we'll discuss shortly, in "A Modern Example: Mixins in Django Generic Views".

8. "Favor Object Composition Over Class Inheritance."

The title of this section is the second principle of object-oriented design from the *Design Patterns* book,[7] and is the best advice I can offer here. Once you get comfortable with inheritance, it's too easy to overuse it. Placing objects in a neat hierarchy appeals to our sense of order; programmers do it just for fun.

However, favoring composition leads to more flexible designs. For example, in the case of the `tkinter.Widget` class, instead of inheriting the methods from all geometry managers, widget instances could hold a reference to a geometry manager, and invoke its methods. After all, a `Widget` should not "be" a geometry manager, but could use the services of one via delegation. Then you could add a new geometry manager without touching the widget class hierarchy and without worrying about name clashes. Even with single inheritance, this principle enhances flexibility, because subclassing is a form of tight coupling, and tall inheritance trees tend to be brittle.

Composition and delegation can replace the use of mixins to make behaviors available to different classes, but cannot replace the use of interface inheritance to define a hierarchy of types.

We will now analyze Tkinter from the point of view of these recommendations.

Tkinter: The Good, the Bad, and the Ugly

> **NOTE**
>
> Keep in mind that Tkinter has been part of the standard library since Python 1.1 was released in 1994. Tkinter is a layer on top of the excellent Tk GUI toolkit of the Tcl language. The Tcl/Tk combo is not originally object oriented, so the Tk API is basically a vast catalog of functions. However, the toolkit is very object oriented in its concepts, if not in its implementation.

Most advice in the previous section is not followed by Tkinter, with #7 being a notable exception. Even then, it's not a great example, because composition would probably work better for integrating the geometry managers into `Widget`, as discussed in #8.

The docstring of `tkinter.Widget` starts with the words "Internal class." This suggests that `Widget` should probably be an ABC. Although `Widget` has no methods of its own, it does define an interface. Its message is: "You can count on every Tkinter widget providing basic widget methods (`__init__`, `destroy`, and dozens of Tk API functions), in addition to the methods of all three geometry managers." We can agree that this is not a great interface definition (it's just too broad), but it is an interface, and `Widget` "defines" it as the union of the interfaces of its superclasses.

The `Tk` class, which encapsulates the GUI application logic, inherits from `Wm` and `Misc`, neither of which are abstract or mixin (`Wm` is not proper mixin because `TopLevel` subclasses only from it). The name of the `Misc` class is—by itself—a very strong *code smell*. `Misc` has more than 100 methods, and all widgets inherit from it. Why is it necessary that every single widget has methods for clipboard handling, text selection, timer management, and the like? You can't really paste into a button or select text from a scrollbar. `Misc` should be split into several specialized mixin classes, and not all widgets should inherit from every one of those mixins.

To be fair, as a Tkinter user, you don't need to know or use multiple inheritance at all. It's an implementation detail hidden behind the widget classes that you will instantiate or subclass in your own code. But you will suffer the consequences of excessive multiple inheritance when you type `dir(tkinter.Button)` and try to find the method you need among the 214 attributes listed.

Despite the problems, Tkinter is stable, flexible, and not necessarily ugly. The legacy (and default) Tk widgets are not themed to match modern user interfaces, but the `tkinter.ttk` package provides pretty, native-looking widgets, making professional GUI development viable since Python 3.1 (2009). Also, some of the legacy widgets, like `Canvas` and `Text`, are incredibly powerful. With just a little coding, you can turn a `Canvas` object into a simple drag-and-drop drawing application. Tkinter and Tcl/Tk are definitely worth a look if you are interested in GUI programming.

However, our theme here is not GUI programming, but the practice of multiple inheritance. A more up-to-date example with explicit mixin classes can be found in Django.

A Modern Example: Mixins in Django Generic Views

> **NOTE**
>
> You don't need to know Django to follow this section. I am just using a small part of the framework as a practical example of multiple inheritance, and I will try to give all the necessary background, assuming you have some experience with server-side web development in another language or framework.

In Django, a view is a callable object that takes, as argument, an object representing an HTTP request and returns an object representing an HTTP response. The different responses are what interests us in this discussion. They can be as simple as a redirect response, with no content body, or as complex as a catalog page in an online store, rendered from an HTML template and listing multiple merchandise with buttons for buying and links to detail pages.

Originally, Django provided a set of functions, called generic views, that implemented some common use cases. For example, many sites need to show search results that include information from numerous items, with the listing spanning multiple pages, and for each item a link to a page with detailed information about it. In Django, a list view and a detail view are designed to work together to solve this problem: a list view renders search results, and a detail view produces pages for individual items.

However, the original generic views were functions, so they were not extensible. If you needed to do something similar but not exactly like a generic list view, you'd have to start from scratch.

In Django 1.3, the concept of class-based views was introduced, along with a set of generic view classes organized as base classes, mixins, and ready-to-use concrete classes. The base classes and mixins are in the `base` module of the `django.views.generic` package, pictured in Figure 14-4. At the top of the diagram we see two classes that take care of very distinct responsibilities: `View` and `TemplateResponseMixin`.

> **TIP**
>
> A great resource to study these classes is the Classy Class-Based Views website, where you can easily navigate through them, see all methods in each class (inherited, overridden, and added methods), view diagrams, browse their documentation, and jump to their source code on GitHub.

`View` is the base class of all views (it could be an ABC), and it provides core functionality like the `dispatch` method, which delegates to “handler” methods like `get`, `head`, `post`, etc., implemented by concrete subclasses to handle the different HTTP verbs.[8] The `RedirectView` class inherits only from `View`, and you can see that it implements `get`, `head`, `post`, etc.

Concrete subclasses of `View` are supposed to implement the handler methods, so why aren’t they part of the `View` interface? The reason: subclasses are free to implement just the handlers they want to support. A `TemplateView` is used only to display content, so it only implements `get`. If an HTTP `POST` request is sent to a `TemplateView`, the inherited `View.dispatch` method checks that there is no `post` handler, and produces an HTTP `405 Method Not Allowed` response.[9]

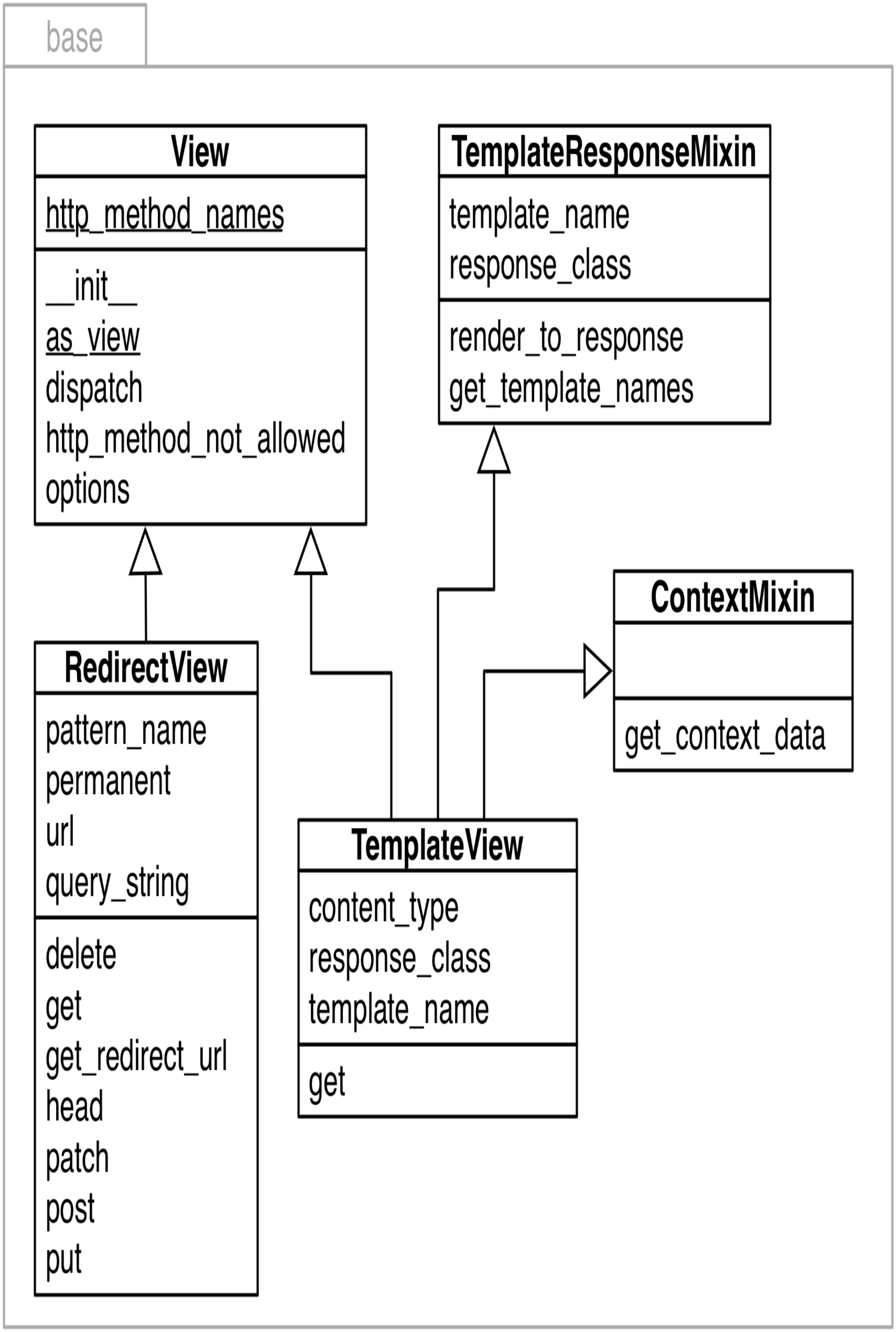
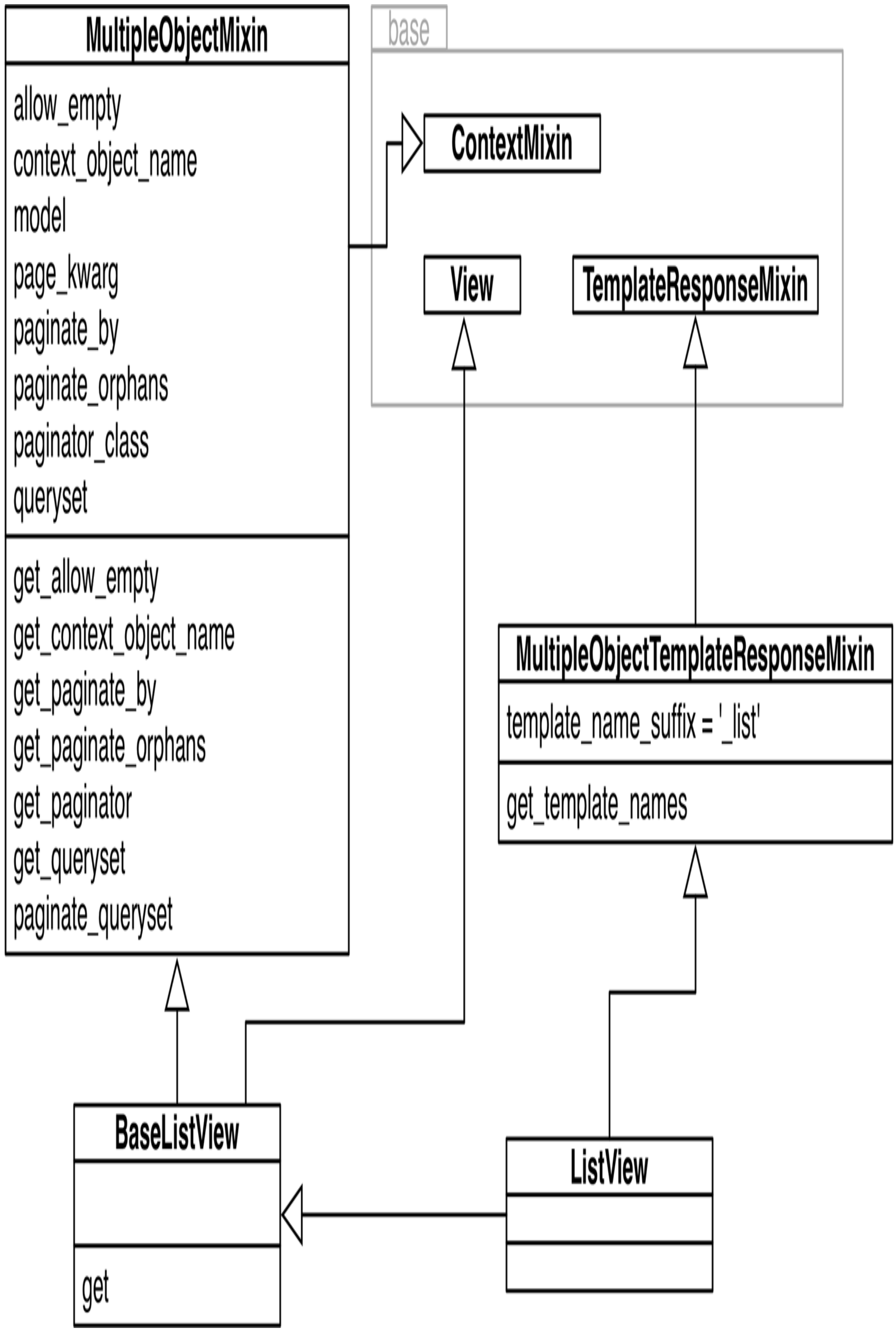

base
View
http_method_names
__init__
as_view
dispatch
http_method_not_allowed
options
TemplateResponseMixin
template_name
response_class
render_to_response
get_template_names
ContextMixin
get_context_data
RedirectView
pattern_name
permanent
url
query_string
delete
get
get_redirect_url
head
patch
post
put
TemplateView
content_type
response_class
template_name
get

Figure 14-4. UML class diagram for the django.views.generic.base module

The `TemplateResponseMixin` provides functionality that is of interest only to views that need to use a template. A `RedirectView`, for example, has no content body, so it has no need of a template and it does not inherit from this mixin. `TemplateResponseMixin` provides behaviors to `TemplateView` and other template-rendering views, such as `ListView`, `DetailView`, etc., defined in other modules of the `django.views.generic` package. Figure 14-5 depicts the `django.views.generic.list` module and part of the `base` module.



MultipleObjectMixin
allow_empty
context_object_name
model
page_kwarg
paginate_by
paginate_orphans
paginator_class
queryset
get_allow_empty
get_context_object_name
get_paginate_by
get_paginate_orphans
get_paginator
get_queryset
paginate_queryset
base
ContextMixin
View
TemplateResponseMixin
MultipleObjectTemplateResponseMixin
template_name_suffix = '_list'
get_template_names
BaseListView
get
ListView

Figure 14-5. UML class diagram for the django.views.generic.list module. Here the three classes of the base module are collapsed (see Figure 14-4). The ListView class has no methods or attributes: it's an aggregate class.

For Django users, the most important class in Figure 14-5 is `ListView`, which is an aggregate class, with no code at all (its body is just a docstring). When instantiated, a `ListView` has an `object_list` instance attribute through which the template can iterate to show the page contents, usually the result of a database query returning multiple objects. All the functionality related to generating this iterable of objects comes from the `MultipleObjectMixin`. That mixin also provides the complex pagination logic—to display part of the results in one page and links to more pages.

Suppose you want to create a view that will not render a template, but will produce a list of objects in JSON format. That's why the `BaseListView` exists. It provides an easy-to-use extension point that brings together `View` and `MultipleObjectMixin` functionality, without the overhead of the template machinery.

The Django class-based views API is a better example of multiple inheritance than Tkinter. In particular, it is easy to make sense of its mixin classes: each has a well-defined purpose, and they are all named with the …`Mixin` suffix.

Class-based views were not universally embraced by Django users. Many do use them in a limited way, as black boxes, but when it's necessary to create something new, a lot of Django coders continue writing monolithic view functions that take care of all those responsibilities, instead of trying to reuse the base views and mixins.

It does take some time to learn how to leverage class-based views and how to extend them to fulfill specific application needs, but I found that it was worthwhile to study them: they eliminate a lot of boilerplate code, make it easier to reuse solutions, and even improve team communication—for example, by defining standard names to templates, and to the variables passed to template contexts. Class-based views are Django views "on rails."

This concludes our tour of multiple inheritance and mixin classes.

Chapter Summary

We started our coverage of inheritance explaining the problem with subclassing built-in types: their native methods implemented in C do not call overridden methods in subclasses, except in very few special cases. That's why, when we need a custom `list`, `dict`, or `str` type, it's easier to subclass `UserList`, `UserDict`, or `UserString`—all defined in the `collections` module, which actually wraps the built-in types and delegate operations to them—three examples of favoring composition over inheritance in the standard library. If the desired behavior is very different from what the built-ins offer, it may be easier to subclass the appropriate ABC from `collections.abc` and write your own implementation.

The rest of the chapter was devoted to the double-edged sword of multiple inheritance. First we saw how the method resolution order, encoded in the `__mro__` class attribute, addresses the problem of potential naming conflicts in inherited methods. We also saw how the `super()` built-in follows the `__mro__` to call a method on a superclass. We then studied how multiple inheritance is used in the Tkinter GUI toolkit that comes with the Python standard library. Tkinter is not an example of current best practices, so we discussed some ways of coping with multiple inheritance, including careful use of mixin classes and avoiding multiple inheritance altogether by using composition instead. After considering how multiple inheritance is abused in Tkinter, we wrapped up by studying the core parts of the Django class-based views hierarchy, which I consider a better example of mixin usage.

Lennart Regebro—a very experienced Pythonista and one of first edition's technical reviewers—finds the design of Django's mixin views hierarchy confusing. But he also wrote:

> *The dangers and badness of multiple inheritance are greatly overblown. I've actually never had a real big problem with it.*

In the end, each of us may have different opinions about how to use multiple inheritance, or whether to use it at all in our own projects.

Meanwhile, rejecting inheritance—even single inheritance—is a growing trend. One of the most successful languages created in the 21st century is Go. It doesn't have a construct called "class", but you can build types that are structs of encapsulated fields and you can attach methods to those structs. Go allows the definition of interfaces that are checked by the compiler using structural typing, a.k.a. *static duck typing*—very similar to what we now have with protocol types since Python 3.8. Go has special syntax for building types and interfaces by composition, but it does not support inheritance—not even among interfaces.

So perhaps the best advice about inheritance is: avoid it if you can. But often, we don't have a choice: the frameworks we use impose their own design choices.

Further Reading

When using ABCs, multiple inheritance is not only common but practically inevitable, because each of the most fundamental collection ABCs (`Sequence`, `Mapping`, and `Set`) extend multiple ABCs. The source code for `collections.abc` (*Lib/_collections_abc.py*) is a good example of multiple inheritance with ABCs—many of which are also mixin classes.

Raymond Hettinger's post Python's super() considered super! explains the workings of `super` and multiple inheritance in Python from a positive perspective. It was written in response to Python's Super is nifty, but you can't use it (a.k.a. Python's Super Considered Harmful) by James Knight.

Despite the titles of those posts, the problem is not really the `super` built-in—which in Python 3 is not as ugly as it was in Python 2. The real issue is multiple inheritance, which is inherently complicated and tricky. Michele Simionato goes beyond criticizing and actually offers a solution in his Setting Multiple Inheritance Straight: he implements traits, a constrained form of mixins that originated in the Self language. Simionato has a long series of illuminating blog posts about multiple inheritance in Python, including The wonders of cooperative inheritance, or using super in Python

3; Mixins considered harmful, part 1 and part 2; and Things to Know About Python Super, part 1, part 2 and part 3. The oldest posts use the Python 2 `super` syntax, but are still relevant.

I read the first edition of Grady Booch's *Object-Oriented Analysis and Design, 3E* (Addison-Wesley, 2007), and highly recommend it as a general primer on object-oriented thinking, independent of programming language. It is a rare book that covers multiple inheritance without prejudice.

In 2021, it's more fashionable than ever to avoid inheritance, so here are two references about how to do that. Brandon Rhodes wrote The Composition Over Inheritance Principle, part of his excellent Python Design Patterns guide on the Web. Augie Fackler and Nathaniel Manista presented The End Of Object Inheritance & The Beginning Of A New Modularity at PyCon 2013—that was before I wrote the first edition, but I only found it in 2019. Fackler and Manista talk about organizing systems around interfaces and functions that handle objects implementing those interfaces, avoiding the tight coupling and failure modes of classes and inheritance. That reminds me a lot of the Go way, but they advocate it for Python.

SOAPBOX

Think About the Classes You Really Need

The vast majority of programmers write applications, not frameworks. Even those who do write frameworks are likely to spend a lot (if not most) of their time writing applications. When we write applications, we normally don’t need to code class hierarchies. At most, we write classes that subclass from ABCs or other classes provided by the framework. As application developers, it’s very rare that we need to write a class that will act as the superclass of another. The classes we code are almost always leaf classes (i.e., leaves of the inheritance tree).

If, while working as an application developer, you find yourself building multilevel class hierarchies, it’s likely that one or more of the following applies:

- You are reinventing the wheel. Go look for a framework or library that provides components you can reuse in your application.
- You are using a badly designed framework. Go look for an alternative.
- You are overengineering. Remember the *KISS principle*.
- You became bored coding applications and decided to start a new framework. Congratulations and good luck!

It’s also possible that all of the above apply to your situation: you became bored and decided to reinvent the wheel by building your own overengineered and badly designed framework, which is forcing you to code class after class to solve trivial problems. Hopefully you are having fun, or at least getting paid for it.

Misbehaving Built-ins: Bug or Feature?

The built-in `dict`, `list`, and `str` types are essential building blocks of Python itself, so they must be fast—any performance issues in them would severely impact pretty much everything else. That’s why CPython adopted the shortcuts that cause their built-in methods to misbehave by not cooperating with methods overridden by subclasses. A possible way out of this dilemma would be to offer two implementations for each of those types: one “internal,” optimized for use by the interpreter and an external, easily extensible one.

But wait, this is what we have: `UserDict`, `UserList`, and `UserString` are not as fast as the built-ins but are easily extensible. The pragmatic approach taken by CPython means we also get to use, in our own applications, the highly optimized implementations that are hard to subclass. Which makes sense, considering that it’s not so often that we need a custom mapping, list, or string, but we use `dict`, `list` and `str` every day. We just need to be aware of the trade-offs involved.

Inheritance Across Languages

Alan Kay coined the term “object oriented,” and Smalltalk had only single inheritance, although there are forks with various forms of multiple inheritance support, including the modern Squeak and Pharo Smalltalk dialects that support traits—a language construct that fulfills the role of a mixin class, while avoiding some of the issues with multiple inheritance.

The first popular language to implement multiple inheritance was C++, and the feature was abused enough that Java—intended as a C++ replacement—was designed without support for multiple inheritance of implementation (i.e., no mixin classes). That is, until Java 8 introduced default methods that make interfaces very similar to the abstract classes used to define interfaces in C++ and in Python. Except that Java interfaces cannot have state—a key distinction. After Java, probably the most widely deployed JVM language is Scala, and it implements traits. Other languages supporting traits are the latest stable versions of PHP and Groovy, and the under-construction languages Rust and Perl 6—so it’s fair to say that traits are trendy as I write this.

Ruby offers an original take on multiple inheritance: it does not support it, but introduces mixins as a language feature. A Ruby class can include a module in its body, so the methods defined in the module become part of the class implementation. This is a "pure" form of mixin, with no inheritance involved, and it's clear that a Ruby mixin has no influence on the type of the class where it's used. This provides the benefits of mixins, while avoiding many of its usual problems.

Two new object-oriented languages that are getting a lot of attention severely limit inheritance: Go and Julia. Both are about programming "objects", but they avoid the term "class". Go has no inheritance at all. Julia has a type hierarchy but subtypes cannot inherit structure, only behaviors, and only abstract types can be subtyped. In addition, Julia methods are implemented using multiple dispatch—a more advanced form of the mechanism we saw in "Single Dispatch Generic Functions".

---

1 If you are curious, the experiment is in the *strkeydict_dictsub.py* file in the *Fluent Python* code repository.

2 By the way, in this regard, PyPy behaves more "correctly" than CPython, at the expense of introducing a minor incompatibility. See "Differences between PyPy and CPython" for details.

3 In Python 2, the second line of `D.pingpong` would be written as `super(D, self).ping()` rather than `super().ping()`.

4 As previously mentioned, Java 8 allows interfaces to provide method implementations as well. The new feature is called Default Methods in the official Java Tutorial.

5 In "Waterfowl and ABCs", Alex Martelli quotes Scott Meyer's *More Effective C++*, which goes even further: "all non-leaf classes should be abstract" (i.e., concrete classes should not have concrete superclasses at all).

6 "A class that is constructed primarily by inheriting from mixins and does not add its own structure or behavior is called an *aggregate class*.", Grady Booch et al., *Object Oriented Analysis and Design, 3E* (Addison-Wesley, 2007), p. 109.

7 Erich Gamma, Richard Helm, Ralph Johnson and John Vlissides, *Design Patterns: Elements of Reusable Object-Oriented Software, Introduction*, p. 20.

8 Django programmers know that the `as_view` class method is the most visible part of the `View` interface, but it's not relevant to us here.

9 If you are into design patterns, you'll notice that the Django dispatch mechanism is a dynamic variation of the Template Method pattern. It's dynamic because the `View` class does not force subclasses to implement all handlers, but `dispatch` checks at runtime if a concrete handler is available for the specific request.

Chapter 15. More About Type Hints

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 15th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

I learned a painful lesson that for small programs, dynamic typing is great. For large programs you need a more disciplined approach. And it helps if the language gives you that discipline rather than telling you "Well, you can do whatever you want".[1]

—Guido van Rossum, a fan of Monty Python

This chapter is a sequel to Chapter 8, covering more of Python's gradual type system. The main topics are:

- Overloaded function signatures;
- `typing.TypedDict` for type hinting `dicts` used as records;
- Type casting;
- Runtime access to type hints;

- Generic types:
    - Declaring a generic class;
    - Variance: invariant, covariant, and contravariant types;
    - Generic static protocols.

What’s new in this chapter

This chapter is new in *Fluent Python, Second Edition*.

Let’s start with a subject that really belonged in Chapter 8, but I moved it here because that was already the longest chapter in the book.

Overloaded signatures

Some Python functions accept different combinations of arguments. The `@typing.overload` allows annotating each different combination. This is particularly important when the return type of the function depends on the type of two or more parameters.

Consider the `sum` built-in function. This is the text of `help(sum)`:

```
>>> help(sum)
sum(iterable, /, start=0)
    Return the sum of a 'start' value (default: 0) plus an
iterable of numbers

    When the iterable is empty, return the start value.
    This function is intended specifically for use with numeric
values and may
    reject non-numeric types.
```

The `sum` built-in is written in C, but *typeshed* has overloaded type hints for it, in `builtins.pyi`:

```
@overload
def sum(__iterable: Iterable[_T]) -> Union[_T, int]: ...
```

```
@overload
def sum(__iterable: Iterable[_T], start: _S) -> Union[_T, _S]:
...
```

First let's look at the overall syntax of overloads. On a stub file (`.pyi`), that's all there would be about `sum`—the implementation would be in a different file.

The type checker tries to match the given arguments with each overloaded signature, in order. The call `sum(range(100), 1000)` doesn't match the first overload, but matches the second.

You can also use `@overload` in a regular Python module, by writing the overloaded signatures right before the function's actual signature and implementation. Example 15-1 shows how `sum` would appear annotated and implemented in a Python module.

Example 15-1. `mysum.py`: definition of the `sum` function with overloaded signatures:

```
import functools
import operator
from collections.abc import Iterable
from typing import overload, Union, TypeVar

T = TypeVar('T')
S = TypeVar('S')  ❶

@overload
def sum(it: Iterable[T]) -> Union[T, int]: ...  ❷
@overload
def sum(it: Iterable[T], /, start: S) -> Union[T, S]: ...  ❸
def sum(it, /, start=0):  ❹
    return functools.reduce(operator.add, it, start)
```

❶ We need this second `TypeVar` in the second overload.

❷ This signature is for the simple case: `sum(my_iterable)`. The result type may be `T`—the type of the elements that `my_iterable` yields—or it may be `int` if the iterable is empty, because the default value of the `start` parameter is `0`.

❸ When `start` is given, it can be of any type `S`, so the result type is `Union[T, S]`. This is why we need `S`. If we reused `T` then the type of `start` would have to be the same type as the elements of `Iterable[T]`.

❹ The signature of the actual function implementation has no type hints.

That's a lot of lines to annotate a one-line function. Probably overkill, I know. At least it wasn't a `foo` function.

If you want to learn about `@overload` by reading code, *typeshed* has hundreds of examples. On *typeshed*, the stub file for Python's built-ins has 186 overloads as I write this—more than any other in the standard library.

> **TAKE ADVANTAGE OF *GRADUAL* TYPING**
>
> Aiming for 100% of annotated code may lead to type hints that add lots of noise but little value. Refactoring to simplify type hinting can lead to cumbersome APIs. Sometimes it's better to be pragmatic and leave a piece of code without type hints.

The handy APIs we call Pythonic are often hard to annotate. In the next section we'll see example of this: six overloads are needed to properly annotate the flexible `max` built-in function.

Max Overload

It is difficult to add type hints to functions that leverage the powerful dynamic features of Python.

While studying *typeshed*, I found bug report (#4051): Mypy failed to warn that it is illegal to pass `None` as one of the arguments to the built-in `max()` function, or to pass an iterable that at some point yields `None`. In either case, you get a runtime exception like this one:

```
TypeError: '>' not supported between instances of 'int' and
'NoneType'
```

The documentation of `max` starts with this sentence:

> *Return the largest item in an iterable or the largest of two or more arguments.*

To me, that's a very intuitive description.

But if I must annotate a function described in those terms, I have to ask: which is it? An iterable or two or more arguments?

The reality is more complicated because `max` also takes two optional keyword arguments: `key` and `default`.

I coded `max` in Python to make it easier to test (the original `max` is in C).

```python
def max(first, *args, key=None, default=MISSING):
    if args:
        series = args
        candidate = first
    else:
        series = iter(first)
        try:
            candidate = next(series)
        except StopIteration:
            if default is not MISSING:
                return default
            raise ValueError(EMPTY_MSG) from None
    if key is None:
        for current in series:
            if candidate < current:
                candidate = current
    else:
        candidate_key = key(candidate)
        for current in series:
            current_key = key(current)
            if candidate_key < current_key:
                candidate = current
                candidate_key = current_key
    return candidate
```

To fix issue #4051, I wrote the code in Example 15-2.[2]

Example 15-2.

```
from typing import Protocol, Any, TypeVar, overload, Callable,
Iterable, Union

class SupportsLessThan(Protocol):
    def __lt__(self, other: Any) -> bool: ...

T = TypeVar('T')
LT = TypeVar('LT', bound=SupportsLessThan)
DT = TypeVar('DT')

MISSING = object()
EMPTY_MSG = 'max() arg is an empty sequence'

@overload
def max(__arg1: LT, __arg2: LT, *args: LT, key: None = ...) -> LT:
    ...
@overload
def max(__arg1: T, __arg2: T, *args: T, key: Callable[[T], LT]) ->
T:
    ...
@overload
def max(__iterable: Iterable[LT], *, key: None = ...) -> LT:
    ...
@overload
def max(__iterable: Iterable[T], *, key: Callable[[T], LT]) -> T:
    ...
@overload
def max(__iterable: Iterable[LT], *, key: None = ...,
        default: DT) -> Union[LT, DT]:
    ...
@overload
def max(__iterable: Iterable[T], *, key: Callable[[T], LT],
        default: DT) -> Union[T, DT]:
    ...
```

My Python implementation of `max` is about the same length as all those typing imports and declarations. Thanks to duck typing, my code has no `isinstance` checks, and provides the same error checking as those type hints—but only at runtime, of course.

The double underscore prefix in some arguments is a convention used on *typeshed* for positional-only arguments. That means you can call `max(10, 20)`, but not `max(__arg1=10, __arg2=20)`.

A key benefit of `@overload` making the return type as precise as possible, according to the types of the arguments given. Let's study the overloads for `max` in groups.

Inputs implementing `SupportsLessThan`, no `default=`

```
@overload
def max(__arg1: LT, __arg2: LT, *_args: LT, key: None = ...) ->
LT:
    ...
# ... lines omitted ...
@overload
def max(__iterable: Iterable[LT], *, key: None = ...) -> LT:
    ...
```

In these cases the inputs are either separate arguments of type `LT` implementing `SupportsLessThan`, or an `Iterable` of such items. The return type of `max` is the same as the actual arguments or items, as described in [Link to Come].

Sample calls that match these overloads:

```
max(1, 2, -3)  # returns 2
max(['Go', 'Python', 'Rust'])  # returns 'Rust'
```

`key=` provided, no `default=`

```
@overload
def max(__arg1: T, __arg2: T, *_args: T, key: Callable[[T], LT])
-> T:
    ...
# ... lines omitted ...
@overload
def max(__iterable: Iterable[T], *, key: Callable[[T], LT]) -> T:
    ...
```

The inputs can be separate items of any type `T` or a single `Iterable[T]`, and `key=` must be a callable that takes an argument of the same type `T`, and returns a value that implements `SupportsLessThan`. The return type of `max` is the same as the actual arguments.

Sample calls that match these overloads:

```
max(1, 2, -3, key=abs)  # returns -3
max(['Go', 'Python', 'Rust'], key=len)  # returns 'Python'
```

`default=` provided, no `key=`

```
@overload
def max(__iterable: Iterable[LT], *, key: None = ...,
        default: DT) -> Union[LT, DT]:
    ...
```

The input is an iterable of items of type `LT` implementing `SupportsLessThan`. The `default=` argument is the return value when the `Iterable` is empty. Therefore the return type of `max` must be a `Union` of type `LT` or the type of the `default` argument.

Sample calls that match these overloads:

```
max([1, 2, -3], default=0)  # returns 2
max([], default=None)  # returns None
```

`key=` and `default=` provided

```
@overload
def max(__iterable: Iterable[T], *, key: Callable[[T], LT],
        default: DT) -> Union[T, DT]:
    ...
```

The inputs are:

- an `Iterable` of items of any type `T`;
- callable that takes an argument of type `T` and returns a value of type `LT` that implements `SupportsLessThan`;
- a default value of any type `DT`.

The return type of `max` must be a `Union` of type `T` or the type of the `default` argument.

```
max([1, 2, -3], key=abs, default=None)  # returns -3
max([], key=abs, default=None)  # returns None
```

Takeaways from Overloading `max`

Type hints allow Mypy to flag a call like `max([None, None])` with this error message:

```
mymax_demo.py:109: error: Value of type variable "_LT" of "max"
  cannot be "None"
```

On the other hand, having to write so many lines to support the type checker may discourage people from writing convenient and flexible functions like `max`. If I had to reinvent the `min` function as well, I could refactor and reuse most of the implementation of `max`. But I'd have to copy & paste all overloaded declarations—even though they would be identical for `min`, except for the function name.

My friend João S. O. Bueno—one of the smartest Python devs I know—tweeted this:

> *Although it is this hard to express the signature of `max`—it fits in one's mind quite easily. My understanding is that the expressiveness of annotation markings is very limited, compared to that of Python.*

Now let's study the `TypedDict` typing construct. It is not as useful as I imagined at first, but has its uses. Experimenting with `TypedDict` demonstrates the limitations of static typing for handling dynamic structures such as JSON data.

TypedDict

> **WARNING**
>
> It’s tempting to use `TypedDict` to protect against errors while handling dynamic data structures like JSON API responses. But the examples here make clear that correct handling of JSON must be done at runtime, and not with static type checking. For runtime checking of JSON-like structures using type hints, check out the `pydantic` package on PyPI.

Python dictionaries are sometimes used as records, with the keys used as field names and field values of different types.

For example, consider a record describing a book in JSON or Python:

```
{"isbn": "0134757599",
 "title": "Refactoring, 2e",
 "authors": ["Martin Fowler", "Kent Beck"],
 "pagecount": 478}
```

Before Python 3.8, there was no good way to annotate a record like that, because the mapping types we saw in “Generic mappings” limit all values to have the same type.

Here are two lame attempts to annotate a record like the JSON object above:

`Dict[str, Any]`

The values may be of any type.

`Dict[str, Union[str, int, List[str]]]`

Hard to read, and doesn’t preserve the relationship between field names and their respective field types: `title` is supposed to be a `str`, it can’t be an `int` or a `List[str]`.

PEP 589—TypedDict: Type Hints for Dictionaries with a Fixed Set of Keys addressed that problem. Here is a simple `TypedDict`:

Example 15-3. `books.py`: the `BookDict` definition.

```python
from typing import TypedDict
import json

class BookDict(TypedDict):
    isbn: str
    title: str
    authors: list[str]
    pagecount: int
```

At first glance, `typing.TypedDict` may seem like a data class builder, similar to `typing.NamedTuple`—covered in Chapter 5.

The syntactic similarity is misleading. `TypedDict` is very different. It exists only for the benefit of type checkers, and has no runtime effect.

`TypedDict` provides two things:

1. Class-like syntax to annotate a `dict` with type hints for the value of each "field".

2. A constructor that tells the type checker to expect a `dict` with the keys and values as specified.

At runtime, a `TypedDict` constructor such as `BookDict` is placebo: it has the same effect as calling the `dict` constructor with the same arguments.

The fact that `BookDict` creates a plain `dict` also means that:

- The "fields" in the pseudo-class definition don't create instance attributes.

- You can't write initializers with default values for the "fields".

- Method definitions are not allowed.

Let's explore the behavior of a `BookDict` at runtime.

Example 15-4. Using a `BookDict`, but not quite as intended.

```python
>>> from books import BookDict
>>> pp = BookDict(title='Programming Pearls',  ❶
...               authors='Jon Bentley',  ❷
...               isbn='0201657880',
```

```
...                 pagecount=256)
>>> pp  ❸
{'title': 'Programming Pearls', 'authors': 'Jon Bentley', 'isbn':
'0201657880',
 'pagecount': 256}
>>> type(pp)
<class 'dict'>
>>> pp.title  ❹
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
AttributeError: 'dict' object has no attribute 'title'
>>> pp['title']
'Programming Pearls'
>>> BookDict.__annotations__  ❺
{'isbn': <class 'str'>, 'title': <class 'str'>, 'authors':
typing.List[str],
 'pagecount': <class 'int'>}
```

❶ You can call `BookDict` like a `dict` constructor with keyword arguments, or passing a `dict` argument—including a `dict` literal.

❷ Ooops… I forgot `authors` takes a list. But gradual typing means no type checking at runtime.

❸ The result of calling `BookDict` is a plain `dict`…

❹ … therefore you can't read the data using `object.field` notation.

❺ The type hints are in `BookDict.__annotations__`, and not in `pp`.

Without a type checker, `TypedDict` is as useful as comments: it may help people read the code, but that's it. In contrast, the class builders from Chapter 5 are useful even if you don't use a type checker because at runtime they generate or enhance a custom class that you can instantiate. They also provide several useful methods or functions listed in Table 5-1.

Example 15-5 builds a valid `BookDict` and tries some operations on it. This shows how `TypedDict` enables Mypy to catch errors, shown in Example 15-6.

Example 15-5. `demo_books.py`: legal and ilegal operations on a `BookDict`.

```
from books import BookDict
from typing import TYPE_CHECKING

def demo() -> None:  ❶
    book = BookDict(  ❷
        isbn='0134757599',
        title='Refactoring, 2e',
        authors=['Martin Fowler', 'Kent Beck'],
        pagecount=478
    )
    authors = book['authors'] ❸
    if TYPE_CHECKING:  ❹
        reveal_type(authors)  ❺
    authors = 'Bob'  ❻
    book['weight'] = 4.2
    del book['title']


if __name__ == '__main__':
    demo()
```

❶ Remember to add a return type, so that Mypy doesn't ignore the function.

❷ This is a valid `BookDict`: all the keys are present, with values of the correct types.

❸ Mypy will infer the type of `authors` from the annotation for the `'authors'` key in `BookDict`.

❹ `typing.TYPE_CHECKING` is only `True` when the program is being type checked. At runtime, it's always false.

❺ The previous `if` statement prevents `reveal_type(authors)` from being called at runtime. `reveal_type` is not a runtime Python function, but a debugging facility provided by Mypy. That's why there is no `import` for it. See its output in Example 15-6.

❻ The last three lines of the `demo` function are illegal. They will cause error messages in Example 15-6.

Type checking `demo_books.py` from Example 15-5, this is what we get:

Example 15-6. Type checking `demo_books.py`.

```
…/typeddict/ $ mypy demo_books.py
demo_books.py:13: note: Revealed type is 'built-ins.list[built-
ins.str]'  ❶
demo_books.py:14: error: Incompatible types in assignment
                  (expression has type "str", variable has type
"List[str]")  ❷
demo_books.py:15: error: TypedDict "BookDict" has no key 'weight'
❸
demo_books.py:16: error: Key 'title' of TypedDict "BookDict" cannot
be deleted  ❹
Found 3 errors in 1 file (checked 1 source file)
```

❶ This note is the result of `reveal_type(authors)`.

❷ The type of the `authors` variable was inferred from the type of the `book['authors']` expression that initialized it. You can't assign a `str` to a variable of type `List[str]`. Type checkers usually don't allow the type of a variable to change.[3]

❸ Cannot assign to a key that is not part of the `BookDict` definition.

❹ Cannot delete a key that is part of the `BookDict` definition.

Now let's see `BookDict` used in function signatures, to type check function calls.

Imagine you need to generate XML from book records, similar to this:

```
<BOOK>
  <ISBN>0134757599</ISBN>
  <TITLE>Refactoring, 2e</TITLE>
  <AUTHOR>Martin Fowler</AUTHOR>
  <AUTHOR>Kent Beck</AUTHOR>
```

```
    <PAGECOUNT>478</PAGECOUNT>
</BOOK>
```

If you were writing MicroPython code to embed in a tiny microcontroller, you might write a function like this:[4]

Example 15-7. `books.py`: `to_xml` function.

```python
AUTHOR_EL = '<AUTHOR>{}</AUTHOR>'

def to_xml(book: BookDict) -> str:  ❶
    elements: list[str] = []  ❷
    for key, value in book.items():
        if isinstance(value, list):  ❸
            elements.extend(
                AUTHOR_EL.format(n) for n in value)  ❹
        else:
            tag = key.upper()
            elements.append(f'<{tag}>{value}</{tag}>')
    xml = '\n\t'.join(elements)
    return f'<BOOK>\n\t{xml}\n</BOOK>'
```

❶ The whole point of the example: using `BookDict` in the function signature.

❷ It's often necessary to annotate collections that start empty, otherwise Mypy can't infer the type of the elements.[5]

❸ Mypy understands `isinstance` checks, and treats `value` as a `list` in this block.

❹ When I used `key == 'authors'` as the condition for the `if` guarding this block, Mypy found an error in this line: `"object" has no attribute "__iter__"`, because it inferred the type of `value` returned from `book.items()` as `object`, which doesn't support the `__iter__` method required by the generator expression. With the `isinstance` check, this works because Mypy knows that `value` is a `list` in this block.

Here is a function that parses a JSON `str` and returns a `BookDict`:

Example 15-8. `books_any.py`: `from_json` function.

```
def from_json(data: str) -> BookDict:
    whatever = json.loads(data)  ❶
    return whatever  ❷
```

❶ The return type of `json.loads()` is `Any`.[6]

❷ I can return `whatever`—of type `Any`—because `Any` is *consistent-with* every type, including the declared return type, `BookDict`.

The second point of Example 15-8 is very important to keep in mind: Mypy will not flag any problem in this code, but at runtime the value in `whatever` may not conform to the `BookDict` structure—in fact, it may not be a `dict` at all!

If you run Mypy with `--disallow-any-expr` it will complain about the two lines in the body of `from_json`:

```
…/typeddict/ $ mypy books_any.py --disallow-any-expr
books_any.py:30: error: Expression has type "Any"
books_any.py:31: error: Expression has type "Any"
Found 2 errors in 1 file (checked 1 source file)
```

In this case, the type error can be silenced by adding a type hint to the initialization of the `whatever` variable, as in Example 15-9:

Example 15-9. `books.py`: `from_json` function with variable annotation.

```
def from_json(data: str) -> BookDict:
    whatever: BookDict = json.loads(data)  ❶
    return whatever  ❷
```

❶ `--disallow-any-expr` does not cause errors when an expression of type `Any` is immediately assigned to a variable with a type hint.

❷ Now `whatever` is of type `BookDict`, the declared return type.

WARNING

Don't be lulled into a false sense of type safety by Example 15-9! Looking at the code at rest, the type checker cannot predict that `json.loads()` will return anything that resembles a `BookDict`. Only runtime validation can guarantee that.

Static type checking is unable to prevent errors with code that is inherently dynamic, such as `json.loads()`, which builds a Python objects of different types at runtime. Example 15-10, Example 15-11, and Example 15-12 demonstrate.

Example 15-10. `demo_not_book.py`: `from_json` returns an invalid `BookDict`, and `to_xml` accepts it.

```
from books import to_xml, from_json
from typing import TYPE_CHECKING

def demo() -> None:
    NOT_BOOK_JSON = """
        {"title": "Andromeda Strain",
         "flavor": "pistachio",
         "authors": true}
    """
    not_book = from_json(NOT_BOOK_JSON)  ❶
    if TYPE_CHECKING:  ❷
        reveal_type(not_book)
        reveal_type(not_book['authors'])

    print(not_book)  ❸
    print(not_book['flavor'])  ❹

    xml = to_xml(not_book)  ❺
    print(xml)  ❻


if __name__ == '__main__':
    demo()
```

❶ This line does not produce a valid `BookDict`—see the content of `NOT_BOOK_JSON`.

❷ Let's have Mypy reveal a couple of types.

❸ This should not be a problem: `print` can handle `object` and every other type.

❹ `BookDict` has no `'flavor'` key, but the JSON source does… what will happen?

❺ Remember the signature: `def to_xml(book: BookDict) -> str:`

❻ How will the XML output look like?

Checking `demo_not_book.py` with Mypy:

Example 15-11. Mypy report for `demo_not_book.py`, reformatted for clarity.

```
…/typeddict/ $ mypy demo_not_book.py
demo_not_book.py:12: note: Revealed type is
   'TypedDict('books.BookDict', {'isbn': built-ins.str,
                                 'title': built-ins.str,
                                 'authors': built-ins.list[built-
ins.str],
                                 'pagecount': built-ins.int})'  ❶
demo_not_book.py:13: note: Revealed type is 'built-ins.list[built-
ins.str]'  ❷
demo_not_book.py:16: error: TypedDict "BookDict" has no key
'flavor'  ❸
Found 1 error in 1 file (checked 1 source file)
```

❶ The revealed type is the nominal type, not the runtime content of `not_book`.

❷ Again, this is the nominal type of `not_book['authors']`, as defined in `BookDict`. Not the runtime type.

❸ This error is for line `print(not_book['flavor'])`: that key does not exist in the nominal type.

Now let’s run `demo_not_book.py`.

Example 15-12. Output of running `demo_not_book.py`.

```
…/typeddict/ $ python3 demo_not_book.py
{'title': 'Andromeda Strain', 'flavor': 'pistachio', 'authors':
True}  ❶
pistachio  ❷
<BOOK>  ❸
        <TITLE>Andromeda Strain</TITLE>
        <FLAVOR>pistachio</FLAVOR>
        <AUTHORS>True</AUTHORS>
</BOOK>
```

❶ This is not really a `BookDict`.

❷ The value of `not_book['flavor']`.

❸ `to_xml` takes a `BookDict` argument, but there is no runtime checking: garbage in, garbage out.

Example 15-12 shows that `demo_not_book.py` outputs nonsense, but has no runtime errors. Using a `TypedDict` while handling JSON data did not provide much type safety.

If you look at the code for `to_xml` in Example 15-7 through the lens of duck typing, the argument `book` must provide an `.items()` method that returns an iterable of tuples like `(key, value)` where:

- `key` must have an `.upper()` method;
- `value` can be anything.

The point of this demonstration: when handling data with a dynamic structure, such as JSON or XML, `TypedDict` is absolutely not a replacement for data validation at runtime. For that, use `pydantic`.

`TypedDict` has more features, including support for optional keys, a limited form of inheritance, and an alternative declaration syntax. If you want to know more about it, please review *PEP 589_TypedDict: Type Hints for Dictionaries with a Fixed Set of Keys*.

Now let’s turn our attention to a function that is best avoided, but sometimes is unavoidable: `typing.cast`.

Type Casting

No type system is perfect, and neither are the static type checkers, the type hints in the *typeshed* project, or the type hints in the third-party packages that have them.

The `typing.cast()` special function provides one way to handle type checking malfunctions or incorrect type hints in code we can’t fix. The Mypy documentation explains:

> *Casts are used to silence spurious type checker warnings and give the type checker a little help when it can’t quite understand what is going on.*

At runtime, `typing.cast` does absolutely nothing. This is its implementation:

```
def cast(typ, val):
    """Cast a value to a type.
    This returns the value unchanged.  To the type checker this
    signals that the return value has the designated type, but at
    runtime we intentionally don't check anything (we want this
    to be as fast as possible).
    """
    return val
```

PEP 484 requires type checkers to “blindly believe” the type stated in the `cast`. The Casts section of PEP 484 gives an example where the type checker needs the guidance of `cast`::

```
from typing import cast

def find_first_str(a: list[object]) -> str:
    index = next(i for i, x in enumerate(a) if isinstance(x,
str))
    # We only get here if there's at least one string in a
    return cast(str, a[index])
```

The `next()` call on the generator expression will either return the index of a `str` item or raise `StopIteration`. Therefore, `find_first_str` will always return a `str` if no exception is raised, and `str` is the declared return type.

But if the last line were just `return a[index]`, Mypy would infer the return type as `object` because the `a` argument is declared as `list[object]`. So the `cast()` is required to guide Mypy.[7]

Here is another example with `cast`, this time to correct an outdated type hint for Python's standard library. In Example 22-12, I create an *asyncio* `Server` object and I want to get the address the server is listening to. I coded this line:

```
addr = server.sockets[0].getsockname()
```

But Mypy reported this error:

```
Value of type "Optional[List[socket]]" is not indexable
```

The type hint for `Server.sockets` on *typeshed* in May 2021 is valid for Python 3.6, where the `sockets` attribute could be `None`. But in Python 3.7 `sockets` became a property with a getter that always returns a `list`—which may be empty if the server has no sockets. And since Python 3.8 the getter returns a `tuple` (used as an immutable sequence).

Since I can't fix *typeshed* right now[8] I added a `cast`, like this:

```
from asyncio.trsock import TransportSocket
from typing import cast

# ... many lines omitted ...

    socket_list = cast(tuple[TransportSocket, ...],
server.sockets)
    addr = socket_list[0].getsockname()
```

Using `cast` in this case required a couple of hours to understand the problem and read *asyncio* source code to find the correct type of the sockets: the `TransportSocket` class from the undocumented `asyncio.trsock` module. I also had to add two `import` statements and another line of code for readability.[9] But the code is safer.

The careful reader may note that `sockets[0]` could raise `IndexError` if `sockets` is empty. However, as far as I understand `asyncio`, that cannot happen in Example 22-12 because the `server` is ready to accept connections by the time I read its `sockets` attribute, therefore it will not be empty. Anyway, `IndexError` is a runtime error. Mypy can't spot the problem even in a trivial case like `print([][0])`.

> **WARNING**
>
> Don't get too comfortable using `cast` to silence Mypy, because Mypy is usually right when it reports an error. If you are using `cast` very often, that's a code smell. Your team may be misusing type hints, or you may have low quality dependencies in your codebase.

Despite the downsides, there are valid uses for `cast`. Here is something Guido van Rossum wrote about it:

> *What's wrong with the occasional `cast()` call or `# type: ignore` comment?*[10]

It is unwise to completely ban the use of `cast`, especially because the other workarounds are worse:

- `# type: ignore` is less informative;[11].
- Using `Any` is contagious: since `Any` is *consistent-with* all types, abusing it may produce cascading effects through type inference, undermining the type checker's ability to detect errors in other parts of the code.

Of course, not all typing mishaps can be fixed with `cast`. Sometimes we need `# type: ignore`, the occasional `Any`, or even leaving a function without type hints.

Next, let's talk about using annotations at runtime.

Reading Type Hints at Runtime

At import time, Python reads the type hints in functions, classes and modules and stores them in attributes named `__annotations__`. For example, Example 15-13 is an annotated signature of [Link to Come].

Example 15-13. Annotated clip function

```
def clip(text: str, max_len: int = 80) -> str:
```

The type hints are stored as a `dict` in the `__annotations__` attribute of the function:

```
>>> from clip_annot import clip
>>> clip.__annotations__
{'text': <class 'str'>, 'max_len': <class 'int'>, 'return':
<class 'str'>}
```

The `'return'` key maps to the return type hint after the `->` symbol in Example 15-13.

Note that the annotations are evaluated by the interpreter. That's why the values in the annotations are the Python classes `str` and `int`, and not the strings `'str'` and `'int'`. The import time evaluation of annotations is the standard in Python 3.9 and even in Python 3.10 (unreleased as of May, 2021), and it is the behavior described in PEP 3107 when the syntax for annotations was introduced way back in 2006.

Problems with Annotations at Runtime

The increased use of type hints raised two problems:

- Importing modules uses more CPU and memory when many type hints are used.
- Referring to types not yet defined requires using strings instead of actual types.

Both issues are relevant. The first is self-explanatory at a high level. The root causes at a lower level are beyond the scope of this book. Let's focus on the second issue.

The second issue is often described as the "forward reference" problem, but one of its common manifestations in source code doesn't look like a forward reference at all: that's when a method returns a new object of the same class. Since the class object is not defined until Python completely evaluates the class body, type hints must use the name of the class as a string. Here is an example:

```
class Rectangle:
    # ... lines omitted ...
    def stretch(self, factor: float) -> 'Rectangle':
        return Rectangle(width=self.width * factor)
```

Writing forward referencing type hints as strings is the standard and required practice as of Python 3.10. Static type checkers were designed to deal with that issue from the beginning.

But at runtime, if you write code to read the `return` annotation for `stretch`, you will get a string `'Rectangle'` instead of a reference to the actual type, the `Rectangle` class. Now your code needs to figure out what that string means.

The `typing` module includes three functions and a class categorized as Introspection helpers, the most important being `typing.get_type_hints`. Part of its documentation states:

`get_type_hints(obj, globals=None, locals=None, include_extras=False)`

> […] This is often the same as `obj.__annotations__`. In addition, forward references encoded as string literals are handled by evaluating them in `globals` and `locals` namespaces. […]

That sounds great, but `get_type_hints` can’t handle all cases, as we’ll see.

PEP 563—Postponed Evaluation of Annotations was approved to make it unnecessary to write annotations as strings, and to reduce the runtime costs of type hints. Its main idea is described in these two periods of the *Abstract*:

> *This PEP proposes changing function annotations and variable annotations so that they are no longer evaluated at function definition time. Instead, they are preserved in annotations in string form.*

Beginning with Python 3.7, that’s how annotations are handled in any module that starts with this `import` statement:

```
from __future__ import annotations
```

To demonstrate its effect, I put a copy of the same `clip` function mentioned before in a *clip_annot_post.py* module with that `__future__` import at the top.

At the console, here’s what I get when you import that module and read the annotations from `clip`:

```
>>> from clip_annot_post import clip
>>> clip.__annotations__
{'text': 'str', 'max_len': 'int', 'return': 'str'}
```

As you can see, all the type hints are now plain strings, despite the fact they are not written as quoted strings in the definition of `clip` (Example 15-13).

The `typing.get_type_hints` function is able to resolve many type hints, including those in `clip`:

```
>>> from clip_annot_post import clip
>>> from typing import get_type_hints
>>> get_type_hints(clip)
{'text': <class 'str'>, 'max_len': <class 'int'>, 'return':
<class 'str'>}
```

Calling `get_type_hints` gives us the real types—even in some cases where the original type hint is written as a quoted string. That's the recommended way to read type hints at runtime.

The PEP 563 behavior was scheduled to become default in Python 3.10—with no `__future__` import needed. However, the maintainers of *FastAPI* and *pydantic* raised the alarm that the change would break their code which relies on type hints at runtime, and cannot use `get_type_hints` reliably.

In the ensuing discussion on the *python-dev* mailing list, Łukasz Langa—the author of PEP 563—described some limitations of that function:

> *[…] it turned out that `typing.get_type_hints()` has limits that make its use in general costly at runtime, and more importantly insufficient to resolve all types. The most common example deals with non-global context in which types are generated (e.g. inner classes, classes within functions, etc.). But one of the crown examples of forward references: classes with methods accepting or returning objects of their own type, also isn't properly handled by `typing.get_type_hints()` if a class generator is used. There's some trickery we can do to connect the dots but in general it's not great.*[12]

Python's Steering Council decided to postpone making PEP 563 the default behavior until Python 3.11 or later, giving more time to developers to come up with a solution that addresses the issues PEP 563 tried to solve, without breaking widespread uses of type hints at runtime. PEP 649—Deferred Evaluation Of Annotations Using Descriptors is under consideration as a possible solution, but a different compromise may be reached.

To summarize: reading type hints at runtime is not 100% reliable as of Python 3.10 and is likely to change in 2022.

Dealing with the Problem

Giving the present situation, I recommend:

1. Avoid reading `__annotations__` directly; use `typing.get_type_hints` instead.

2. Wrap any calls to `typing.get_type_hints` in a function of your own, so that future changes that may be required are localized.

To demonstrate the second point, here are the first lines of the `Checked` class defined in Example 25-5, which we'll study in Chapter 25.

```
class Checked:
    @classmethod
    def _fields(cls) -> dict[str, type]:
        return get_type_hints(cls)
    # ... more lines ...
```

The `Checked._fields` class method protects other parts of the module from depending directly on `typing.get_type_hints`. If `get_type_hints` changes in the future, I can add logic to `Checked._fields` to work around eventual issues, hopefully avoiding changes elsewhere in my code.

The remaining sections of this chapter cover generics, starting with how to define a generic class that can be parameterized by its users.

Implementing a generic class

In Example 13-7 we defined the `Tombola` ABC: an interface for classes that work like a bingo cage. The `LottoBlower` class from Example 13-10 is a concrete implementation. Now we’ll study a generic version of `LottoBlower` used like this:

Example 15-14. generic_lotto_demo.py: using a generic lottery blower class

```
from generic_lotto import LottoBlower

machine = LottoBlower[int](range(1, 11))  ❶

first = machine.pick()  ❷
remain = machine.inspect()  ❸
```

❶ To instantiate a generic class we give it a actual type parameter, like `int` here.

❷ Mypy will correctly infer that `first` is an `int`…

❸ … and that `remain` is a `tuple` of integers.

In addition, Mypy reports violations of the parameterized type with helpful messages, such as these:

Example 15-15. generic_lotto_errors.py: errors reported by Mypy

```
from generic_lotto import LottoBlower

machine = LottoBlower[int]([1, .2])
## error: List item 1 has incompatible type "float";  ❶
##        expected "int"

machine = LottoBlower[int](range(1, 11))

machine.load('ABC')
## error: Argument 1 to "load" of "LottoBlower"  ❷
##        has incompatible type "str";
##        expected "Iterable[int]"
## note:  Following member(s) of "str" have conflicts:
## note:      Expected:
## note:          def __iter__(self) -> Iterator[int]
## note:      Got:
## note:          def __iter__(self) -> Iterator[str]
```

❶ Upon instantiation of `LottoBlower[int]`, Mypy flags the `float`.

❷ When calling `.load('ABC')`, Mypy explains why a `str` won't do: `str.__iter__` returns an `Iterator[str]`, but `LottoBlower[int]` requires an `Iterator[int]`.

Example 15-16 is the implementation.

Example 15-16. generic_lotto.py: a generic lottery blower class

```
import random

from collections.abc import Iterable
from typing import TypeVar, Generic

from tombola import Tombola

T = TypeVar('T')

class LottoBlower(Tombola, Generic[T]):  ❶

    def __init__(self, items: Iterable[T]) -> None:  ❷
        self._balls = list[T](items)

    def load(self, items: Iterable[T]) -> None:  ❸
        self._balls.extend(items)

    def pick(self) -> T:  ❹
        try:
            position = random.randrange(len(self._balls))
        except ValueError:
            raise LookupError('pick from empty LottoBlower')
        return self._balls.pop(position)

    def loaded(self) -> bool:  ❺
        return bool(self._balls)

    def inspect(self) -> tuple[T, ...]:  ❻
        return tuple(self._balls)
```

❶ Generic class declarations often use multiple inheritance, because we need to subclass `Generic` to declare the formal type parameters—in this case, `T`.

❷ The `items` argument in `__init__` is of type `Iterable[T]`, which becomes `Iterable[int]` when an instance is declared as `LottoBlower[int]`.

❸ The `load` method is likewise constrained.

❹ The return type of `T` now becomes `int` in a `LottoBlower[int]`.

❺ No type variable here.

❻ Finally, `T` sets the type of the items in the returned `tuple`.

> **TIP**
>
> The *User-defined generic types* section of the `typing` module documentation is short, presents good examples, and provides a few more details that I do not cover here.

Now that we've seen how to implement a generic class, let's define the terminology to talk about generics.

Basic Jargon for Generic Types

Here are a few definitions that I found useful when studying generics.[13]

Generic type

A type declared with one or more type variables.
Examples: `LottoBlower[T]`, `abc.Mapping[KT, VT]`.

Formal type parameter

The type variables that appear in a generic type declaration.
Example: `T`, `KT`, and `VT` in the generic type examples above.

Parameterized type

A type declared with actual type parameters.
Examples: `list[int]`, `abc.Mapping[str, float]`.

Actual type parameter

The actual types given as parameters when a parameterized type is declared.
Example: the `int` in `LottoBlower[int]`.

The next topic is about how to make generic types more flexible, introducing the concepts of covariance, contravariance, and invariance.

Variance

The interaction of generics and a type hierarchy introduces a new typing concept: variance. We will approach this abstract concept through an analogy. Imagine that a school cafeteria has a rule that only juice dispensers can be installed. General beverage dispensers are not allowed because they may serve sodas, which are banned by the school board.[14]

An Invariant Dispenser

Let's try to model the cafeteria scenario with a generic `BeverageDispenser` class that can be parameterized on the type of beverage. See Example 15-17.

Example 15-17. `invariant.py`: type definitions and `install` function.

```
from typing import TypeVar, Generic

class Beverage:  ❶
    """Any beverage."""

class Juice(Beverage):
    """Any fruit juice."""

class OrangeJuice(Juice):
    """Delicious juice from Brazilian oranges."""
```

```python
T = TypeVar('T')  ❷

class BeverageDispenser(Generic[T]):  ❸
    """A dispenser parameterized on the beverage type."""
    def __init__(self, beverage: T) -> None:
        self.beverage = beverage

    def dispense(self) -> T:
        return self.beverage

def install(dispenser: BeverageDispenser[Juice]) -> None:  ❹
    """Install a fruit juice dispenser."""
```

❶ `Beverage`, `Juice` and `OrangeJuice` form a type hierarchy.

❷ Simple `TypeVar` declaration.

❸ `BeverageDispenser` is parameterized on the type of beverage.

❹ `install` is a module-global function. Its type hint enforces the rule that only a juice dispenser is acceptable.

Given the definitions in Example 15-17, the following code is legal:

```python
juice_dispenser = BeverageDispenser(Juice())
install(juice_dispenser)
```

However, this is not legal:

```python
beverage_dispenser = BeverageDispenser(Beverage())
install(beverage_dispenser)
## mypy: Argument 1 to "install" has
## incompatible type "BeverageDispenser[Beverage]"
##          expected "BeverageDispenser[Juice]"
```

A dispenser that serves any `Beverage` is not acceptable because the cafeteria requires a dispenser that is specialized for `Juice`.

Somewhat surprisingly, this code is also illegal:

```
orange_juice_dispenser = BeverageDispenser(OrangeJuice())
install(orange_juice_dispenser)
## mypy: Argument 1 to "install" has
## incompatible type "BeverageDispenser[OrangeJuice]"
##          expected "BeverageDispenser[Juice]"
```

A dispenser specialized for `OrangeJuice` is not allowed either. Only `BeverageDispenser[Juice]` will do. In the typing jargon, this means that the `BeverageDispenser` generic class is invariant.

Python mutable collection types—such as `list` and `set`—are invariant. The `LottoBlower` class from Example 15-16 is also invariant.

A Covariant Dispenser

If we want to be more flexible and model dispensers as a generic class that can accept some beverage type and also its subtypes, we must make it covariant. This is how we'd declare `BeverageDispenser`:

Example 15-18. `covariant.py`: type definitions and `install` function.

```
T_co = TypeVar('T_co', covariant=True)  ❶


class BeverageDispenser(Generic[T_co]):  ❷
    def __init__(self, beverage: T_co) -> None:
        self.beverage = beverage

    def dispense(self) -> T_co:
        return self.beverage

def install(dispenser: BeverageDispenser[Juice]) -> None:  ❸
    """Install a fruit juice dispenser."""
```

❶ Set `covariant=True` when declaring the type variable; `_co` is a conventional suffix for covariant type parameters on *typeshed*.

❷ Use `T_co` to parameterize the `Generic` special class.

❸ Type hints for `install` are the same as in Example 15-17.

The following code works because now both the `Juice` dispenser and the `OrangeJuice` dispenser are valid in a covariant `BeverageDispenser`.

```
juice_dispenser = BeverageDispenser(Juice())
install(juice_dispenser)

orange_juice_dispenser = BeverageDispenser(OrangeJuice())
install(orange_juice_dispenser)
```

But a dispenser for any `Beverage` is not acceptable:

```
beverage_dispenser = BeverageDispenser(Beverage())
install(beverage_dispenser)
## mypy: Argument 1 to "install" has
## incompatible type "BeverageDispenser[Beverage]"
##          expected "BeverageDispenser[Juice]"
```

That's covariance: the subtype relationship of the parameterized dispensers varies in the same direction of the subtype relationship of the type parameters.

A Contravariant Trash Can

Now we'll model the cafeteria rule for deploying a trash can. Let's assume food and drinks are served in biodegradable packages, and leftovers as well as single-use utensils are also biodegradable. The trash cans must be suitable for biodegradable refuse.

This code models the cafeteria trash can rule:

Example 15-19. `contravariant.py`: type definitions and `install` function.

```
from typing import TypeVar, Generic

class Refuse:  ❶
    """Any refuse."""

class Biodegradable(Refuse):
    """Biodegradable refuse."""
```

```python
class Compostable(Biodegradable):
    """Compostable refuse."""

T_contra = TypeVar('T_contra', contravariant=True)  ❷

class TrashCan(Generic[T_contra]):  ❸
    def put(self, refuse: T_contra) -> None:
        """Store trash until dumped."""

def deploy(trash_can: TrashCan[Biodegradable]):
    """Deploy a trash can for biodegradable refuse."""
```

❶ A type hierarchy for refuse: `Refuse` is the most general type, `Compostable` is the most specific.

❷ `T_contra` is a conventional name for a contravariant type variable.

❸ `TrashCan` is contravariant on the type of refuse.

Given those definitions, these types of trash cans are acceptable:

```python
bio_can: TrashCan[Biodegradable] = TrashCan()
deploy(bio_can)

trash_can: TrashCan[Refuse] = TrashCan()
deploy(trash_can)
```

The more general `TrashCan[Refuse]` is acceptable because it can take any kind of refuse, including `Biodegradable` and `Compostable`.

However, a `TrashCan[Compostable]` won't do, because it is cannot take `Biodegradable` or general `Trash`:

```python
compost_can: TrashCan[Compostable] = TrashCan()
deploy(compost_can)
## mypy: Argument 1 to "deploy" has
## incompatible type "TrashCan[Compostable]"
##          expected "TrashCan[Biodegradable]"
```

Let's summarize the concepts we just saw.

Variance Review

Invariant Types

A generic type `L` is invariant when there is no supertype or subtype relationship between two parameterized types, regardless of the relationship that may exist between the actual parameters. In other words, if `L` is invariant, then `L[A]` is not a supertype or a subtype of `L[B]`. They are inconsistent in both ways.

As mentioned, Python's mutable collections are invariant by default. The `list` type is a good example: `list[int]` is not *consistent-with* `list[float]` and vice-versa.

In general, if a formal type parameter appears in type hints of method arguments and the same parameter appears in method return types, that parameter must be invariant to ensure type safety when updating and reading from the collection.

For example, here is part of the type hints for the `list` built-in on *typeshed*:

```
class list(MutableSequence[_T], Generic[_T]):
    @overload
    def __init__(self) -> None: ...
    @overload
    def __init__(self, iterable: Iterable[_T]) -> None: ...
    # ... lines omitted ...
    def append(self, __object: _T) -> None: ...
    def extend(self, __iterable: Iterable[_T]) -> None: ...
    def pop(self, __index: int = ...) -> _T: ...
    # etc...
```

Note that `_T` appears in the arguments of `__init__`, `append`, and `extend` and as the return type of `pop`. There is no way to make such a class type safe if it is covariant or contravariant in `_T`.

Covariant Types

Consider two types `A` and `B` where `B` is *consistent-with* `A`, and neither of them is `Any`. Some authors use the `<:` and `:>` symbols to denote type relationships like this:

`A :> B`

`A` is a supertype or the same as `B`.

`B <: A`

`B` is a subtype or the same as `A`.

Given `A :> B`, a generic type `C` is covariant when `C[A] :> C[B]`.

Note the direction of the `:>` symbol is the same in both cases where `A` is to the left of `B`. Covariant generic types follow the subtype relationship of the actual type parameters.

Immutable containers can be covariant. For example, this how the `typing.FrozenSet` class is documented as a covariant with a type variable using the conventional name `T_co`:

```
class FrozenSet(frozenset, AbstractSet[T_co]):
```

Applying the `:>` notation to parameterized types, we have:

```
           float :> int
frozenset[float] :> frozenset[int]
```

Iterators are another example of covariant generics: they are not read-only collections like a `frozenset`, but they only produce output. Any code expecting an `abc.Iterator[float]` yielding floats can safely use an `abc.Iterator[int]` yielding integers.

Contravariant Types

Given `A :> B`, a generic type `K` is contravariant if `K[A] <: K[B]`.

Contravariant generic types reverse the subtype relationship of the actual type parameters.

The `TrashCan` class exemplifies this:

```
            Refuse :> Biodegradable
  TrashCan[Refuse] <: TrashCan[Biodegradable]
```

A contravariant container is usually a write-only data structure, also known as a "sink".

There are no examples of contravariant generics with a single formal type parameter in the Python 3.9 standard library. But `Generator`, `Coroutine`, and `AsyncGenerator` all have multiple formal type parameters, and each of them has one contravariant formal parameter.

Those three generic types are all related to generator-like constructs used as coroutines—as opposed to simple iterators. The `Generator` type appears in Chapter 19; `Coroutine` and `AsyncGenerator`, in Chapter 22.

For the present discussion about variance, the main point is that the contravariant formal parameter defines the type of the only argument used to send data to the object, while a different covariant formal parameter defines the type of outputs produced by the object—the yield type. The precise meanings of "send" and "yield" are explained in Chapter 19.

We can derive useful guidelines from these observations of covariant outputs and contravariant inputs.

Variance Rules of Thumb

1. If a formal type parameter defines a type for data that comes out of the object, it can be covariant.

2. If a formal type parameter defines a type for data that goes into the object after its initial construction, it can be contravariant.

3. If a formal type parameter defines a type for data that comes out of the object and the same parameter defines a type for data that goes

into it, it must be invariant.

4. To err on the safe side, make formal parameters invariant.

By default, `TypeVar` creates formal parameters that are invariant, and that's how the mutable collections in the standard library are annotated.

The generic `typing.Generator` is a great example of rules #1 and #2, as long as you understand how classic coroutines work—because that's what that type describes. After Chapter 19 covers classic coroutines in depth, "Generic Type Hints for Classic Coroutines" continues the present discussion about variance.

Next, let's see how to define generic static protocols, applying the idea of covariance to a couple of new examples.

Implementing a generic static protocol

The Python 3.9 standard library provides a couple of generic static protocols. One of them is `SupportsAbs`, implemented like this in the *typing* module:

```
@runtime_checkable
class SupportsAbs(Protocol[T_co]):
    """An ABC with one abstract method __abs__ that is covariant
in its return type."""
    __slots__ = ()

    @abstractmethod
    def __abs__(self) -> T_co:
        pass
```

`T_co` is declared according to the naming convention:

```
T_co = TypeVar('T_co', covariant=True)
```

Thanks to `SupportsAbs`, Mypy recognizes this code as valid:

Example 15-20. `abs_demo.py`: use of the generic `SupportsAbs` protocol.

```
#!/usr/bin/env python3

import math
from typing import NamedTuple, SupportsAbs

class Vector2d(NamedTuple):
    x: float
    y: float

    def __abs__(self) -> float:  ❶
        return math.hypot(self.x, self.y)

def is_unit(v: SupportsAbs[float]) -> bool:  ❷
    """'True' if the magnitude of 'v' is close to 1."""
    return math.isclose(abs(v), 1.0)  ❸

assert issubclass(Vector2d, SupportsAbs)  ❹

v0 = Vector2d(0, 1)  ❺
sqrt2 = math.sqrt(2)
v1 = Vector2d(sqrt2 / 2, sqrt2 / 2)
v2 = Vector2d(1, 1)
v3 = complex(.5, math.sqrt(3) / 2)
v4 = 1  ❻

assert is_unit(v0)
assert is_unit(v1)
assert not is_unit(v2)
assert is_unit(v3)
assert is_unit(v4)

print('OK')
```

❶ Defining `__abs__` makes `Vector2d` *consistent-with* `SupportsAbs`.

❷ Parameterizing `SupportsAbs` with `float` ensures…

❸ …that Mypy accepts `abs(v)` as the first argument for `math.isclose`.

❹ Thanks to `@runtime_checkable` in the definition of `SupportsAbs`, this is a valid runtime assertion.

❺ The remaining code all passes Mypy checks and runtime assertions.

❻ The `int` type is also *consistent-with* `SupportsAbs`. According to *typeshed*, `int.__abs__` returns an `int`, which is *consistent-with* the `float` type parameter declared in the `is_unit` type hint for the `v` argument.

Similarly, we can write a generic version of the `RandomPicker` protocol presented in Example 13-18, which was defined with a single method `pick` returning `Any`.

Example 15-21 shows how to make a generic `RandomPicker` covariant on the return type of `pick`.

Example 15-21. `generic_randompick.py`: definition of generic `RandomPicker`.

```
from typing import Protocol, runtime_checkable, TypeVar

T_co = TypeVar('T_co', covariant=True)  ❶

@runtime_checkable
class RandomPicker(Protocol[T_co]):  ❷
    def pick(self) -> T_co: ...  ❸
```

❶ Declare `T_co` as `covariant`.

❷ This makes `RandomPicker` generic with a covariant formal type parameter.

❸ Use `T_co` as the return type.

The generic `RandomPicker` protocol can be covariant because its only formal parameter is used in a return type.

With this, we can call it a chapter.

Chapter summary

The chapter started with a simple example of using `@overload`, followed by much more complex example that we studied in detail: the overloaded signatures required to correctly annotate the `max` built-in function.

The `typing.TypedDict` special construct came next. I chose to cover it here, and not in Chapter 5 where we saw `typing.NamedTuple`, because `TypedDict` is not a class builder: it's merely a way to add type hints to variable or argument that requires a `dict` with a specific set of string keys, and specific types for each key—which happens when we use a `dict` as a record, often in the context of handling with JSON data. That section was a bit long because using `TypedDict` can give a false sense of security, and I wanted to show how runtime checks and error handling are really inevitable when trying to make statically structured records out of mappings that are dynamic in nature.

Next we talked about `typing.cast`, a function designed to let us guide work of the type checker. It's important to carefully consider when to use `cast`, because overusing it hinders the type checker.

Runtime access to type hints came next. The key point was to use `typing.get_type_hints` instead of reading the `__annotations__` attribute directly. However, we also discussed how that function may be unreliable with some annotations, and we saw that Python core developers are still working on a way to make type hints usable at runtime, while reducing their impact on CPU and memory usage.

The final sections were about generics, starting with the `LottoBlower` generic class—which we later learn is an invariant generic class. That example was followed by definitions of four basic terms: *generic type*, *formal type parameter*, *parameterized type*, and *actual type parameter*.

The major topic of variance was presented next, using cafeteria beverage dispensers and trash cans as "real life" examples of invariant, covariant and contravariant generic types. Next we reviewed, formalized and further applied those concepts to examples in Python's standard library.

Lastly, we saw how a generic static protocol is defined, first considering the `typing.SupportsAbs` protocol, and then applying the same idea to the `RandomPicker` example making it more strict than the original protocol from Chapter 13.

> **NOTE**
>
> Python's type system is a huge and rapidly evolving subject. This chapter is not comprehensive. I chose to focus on topics that are either widely applicable, particularly challenging, or conceptually important.

Further Reading

Python's static type system was complex as initially designed, and is getting more complex with each passing year. Table 15-1 lists all the PEPs that I am aware of as of May 2021. Python's official documentation hardly keeps up with all that, so *Mypy's documentation* is an essential reference. *Robust Python* by Patrick Viafore (O'Reilly, 2021) is the only book that I know about focusing on Python's static type system.

Table 15-1. PEPs about type hints, with lin *ks in the titles. PEP with numbers marked with ** *are important enough to be mentioned in the o* *peningparagraphofthe*`typing`*documenta* *tion. Question marks in the* ***Python*** *column ind* icatePEPsunderdiscussionornotyetimpl

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PEP	Title	Python	Year
3107	Function Annotations	3.0	2006
483*	The Theory of Type Hints	n/a	2014
484*	Type Hints	3.5	2014
482	Literature Overview for Type Hints	n/a	2015
526*	Syntax for Variable Annotations	3.6	2016
544*	Protocols: Structural subtyping (static duck typing)	3.8	2017
557	Data Classes	3.7	2017
560	Core support for typing module and generic types	3.7	2017
561	Distributing and Packaging Type Information	3.7	2017
563	Postponed Evaluation of Annotations	3.7	2017
586*	Literal Types	3.8	2018
585	Type Hinting Generics In Standard Collections	3.9	2019
589*	TypedDict: Type Hints for Dictionaries with a Fixed Set of	3.8	2019

	Keys		
591*	Adding a final qualifier to typing	3.8	2019
593	Flexible function and variable annotations	?	2019
604	Allow writing union types as X | Y	3.10	2019
612	Parameter Specification Variables	3.10	2019
613	Explicit Type Aliases	3.10	2020
645	Allow writing optional types as x?	?	2020
646	Variadic Generics	?	2020
647	User-Defined Type Guards	3.10	2021
649	Deferred Evaluation Of Annotations Using Descriptors	?	2021
655	Marking individual TypedDict items as required or potentially-missing	?	2021

The subtle topic of variance has its own section in PEP 484, and is also covered in the *Generics* page of Mypy, as well as in their invaluable *Common Issues* page.

PEP 362—Function Signature Object is worth reading if you intend to use the `inspect` module that complements the `typing.get_type_hints` function.

If you are interested in the history of Python, you may like to know that Guido van Rossum posted *Adding Optional Static Typing to Python* on December 23, 2004.

Python 3 types in the wild: a tale of two type systems is a research paper by Ingkarat Rak-amnouykit and others from the Rensselaer Polytechnic Institute and IBM TJ Watson Research Center. The paper surveys the use of type hints in open source projects on GitHub, showing that most projects don't use them, and also that most projects that have type hints apparently don't use a type checker. I found most interesting the discussion of the different semantics of *Mypy* and Google's *pytype*, which they conclude are "essentially two different type systems".

Gilad Bracha's seminal paper *Pluggable Types*, submits that one of the advantages of gradual typing is to allow multiple type systems for the same language:

> *Once our runtime is independent of the type system, we can choose to treat type systems as plug-ins. We can have zero, one or many type systems, suited to differing purposes, all at the same time. There are static type systems that deal with aliasing, ownership, with information flow, as well as traditional types systems. Indeed, a very wide range of static analyses can be cast as type systems.*

Another seminal paper about gradual typing is *Static Typing Where Possible, Dynamic Typing When Needed: The End of the Cold War Between Programming Languages* by Eric Meijer and Peter Drayton.[15]

I learned a lot reading the relevant parts of a some books about other languages that implement some of the same ideas:

- *Atomic Kotlin*—Bruce Eckel and Svetlana Isakova (Leanpub, 2020)
- *Effective Java, 3rd Edition*—Joshua Bloch (Addison-Wesley, 2017)
- *Programming with Types: TypeScript Examples*—Vlad Riscutia (Manning, 2019)
- *Programming TypeScript*—Boris Cherny (O'Reilly, 2019)
- *The Dart Programming Language*—Gilad Bracha (Addison-Wesley, 2016).[16]

For some critical views on type systems, I recommend Victor Youdaiken's posts *Bad ideas in type theory* and *Types considered harmful II*, Finally, I was surprised to find Generics Considered Harmful by Ken Arnold, a core contributor to Java from the beginning, as well as co-author of the first four editions of the officially branded *The Java Programming Language* book—in collaboration with James Gosling, the lead designer of Java.

Sadly, Arnold's criticism of Java's type system applies to Python's as well. While reading the many rules and special cases of the typing PEPs, I was constantly reminded of this passage from Gosling's post:

> *Which brings up the problem that I always cite for C++: I call it the "N^{th} order exception to the exception rule." It sounds like this: "You can do x, except in case y, unless y does z, in which case you can if …"*

Fortunately, Python has a key advantage over Java and C++: we have a gradual type system. We can completely or partially omit type hints when the complexity they add is not worthwhile.

SOAPBOX

Typing Rabbit Holes

When using a type checker, we are sometimes forced to discover and import classes we did not need to know about, and our code has no need to reference—except to write type hints. Such classes are undocumented, probably because they are considered implementation details by the authors of the packages. Here are two examples from the standard library.

To use `cast()` in the `server.sockets` example in "Type Casting", I had to scour the vast *asyncio* documentation and then browse the source code of several modules in that package to discover the undocumented `TransportSocket` class in the equally undocumented `asyncio.trsock` module. Using `socket.socket` instead of `TransportSocket` would be incorrect, because the latter is explicitly not a subtype of the former, according to a docstring in the source code.

I fell into a similar rabbit hole when I added type hints to Example 20-13, a simple demonstration of `multiprocessing`. That example uses `SimpleQueue` objects, which you get by calling `multiprocessing.SimpleQueue()`. However, I could not use that name in a type hint, because it turns out that `multiprocessing.SimpleQueue` is not a class! It's a bound method of the undocumented `multiprocessing.BaseContext` class, which builds and returns an instance of the `SimpleQueue` class defined in the undocumented `multiprocessing.queues` module.

In each of those cases I had to spend a couple of hours to find the right undocumented class to import, just to write a single type hint. This kind of research is part of the job when writing a book. But when writing application code, I'd probably avoid such scavenger hunts for a single offending line and just write `# type: ignore`. Sometimes that's the only cost-effective solution.

Variance notation in other languages

Variance is a difficult topic and Python's type hints syntax is not as good as it could be. This is evidenced by this direct quote from PEP 484:

> *Covariance or contravariance is not a property of a type variable, but a property of a generic class defined using this variable.*[17]

If that is the case, why are covariance and contravariance declared with `TypeVar` and not on the generic class?

The authors of PEP 484 worked under the severe self-imposed constraint that type hints should be supported without making any change to the interpreter. This required the introduction of `TypeVar` to define type variables, and also the abuse of `[]` to provide `Klass[T]` syntax for generics—instead of the `Klass<T>` notation used in other popular languages, including C#, Java, Kotlin, and TypeScript. None of these languages require type variables to be declared before use.

In addition, the syntax of Kotlin and C# makes it clear whether the type parameter is covariant, contravariant or invariant exactly where it makes sense: in the class or interface declaration.

In Kotlin, we could declare the `BeverageDispenser` like this:

```
class BeverageDispenser<out T> {
    // etc...
}
```

The `out` modifier in the formal type parameter means `T` is an "output" type, therefore `BeverageDispenser` is covariant.

You can probably guess how `TrashCan` would be declared:

```
class TrashCan<in T> {
    // etc...
}
```

Given `T` as an “input” formal type parameter, then `TrashCan` is contravariant.

If neither `in` nor `out` appear, then the class is invariant on the parameter.

It’s easy to recall the “Variance Rules of Thumb” when `out` and `in` are used in the formal type parameters.

This suggests that a good naming convention for covariant and contravariant type variables in Python would be:

```
T_out = TypeVar('T_out', covariant=True)
T_in = TypeVar('T_in', contravariant=True)
```

Then we could define the classes like this:

```
class BeverageDispenser(Generic[T_out]):
    ...

class TrashCan(Generic[T_in]):
    ...
```

Is it too late to change the naming convention established in PEP 484?

False Positives 147 × False Negatives 19

Many *typeshed* bugs are tagged *false positive* or *false negative*.

It’s a *false positive* when the type hints are too restrictive and make type checkers report false errors. That was the case with the `statistics.mode` type hints which accepted only numbers, while the function can handle any hashable, as discussed in “Restricted `TypeVar`”.

The `max` issue #4051 discussed before is a *false negative*: the type hints were not strict enough, so type checkers were unable to catch some invalid arguments.

On May 27, 2020, I counted 147 *false positive* issues (41 open) and 19 *false negatives* (8 open) on *typeshed*. That’s a ratio of 7.7 *false positive* for each *false negative*.

In the *typeshed* sample, type hints are strongly biased to raise false alarms. I don't know what causes this. It may be because it's easier to write type hints that are overly restrictive, either due to limitations in Python's type system or due to our collective experience with traditional nominally typed languages that provide less flexible APIs than Python allows.

The Python type hinting PEPs and tools were developed by teams working on some of the largest Python-powered systems in the world. So this *false positive* bias may be intentional: in large systems the cost of detecting and fixing a bug in production may be very high, so it's better for them to err on the side of caution. I wonder if the bias is as good for every Python user as it is for the Web-scale companies that sponsored most of the work on *typeshed* and the static type checkers.

---

1 From YouTube video of *A Language Creators' Conversation: Guido van Rossum, James Gosling, Larry Wall & Anders Hejlsberg*, streamed live on April 2, 2019. Quote starts at 1:32:05, edited for brevity. Full transcript available at *https://github.com/fluentpython/language-creators*.

2 I am grateful to Jelle Zijlstra—a *typeshed* maintainer—who taught me several things, including how to reduce my original 9 overloads to 6.

3 As of May 2020, pytype allows it. But its FAQ says it will be disallowed in the future. See question "Why didn't pytype catch that I changed the type of an annotated variable?" in the pytype FAQ.

4 I prefer to use the lxml package to generate and parse XML: it's easy to get started, full-featured, and fast. Unfortunately, lxml and Python's own ElementTree don't fit the limited RAM of my hypothetical microcontroller.

5 The Mypy documentation discusses this in its Common issues and solutions page, section Types of empty collections.

6 Brett Cannon, Guido van Rossum, and others have been discussing how to type hint `json.loads()` since 2016 in Mypy issue #182: Define a JSON type.

7 The use of `enumerate` in the example is intended to confuse the type checker. A simpler implementation yielding strings directly instead of going through the `enumerate` index is correctly analysed by Mypy, and the `cast()` is not needed.

8 I reported *typeshed* issue #5535 "Wrong type hint for asyncio.base_events.Server sockets attribute." and it was quickly fixed by Sebastian Rittau. However, I decided to keep the example because it illustrates a common use case for `cast`, and the `cast` I wrote is harmless.

9 To be honest, I originally appended a `# type: ignore` comment to the line with `server.sockets[0]` because after a little research I found similar lines the *asyncio* documentation and in a test case, so I suspected the problem was not in my code.

10 19 May 2020 message to the typing-sig mailing list.

11 The syntax `# type: ignore[code]` allows you to specify which Mypy error code is being silenced, but the codes are not always easy to interpret. See *error codes* in the Mypy documentation

12 Message *PEP 563 in light of PEP 649*, posted April 16, 2021.

13 The terms are from Joshua Bloch's classic book *Effective Java, Third Edition* (Addison Wesley, 2017). The definitions and examples are mine.

14 I first saw the cafeteria analogy for variance in Erik Meijer's *Foreword* in *The Dart Programming Language* book by Gilad Bracha (Addison-Wesley, 2016).

15 As a reader of footnotes, so you may recall that I credited Erik Meijer for the cafeteria analogy to explain variance.

16 That book was written for Dart 1. There are significant changes in Dart 2—including in the type system. Nevertheless, Bracha is an important resarcher in the field of programming language design, and I found the book valuable for his perspective on the design of Dart.

17 Last paragraph of section *Covariance and Contravariance* in PEP 484.

Chapter 16. Operator Overloading: Doing It Right

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 16th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *There are some things that I kind of feel torn about, like operator overloading. I left out operator overloading as a fairly personal choice because I had seen too many people abuse it in C++.*[1]
>
> —James Gosling, Creator of Java

Operator overloading allows user-defined objects to interoperate with infix operators such as `+` and `|` or unary operators like `-` and `~`. More generally, function invocation (`()`), attribute access (`.`), and item access/slicing (`[]`) are also operators in Python, but this chapter covers unary and infix operators.

In "Emulating Numeric Types" (Chapter 1) we saw some trivial implementations of operators in a bare bones `Vector` class. The `__add__` and `__mul__` methods in Example 1-2 were written to show how special methods support operator overloading, but there are subtle problems in their implementations that we overlooked. Also, in Example 11-2, we noted that the `Vector2d.__eq__` method considers this to be `True`: `Vector(3, 4)`

`== [3, 4]`—which may or not make sense. We will address those matters in this chapter, as well as:

- How an infix operator method should signal it cannot handle an operand
- Using duck typing or goose typing to deal with operands of various types
- The special behavior of the rich comparison operators (e.g., `==`, `>`, `<=`, etc.)
- The default handling of augmented assignment operators such as `+=`, and how to overload them

What's new in this chapter

Goose typing is a key part of Python, but the `numbers` ABCs are not supported in static typing, so I changed Example 16-11 to use duck typing instead of an explicit `isinstance` check against `numbers.Real`.[2]

I covered the `@` matrix multiplication operator *Fluent Python, First Edition* as an upcoming change when 3.5 was still in alpha. Accordingly, "Using @ as an infix operator" is no longer a sidebar, but is integrated in the flow of the chapter. I leveraged goose typing to make the implementation of `__matmul__` in that section safer than the one in the first edition, without compromising on flexibility.

"Further Reading" now has a couple of new references—including a blog post by Guido van Rossum. I also added mentions of two libraries that showcase effective use of operator overloading outside the domain of mathematics: `pathlib` and `Scapy`.

Operator Overloading 101

Operator overloading has a bad name in some circles. It is a language feature that can be (and has been) abused, resulting in programmer confusion, bugs, and unexpected performance bottlenecks. But if well used, it leads to pleasurable APIs and readable code. Python strikes a good balance between flexibility, usability, and safety by imposing some limitations:

- We cannot overload operators for the built-in types.
- We cannot create new operators, only overload existing ones.
- A few operators can't be overloaded: `is`, `and`, `or`, `not` (but the bitwise `&`, `|`, `~`, can).

In Chapter 12, we already had one infix operator in `Vector`: `==`, supported by the `__eq__` method. In this chapter, we'll improve the implementation of `__eq__` to better handle operands of types other than `Vector`. However, the rich comparison operators (`==`, `!=`, `>`, `<`, `>=`, `<=`) are special cases in operator overloading, so we'll start by overloading four arithmetic operators in `Vector`: the unary `-` and `+`, followed by the infix `+` and `*`.

Let's start with the easiest topic: unary operators.

Unary Operators

In *The Python Language Reference*, "6.5. Unary arithmetic and bitwise operations" lists three unary operators, shown here with their associated special methods:

`-` (`__neg__`)

Arithmetic unary negation. If `x` is `-2` then `-x == 2`.

`+` (`__pos__`)

Arithmetic unary plus. Usually `x == +x`, but there are a few cases when that's not true. See "When x and +x Are Not Equal" if you're curious.

`~` (`__invert__`)

Bitwise inverse of an integer, defined as `~x == -(x+1)`. If `x` is `2` then `~x == -3`.

The Data Model” chapter of *The Python Language Reference* also lists the `abs(…)` built-in function as a unary operator. The associated special method is `__abs__`, as we’ve seen before, starting with “Emulating Numeric Types”.

It’s easy to support the unary operators. Simply implement the appropriate special method, which will receive just one argument: `self`. Use whatever logic makes sense in your class, but stick to the fundamental rule of operators: always return a new object. In other words, do not modify `self`, but create and return a new instance of a suitable type.

In the case of `-` and `+`, the result will probably be an instance of the same class as `self`; for `+`, returning a copy of `self` is the best approach most of the time. For `abs(…)`, the result should be a scalar number. As for `~`, it’s difficult to say what would be a sensible result if you’re not dealing with bits in an integer, but in an *ORM* it could make sense to return the negation of an SQL `WHERE` clause, for example.

As promised before, we’ll implement several new operators on the `Vector` class from Chapter 12. Example 16-1 shows the `__abs__` method we already had in Example 12-16, and the newly added `__neg__` and `__pos__` unary operator method.

Example 16-1. vector_v6.py: unary operators - and + added to Example 12-16

```
    def __abs__(self):
        return math.hypot(*self)

    def __neg__(self):
        return Vector(-x for x in self)  ❶

    def __pos__(self):
        return Vector(self)  ❷
```

❶ To compute `-v`, build a new `Vector` with every component of `self` negated.

❷ To compute `+v`, build a new `Vector` with every component of `self`.

Recall that `Vector` instances are iterable, and the `Vector.__init__` takes an iterable argument, so the implementations of `__neg__` and `__pos__` are short and sweet.

We’ll not implement `__invert__`, so if the user tries `~v` on a `Vector` instance, Python will raise `TypeError` with a clear message: “bad operand type for unary ~: `'Vector'`.”

The following sidebar covers a curiosity that may help you win a bet about unary `+` someday. The next important topic is “Overloading + for Vector Addition”.

WHEN X AND +X ARE NOT EQUAL

Everybody expects that `x == +x`, and that is true almost all the time in Python, but I found two cases in the standard library where `x != +x`.

The first case involves the `decimal.Decimal` class. You can have `x != +x` if `x` is a `Decimal` instance created in an arithmetic context and `+x` is then evaluated in a context with different settings. For example, `x` is calculated in a context with a certain precision, but the precision of the context is changed and then `+x` is evaluated. See Example 16-2 for a demonstration.

Example 16-2. A change in the arithmetic context precision may cause x to differ from +x

```
>>> import decimal
>>> ctx = decimal.getcontext()  ❶
>>> ctx.prec = 40  ❷
>>> one_third = decimal.Decimal('1') / decimal.Decimal('3')  ❸
>>> one_third  ❹
Decimal('0.3333333333333333333333333333333333333333')
>>> one_third == +one_third  ❺
True
>>> ctx.prec = 28  ❻
>>> one_third == +one_third  ❼
False
>>> +one_third  ❽
Decimal('0.3333333333333333333333333333')
```

❶ Get a reference to the current global arithmetic context.

❷ Set the precision of the arithmetic context to 40.

❸ Compute 1/3 using the current precision.

❹ Inspect the result; there are 40 digits after the decimal point.

❺ `one_third == +one_third` is `True`.

❻ Lower precision to 28—the default for `Decimal` arithmetic in Python 3.4.

- ❼ Now `one_third == +one_third` is `False`.
- ❽ Inspect `+one_third`; there are 28 digits after the `'.'` here.

The fact is that each occurrence of the expression `+one_third` produces a new `Decimal` instance from the value of `one_third`, but using the precision of the current arithmetic context.

The second case where `x != +x` you can find in the `collections.Counter` documentation. The `Counter` class implements several arithmetic operators, including infix `+` to add the tallies from two `Counter` instances. However, for practical reasons, `Counter` addition discards from the result any item with a negative or zero count. And the prefix `+` is a shortcut for adding an empty `Counter`, therefore it produces a new `Counter` preserving only the tallies that are greater than zero. See Example 16-3.

Example 16-3. Unary + produces a new Counter without zeroed or negative tallies

```
>>> ct = Counter('abracadabra')
>>> ct
Counter({'a': 5, 'r': 2, 'b': 2, 'd': 1, 'c': 1})
>>> ct['r'] = -3
>>> ct['d'] = 0
>>> ct
Counter({'a': 5, 'b': 2, 'c': 1, 'd': 0, 'r': -3})
>>> +ct
Counter({'a': 5, 'b': 2, 'c': 1})
```

Now, back to our regularly scheduled programming.

Overloading + for Vector Addition

> **NOTE**
>
> The `Vector` class is a sequence type, and the section “3.3.6. Emulating container types” in the “Data Model” chapter says sequences should support the `+` operator for concatenation and `*` for repetition. However, here we will implement `+` and `*` as mathematical vector operations, which are a bit harder but more meaningful for a `Vector` type.

Adding two Euclidean vectors results in a new vector in which the components are the pairwise additions of the components of the addends. To illustrate:

```
>>> v1 = Vector([3, 4, 5])
>>> v2 = Vector([6, 7, 8])
>>> v1 + v2
Vector([9.0, 11.0, 13.0])
>>> v1 + v2 == Vector([3 + 6, 4 + 7, 5 + 8])
True
```

What happens if we try to add two `Vector` instances of different lengths? We could raise an error, but considering practical applications (such as information retrieval), it’s better to fill out the shortest `Vector` with zeros. This is the result we want:

```
>>> v1 = Vector([3, 4, 5, 6])
>>> v3 = Vector([1, 2])
>>> v1 + v3
Vector([4.0, 6.0, 5.0, 6.0])
```

Given these basic requirements, the implementation of `__add__` is short and sweet, as shown in Example 16-4.

Example 16-4. Vector.add method, take #1

```
    # inside the Vector class

    def __add__(self, other):
        pairs = itertools.zip_longest(self, other, fillvalue=0.0)  ❶
        return Vector(a + b for a, b in pairs)  ❷
```

❶ `pairs` is a generator that will produce tuples `(a, b)` where `a` is from `self`, and `b` is from `other`. If `self` and `other` have different lengths, `fillvalue` supplies the missing values for the shortest iterable.

❷ A new `Vector` is built from a generator expression producing one sum for each item in `pairs`.

Note how `__add__` returns a new `Vector` instance, and does not affect `self` or `other`.

> **WARNING**
>
> Special methods implementing unary or infix operators should never change their operands. Expressions with such operators are expected to produce results by creating new objects. Only augmented assignment operators may change the first operand (`self`), as discussed in "Augmented Assignment Operators".

Example 16-4 allows adding `Vector` to a `Vector2d`, and `Vector` to a tuple or to any iterable that produces numbers, as Example 16-5 proves.

Example 16-5. Vector.__add__ take #1 supports non-`Vector` objects, too

```
>>> v1 = Vector([3, 4, 5])
>>> v1 + (10, 20, 30)
Vector([13.0, 24.0, 35.0])
>>> from vector2d_v3 import Vector2d
>>> v2d = Vector2d(1, 2)
>>> v1 + v2d
Vector([4.0, 6.0, 5.0])
```

Both additions in Example 16-5 work because `__add__` uses `zip_longest(…)`, which can consume any iterable, and the generator expression to build the new `Vector` merely performs `a + b` with the pairs produced by `zip_longest(…)`, so an iterable producing any number items will do.

However, if we swap the operands (Example 16-6), the mixed-type additions fail..

Example 16-6. Vector.__add__ take #1 fails with non-`Vector` left operands

```
>>> v1 = Vector([3, 4, 5])
>>> (10, 20, 30) + v1
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: can only concatenate tuple (not "Vector") to tuple
```

```
>>> from vector2d_v3 import Vector2d
>>> v2d = Vector2d(1, 2)
>>> v2d + v1
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: unsupported operand type(s) for +: 'Vector2d' and 'Vector'
```

To support operations involving objects of different types, Python implements a special dispatching mechanism for the infix operator special methods. Given an expression `a + b`, the interpreter will perform these steps (also see Figure 16-1):

1. If `a` has `__add__`, call `a.__add__(b)` and return result unless it's `NotImplemented`.
2. If `a` doesn't have `__add__`, or calling it returns `NotImplemented`, check if `b` has `__radd__`, then call `b.__radd__(a)` and return result unless it's `NotImplemented`.
3. If `b` doesn't have `__radd__`, or calling it returns `NotImplemented`, raise `TypeError` with an *unsupported operand types* message.

The `__radd__` method is called the "reflected" or "reversed" version of `__add__`. I prefer to call them "reversed" special methods.[3] Three of this book's technical reviewers—Alex, Anna, and Leo—told me they like to think of them as the "right" special methods, because they are called on the right-hand operand. Whatever "r"-word you prefer, that's what the "r" prefix stands for in `__radd__`, `__rsub__`, and the like.

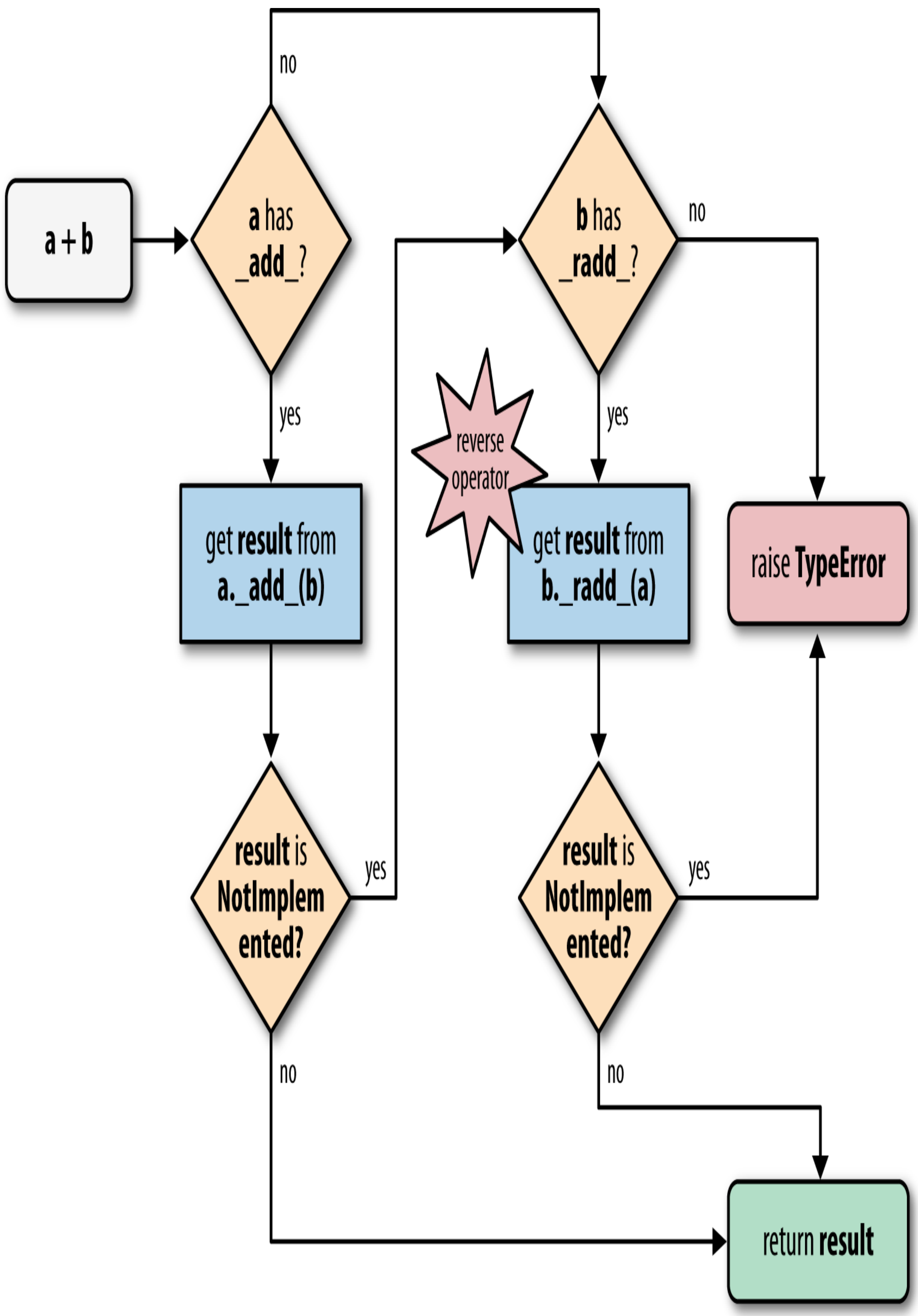

Figure 16-1. Flowchart for computing a + b with __add__ and __radd__

Therefore, to make the mixed-type additions in Example 16-6 work, we need to implement the `Vector.__radd__` method, which Python will invoke as a fall back if the left operand does not implement `__add__` or if it does but returns `NotImplemented` to signal that it doesn't know how to handle the right operand.

> **WARNING**
>
> Do not confuse `NotImplemented` with `NotImplementedError`. The first, `NotImplemented`, is a special singleton value that an infix operator special method should `return` to tell the interpreter it cannot handle a given operand. In contrast, `NotImplementedError` is an exception that stub methods in abstract classes may `raise` to warn that subclasses must implement them.

The simplest possible `__radd__` that works is shown in Example 16-7.

Example 16-7. Vector.__add__ and __radd__ methods

```
    # inside the Vector class

    def __add__(self, other):  ❶
        pairs = itertools.zip_longest(self, other, fillvalue=0.0)
        return Vector(a + b for a, b in pairs)

    def __radd__(self, other):  ❷
        return self + other
```

❶ No changes to `__add__` from Example 16-4; listed here because `__radd__` uses it.

❷ `__radd__` just delegates to `__add__`.

Often, `__radd__` can be as simple as that: just invoke the proper operator, therefore delegating to `__add__` in this case. This applies to any commutative operator; `+` is commutative when dealing with numbers or our vectors, but it's not commutative when concatenating sequences in Python.

The methods in Example 16-4 work with `Vector` objects, or any iterable with numeric items, such as a `Vector2d`, a `tuple` of integers, or an `array` of floats. But if provided with a noniterable object, `__add__` fails with a message that is not very helpful, as in Example 16-8.

Example 16-8. Vector.__add__ method needs an iterable operand

```
>>> v1 + 1
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "vector_v6.py", line 328, in __add__
    pairs = itertools.zip_longest(self, other, fillvalue=0.0)
TypeError: zip_longest argument #2 must support iteration
```

Another unhelpful message is given if an operand is iterable but its items cannot be added to the `float` items in the `Vector`. See Example 16-9.

Example 16-9. Vector.__add__ method needs an iterable with numeric items

```
>>> v1 + 'ABC'
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "vector_v6.py", line 329, in __add__
    return Vector(a + b for a, b in pairs)
  File "vector_v6.py", line 243, in __init__
    self._components = array(self.typecode, components)
  File "vector_v6.py", line 329, in <genexpr>
    return Vector(a + b for a, b in pairs)
TypeError: unsupported operand type(s) for +: 'float' and 'str'
```

The problems in Examples 16-8 and 16-9 actually go deeper than obscure error messages: if an operator special method cannot return a valid result because of type incompatibility, it should return `NotImplemented` and not raise `TypeError`. By returning `NotImplemented`, you leave the door open for the implementer of the other operand type to perform the operation when Python tries the reversed method call.

In the spirit of duck typing, we will refrain from testing the type of the `other` operand, or the type of its elements. We'll catch the exceptions and return `NotImplemented`. If the interpreter has not yet reversed the operands, it will try that. If the reverse method call returns `NotImplemented`, then Python will raise `TypeError` with a standard error message like "unsupported operand type(s) for +: *Vector* and *str*."

The final implementation of the special methods for `Vector` addition are in Example 16-10.

Example 16-10. vector_v6.py: operator + methods added to vector_v5.py (Example 12-16)

```
    def __add__(self, other):
        try:
            pairs = itertools.zip_longest(self, other, fillvalue=0.0)
            return Vector(a + b for a, b in pairs)
        except TypeError:
            return NotImplemented

    def __radd__(self, other):
        return self + other
```

> **WARNING**
>
> If an infix operator method raises an exception, it aborts the operator dispatch algorithm. In the particular case of `TypeError`, it is often better to catch it and `return NotImplemented`. This allows the interpreter to try calling the reversed operator method, which may correctly handle the computation with the swapped operands, if they are of different types.

At this point, we have safely overloaded the `+` operator by writing `__add__` and `__radd__`. We will now tackle another infix operator: `*`.

Overloading * for Scalar Multiplication

What does `Vector([1, 2, 3]) * x` mean? If `x` is a number, that would be a scalar product, and the result would be a new `Vector` with each component multiplied by `x`—also known as an elementwise multiplication:

```
>>> v1 = Vector([1, 2, 3])
>>> v1 * 10
Vector([10.0, 20.0, 30.0])
>>> 11 * v1
Vector([11.0, 22.0, 33.0])
```

> **NOTE**
>
> Another kind of product involving `Vector` operands would be the dot product of two vectors—or matrix multiplication, if you take one vector as a 1 × N matrix and the other as an N × 1 matrix. We will implement that operator in our `Vector` class in "Using @ as an infix operator".

Back to our scalar product, again we start with the simplest `__mul__` and `__rmul__` methods that could possibly work:

```
# inside the Vector class

def __mul__(self, scalar):
    return Vector(n * scalar for n in self)

def __rmul__(self, scalar):
    return self * scalar
```

Those methods do work, except when provided with incompatible operands. The `scalar` argument has to be a number that when multiplied by a `float` produces another `float` (because our `Vector` class uses an `array` of floats internally). So a `complex` number will not do, but the scalar can be an `int`, a `bool` (because `bool` is a subclass of `int`), or even a `fractions.Fraction` instance. In Example 16-11, the `__mul__` method does not make an explicit type check on `scalar`, but instead converts it into a `float`, and returns `NotImplemented` if that fails. Yet another example of duck typing.

> **NOTE**
>
> In *Fluent Python, First Edition*, I used goose typing in Example 16-11: testing the second operand with `isinstance(scalar, numbers.Real)`. Currently I avoid using the `numbers` ABCs because they are not supported by PEP 484, and using types at runtime that cannot also be statically checked seems a bad idea to me. I hope one day those ABCs can be fixed so we can use them with goose typing as well as static typing. On the other hand, `__matmul__` in Example 16-12 provides a good example of goose typing, new in this edition.

*Example 16-11. vector_v7.py: operator * methods added*

```
class Vector:
    typecode = 'd'

    def __init__(self, components):
        self._components = array(self.typecode, components)

    # many methods omitted in book listing, see vector_v7.py
    # in https://github.com/fluentpython/example-code-2e ...

    def __mul__(self, scalar):
        try:
            factor = float(scalar)
        except TypeError:  ❶
            return NotImplemented  ❷
        return Vector(n * factor for n in self)

    def __rmul__(self, scalar):
        return self * scalar  ❸
```

❶ If `scalar` cannot be converted to `float`…

❷ …return `NotImplemented`, to let Python try `__rmul__` on the `scalar` operand.

❸ In this example, `__rmul__` works fine by just performing `self * scalar`, delegating to the `__mul__` method.

With Example 16-11, we can multiply `Vectors` by scalar values of the usual and not so usual numeric types:

```
>>> v1 = Vector([1.0, 2.0, 3.0])
>>> 14 * v1
Vector([14.0, 28.0, 42.0])
>>> v1 * True
Vector([1.0, 2.0, 3.0])
>>> from fractions import Fraction
>>> v1 * Fraction(1, 3)
Vector([0.3333333333333333, 0.6666666666666666, 1.0])
```

Now that we can multiply `Vector` by scalars, let's see how to implement `Vector` by `Vector` products.

Using @ as an infix operator

The @ sign is well-known as the prefix of function decorators, but since 2015, it can also be used as an infix operator. For years, the dot product was written as `numpy.dot(a, b)` in NumPy. The function call notation makes longer formulas harder to translate from mathematical notation to Python,[4] so the numerical computing community lobbied for PEP 465—A dedicated infix operator for matrix multiplication which was implemented in Python 3.5. Today you can write `a @ b` to compute the dot product of two NumPy arrays.

The @ operator is supported by the special methods `__matmul__`, `__rmatmul__`, and `__imatmul__`, named for "matrix multiplication." These methods are not used anywhere in the standard library at this time, but are recognized by the interpreter since Python 3.5, so the NumPy team—and the rest of us—can support the @ operator in user-defined types. The parser was also changed to handle the new operator (`a @ b` was a syntax error in Python 3.4).

These simple tests show how @ should work with `Vector` instances:

```
>>> va = Vector([1, 2, 3])
>>> vz = Vector([5, 6, 7])
>>> va @ vz == 38.0  # 1*5 + 2*6 + 3*7
True
>>> [10, 20, 30] @ vz
380.0
>>> va @ 3
Traceback (most recent call last):
...
TypeError: unsupported operand type(s) for @: 'Vector' and 'int'
```

Here is the code of the relevant special methods:

Example 16-12. vector_v7.py: operator @ methods

```
class Vector:
    # many methods omitted in book listing

    def __matmul__(self, other):
        if (isinstance(other, abc.Sized) and ❶
            isinstance(other, abc.Iterable)):
            if len(self) == len(other): ❷
                return sum(a * b for a, b in zip(self, other)) ❸
```

```
            else:
                raise ValueError('@ requires vectors of equal 
length.')
        else:
            return NotImplemented

    def __rmatmul__(self, other):
        return self @ other
```

❶ Both operands must implement `__len__` and `__iter__`…

❷ …and have the same length to allow…

❸ …a beautiful application of `sum`, `zip` and generator expression.

Example 16-12 is a good example of *goose typing* in practice. If we tested the `other` operand against `Vector`, we'd deny users the flexibility of using lists or arrays as operands to `@`. As long as one operand is a `Vector`, our `@` implementation supports other operands that are instances of `abc.Sized` and `abc.Iterable`. Both of these ABCs implement the `__subclasshook__`, therefore any object providing `__len__` and `__iter__` satisfies our test—no need to actually subclass those ABCs, as explained in "Structural typing with ABCs". In particular, our `Vector` class does not subclass either `abc.Sized` or `abc.Iterable`, but it does pass the `isinstance` checks against those ABCs because it has the necessary methods.

Let's review the arithmetic operators supported by Python, before diving into the special category of "Rich Comparison Operators".

Wrapping-up arithmetic operators

Implementing `+`, `*`, and `@` we saw the most common patterns for coding infix operators. The techniques we described are applicable to all operators listed in Table 16-1 (the in-place operators will be covered in "Augmented Assignment Operators").

Table 16-1. Infix operator method names (the in-plac *e operators are used for augmented assignment; compa* *rison operators are in Table 16-2)*

Operator	Forward	Reverse	In-place	Description
`+`	`__add__`	`__radd__`	`__iadd__`	Addition or concatenation
`-`	`__sub__`	`__rsub__`	`__isub__`	Subtraction
`*`	`__mul__`	`__rmul__`	`__imul__`	Multiplication or repetition
`/`	`__truediv__`	`__rtruediv__`	`__itruediv__`	True division
`//`	`__floordiv__`	`__rfloordiv__`	`__ifloordiv__`	Floor division
`%`	`__mod__`	`__rmod__`	`__imod__`	Modulo

`divmod()`	`__divmod__`	`__rdivmod__`	`__idivmod__`	Returns tuple of floor division quotient and modulo
`**`, `pow()`	`__pow__`	`__rpow__`	`__ipow__`	Exponentiation[a]
`@`	`__matmul__`	`__rmatmul__`	`__imatmul__`	Matrix multiplication
`&`	`__and__`	`__rand__`	`__iand__`	Bitwise and
`|`	`__or__`	`__ror__`	`__ior__`	Bitwise or
`^`	`__xor__`	`__rxor__`	`__ixor__`	Bitwise xor
`<<`	`__lshift__`	`__rlshift__`	`__ilshift__`	Bitwise shift left
`>>`	`__rshift__`	`__rrshift__`	`__irshift__`	Bitwise shift right

a `pow` takes an optional third argument, `modulo`: `pow(a, b, modulo)`, also supported by the special methods when invoked directly (e.g., `a.__pow__(b, modulo)`).

The rich comparison operators use a different set of rules. We cover them next.

Rich Comparison Operators

The handling of the rich comparison operators `==`, `!=`, `>`, `<`, `>=`, `<=` by the Python interpreter is similar to what we just saw, but differs in two important aspects:

- The same set of methods are used in forward and reverse operator calls. The rules are summarized in Table 16-2. For example, in the case of `==`, both the forward and reverse calls invoke `__eq__`, only swapping arguments; and a forward call to `__gt__` is followed by a reverse call to `__lt__` with the swapped arguments.
- In the case of `==` and `!=`, if the reverse call fails, Python compares the object IDs instead of raising `TypeError`.

Table 16-2. Rich comparison operators

:reverse methods invoked when the init

ialmethod callreturnsNotImplemented

Group	Infix operator	Forward method call	Reverse method call	Fall back
Equality	`a == b`	`a.__eq__(b)`	`b.__eq__(a)`	Return `id(a) == id(b)`
	`a != b`	`a.__ne__(b)`	`b.__ne__(a)`	Return `not (a == b)`
Ordering	`a > b`	`a.__gt__(b)`	`b.__lt__(a)`	Raise `TypeError`
	`a < b`	`a.__lt__(b)`	`b.__gt__(a)`	Raise `TypeError`
	`a >= b`	`a.__ge__(b)`	`b.__le__(a)`	Raise `TypeError`
	`a <= b`	`a.__le__(b)`	`b.__ge__(a)`	Raise `TypeError`

NEW BEHAVIOR IN PYTHON 3

The fallback step for all comparison operators changed from Python 2. For `__ne__`, Python 3 now returns the negated result of `__eq__`. For the ordering comparison operators, Python 3 raises `TypeError` with a message like `'unorderable types: int() < tuple()'`. In Python 2, those comparisons produced weird results taking into account object types and IDs in some arbitrary way. However, it really makes no sense to compare an `int` to a `tuple`, for example, so raising `TypeError` in such cases is a real improvement in the language.

Given these rules, let's review and improve the behavior of the `Vector.__eq__` method, which was coded as follows in *vector_v5.py* (Example 12-16):

```
class Vector:
    # many lines omitted

    def __eq__(self, other):
        return (len(self) == len(other) and
                all(a == b for a, b in zip(self, other)))
```

That method produces the results in Example 16-13.

Example 16-13. Comparing a Vector to a Vector, a Vector2d, and a tuple

```
>>> va = Vector([1.0, 2.0, 3.0])
>>> vb = Vector(range(1, 4))
>>> va == vb  ❶
True
>>> vc = Vector([1, 2])
>>> from vector2d_v3 import Vector2d
>>> v2d = Vector2d(1, 2)
>>> vc == v2d  ❷
True
>>> t3 = (1, 2, 3)
>>> va == t3  ❸
True
```

❶ Two `Vector` instances with equal numeric components compare equal.

❷ A `Vector` and a `Vector2d` are also equal if their components are equal.

❸ A `Vector` is also considered equal to a `tuple` or any iterable with numeric items of equal value.

The last one of the results in Example 16-13 is probably not desirable. Do we really want a `Vector` to be considered equal to a `tuple` containing the same numbers? I have no hard rule about this; it depends on the application context. The Zen of Python says:

> *In the face of ambiguity, refuse the temptation to guess.*

Excessive liberality in the evaluation of operands may lead to surprising results, and programmers hate surprises.

Taking a clue from Python itself, we can see that `[1,2] == (1, 2)` is `False`. Therefore, let's be conservative and do some type checking. If the second operand is a `Vector` instance (or an instance of a `Vector` subclass), then use the same logic as the current `__eq__`. Otherwise, return `NotImplemented` and let Python handle that. See Example 16-14.

Example 16-14. vector_v8.py: improved __eq__ in the Vector class

```
    def __eq__(self, other):
        if isinstance(other, Vector):  ❶
            return (len(self) == len(other) and
                    all(a == b for a, b in zip(self, other)))
```

```
        else:
            return NotImplemented  ❷
```

❶ If the `other` operand is an instance of `Vector` (or of a `Vector` subclass), perform the comparison as before.

❷ Otherwise, return `NotImplemented`.

If you run the tests in Example 16-13 with the new `Vector.__eq__` from Example 16-14, what you get now is shown in Example 16-15.

Example 16-15. Same comparisons as Example 16-13: last result changed

```
>>> va = Vector([1.0, 2.0, 3.0])
>>> vb = Vector(range(1, 4))
>>> va == vb  ❶
True
>>> vc = Vector([1, 2])
>>> from vector2d_v3 import Vector2d
>>> v2d = Vector2d(1, 2)
>>> vc == v2d  ❷
True
>>> t3 = (1, 2, 3)
>>> va == t3  ❸
False
```

❶ Same result as before, as expected.

❷ Same result as before, but why? Explanation coming up.

❸ Different result; this is what we wanted. But why does it work? Read on…

Among the three results in Example 16-15, the first one is no news, but the last two were caused by `__eq__` returning `NotImplemented` in Example 16-14. Here is what happens in the example with a `Vector` and a `Vector2d`, step by step:

1. To evaluate `vc == v2d`, Python calls `Vector.__eq__(vc, v2d)`.
2. `Vector.__eq__(vc, v2d)` verifies that `v2d` is not a `Vector` and returns `NotImplemented`.

3. Python gets `NotImplemented` result, so it tries `Vector2d.__eq__(v2d, vc)`.
4. `Vector2d.__eq__(v2d, vc)` turns both operands into tuples an compares them: the result is `True` (the code for `Vector2d.__eq__` is in Example 11-11).

As for the comparison between `Vector` and `tuple` in Example 16-15, the actual steps are:

1. To evaluate `va == t3`, Python calls `Vector.__eq__(va, t3)`.
2. `Vector.__eq__(va, t3)` verifies that `t3` is not a `Vector` and returns `NotImplemented`.
3. Python gets `NotImplemented` result, so it tries `tuple.__eq__(t3, va)`.
4. `tuple.__eq__(t3, va)` has no idea what a `Vector` is, so it returns `NotImplemented`.
5. In the special case of `==`, if the reversed call returns `NotImplemented`, Python compares object IDs as a last resort.

How about `!=`? We don't need to implement it because the fallback behavior of the `__ne__` inherited from `object` suits us: when `__eq__` is defined and does not return `NotImplemented`, `__ne__` returns that result negated.

In other words, given the same objects we used in Example 16-15, the results for `!=` are consistent:

```
>>> va != vb
False
>>> vc != v2d
False
>>> va != (1, 2, 3)
True
```

The `__ne__` inherited from `object` works like the following code—except that the original is written in C:[5]

```
    def __ne__(self, other):
        eq_result = self == other
        if eq_result is NotImplemented:
            return NotImplemented
        else:
            return not eq_result
```

After covering the essentials of infix operator overloading, let’s turn to a different class of operators: the augmented assignment operators.

Augmented Assignment Operators

Our `Vector` class already supports the augmented assignment operators `+=` and `*=`. Example 16-16 shows them in action.

Example 16-16. Augmented assignment works with immutable targets by creating new instances and rebinding

```
>>> v1 = Vector([1, 2, 3])
>>> v1_alias = v1  ❶
>>> id(v1)  ❷
4302860128
>>> v1 += Vector([4, 5, 6])  ❸
>>> v1  ❹
Vector([5.0, 7.0, 9.0])
>>> id(v1)  ❺
4302859904
>>> v1_alias  ❻
Vector([1.0, 2.0, 3.0])
>>> v1 *= 11  ❼
>>> v1  ❽
Vector([55.0, 77.0, 99.0])
>>> id(v1)
4302858336
```

❶ Create alias so we can inspect the `Vector([1, 2, 3])` object later.

❷ Remember the ID of the initial `Vector` bound to `v1`.

❸ Perform augmented addition.

❹ The expected result…

❺

…but a new `Vector` was created.

❻ Inspect `v1_alias` to confirm the original `Vector` was not altered.

❼ Perform augmented multiplication.

❽ Again, the expected result, but a new `Vector` was created.

If a class does not implement the in-place operators listed in Table 16-1, the augmented assignment operators are just syntactic sugar: `a += b` is evaluated exactly as `a = a + b`. That's the expected behavior for immutable types, and if you have `__add__` then `+=` will work with no additional code.

However, if you do implement an in-place operator method such as `__iadd__`, that method is called to compute the result of `a += b`. As the name says, those operators are expected to change the left-hand operand in place, and not create a new object as the result.

> **WARNING**
>
> The in-place special methods should never be implemented for immutable types like our `Vector` class. This is fairly obvious, but worth stating anyway.

To show the code of an in-place operator, we will extend the `BingoCage` class from Example 13-9 to implement `__add__` and `__iadd__`.

We'll call the subclass `AddableBingoCage`. Example 16-17 is the behavior we want for the `+` operator.

Example 16-17. A new AddableBingoCage instance can be created with

```
>>> vowels = 'AEIOU'
>>> globe = AddableBingoCage(vowels)  ❶
>>> globe.inspect()
('A', 'E', 'I', 'O', 'U')
>>> globe.pick() in vowels  ❷
True
>>> len(globe.inspect())  ❸
4
>>> globe2 = AddableBingoCage('XYZ')  ❹
```

```
>>> globe3 = globe + globe2
>>> len(globe3.inspect())  ❺
7
>>> void = globe + [10, 20]  ❻
Traceback (most recent call last):
  ...
TypeError: unsupported operand type(s) for +: 'AddableBingoCage'
and 'list'
```

❶ Create a `globe` instance with five items (each of the `vowels`).

❷ Pop one of the items, and verify it is one the `vowels`.

❸ Confirm that the `globe` is down to four items.

❹ Create a second instance, with three items.

❺ Create a third instance by adding the previous two. This instance has seven items.

❻ Attempting to add an `AddableBingoCage` to a `list` fails with `TypeError`. That error message is produced by the Python interpreter when our `__add__` method returns `NotImplemented`.

Because an `AddableBingoCage` is mutable, Example 16-18 shows how it will work when we implement `__iadd__`.

Example 16-18. An existing AddableBingoCage can be loaded with += (continuing from Example 16-17)

```
>>> globe_orig = globe  ❶
>>> len(globe.inspect())  ❷
4
>>> globe += globe2  ❸
>>> len(globe.inspect())
7
>>> globe += ['M', 'N']  ❹
>>> len(globe.inspect())
9
>>> globe is globe_orig  ❺
True
>>> globe += 1  ❻
Traceback (most recent call last):
  ...
```

```
    TypeError: right operand in += must be 'AddableBingoCage' or an
iterable
```

❶ Create an alias so we can check the identity of the object later.

❷ `globe` has four items here.

❸ An `AddableBingoCage` instance can receive items from another instance of the same class.

❹ The right-hand operand of `+=` can also be any iterable.

❺ Throughout this example, `globe` has always referred to the `globe_orig` object.

❻ Trying to add a noniterable to an `AddableBingoCage` fails with a proper error message.

Note that the `+=` operator is more liberal than `+` with regard to the second operand. With `+`, we want both operands to be of the same type (`AddableBingoCage`, in this case), because if we accepted different types this might cause confusion as to the type of the result. With the `+=`, the situation is clearer: the left-hand object is updated in place, so there's no doubt about the type of the result.

> **TIP**
>
> I validated the contrasting behavior of `+` and `+=` by observing how the `list` built-in type works. Writing `my_list + x`, you can only concatenate one `list` to another `list`, but if you write `my_list += x`, you can extend the left-hand `list` with items from any iterable `x` on the right-hand side. This how the `list.extend()` method works: it accepts any iterable argument.

Now that we are clear on the desired behavior for `AddableBingoCage`, we can look at its implementation in Example 16-19.

Example 16-19. bingoaddable.py: AddableBingoCage extends BingoCage to support + and +=

```
from tombola import Tombola
from bingo import BingoCage


class AddableBingoCage(BingoCage):  ❶

    def __add__(self, other):
        if isinstance(other, Tombola):  ❷
            return AddableBingoCage(self.inspect() + other.inspect())
        else:
            return NotImplemented

    def __iadd__(self, other):
        if isinstance(other, Tombola):
            other_iterable = other.inspect()  ❸
        else:
            try:
                other_iterable = iter(other)  ❹
            except TypeError:  ❺
                self_cls = type(self).__name__
                msg = "right operand in += must be {!r} or an
iterable"
                raise TypeError(msg.format(self_cls))
        self.load(other_iterable)  ❻
        return self  ❼
```

❶ `AddableBingoCage` extends `BingoCage`.

❷ Our `__add__` will only work with an instance of `Tombola` as the second operand.

❸ Retrieve items from `other`, if it is an instance of `Tombola`.

❹ Otherwise, try to obtain an iterator over `other`.[6]

❺ If that fails, raise an exception explaining what the user should do. When possible, error messages should explicitly guide the user to the solution.

❻ If we got this far, we can load the `other_iterable` into `self`.

❼ Very important: augmented assignment special methods must return `self`.

We can summarize the whole idea of in-place operators by contrasting the `return` statements that produce results in `__add__` and `__iadd__` in Example 16-19:

`__add__`

The result is produced by calling the constructor `AddableBingoCage` to build a new instance.

`__iadd__`

The result is produced by returning `self`, after it has been modified.

To wrap up this example, a final observation on Example 16-19: by design, no `__radd__` was coded in `AddableBingoCage`, because there is no need for it. The forward method `__add__` will only deal with right-hand operands of the same type, so if Python is trying to compute `a + b` where `a` is an `AddableBingoCage` and `b` is not, we return `NotImplemented`—maybe the class of `b` can make it work. But if the expression is `b + a` and `b` is not an `AddableBingoCage`, and it returns `NotImplemented`, then it's better to let Python give up and raise `TypeError` because we cannot handle `b`.

TIP

In general, if a forward infix operator method (e.g., `__mul__`) is designed to work only with operands of the same type as `self`, it's useless to implement the corresponding reverse method (e.g., `__rmul__`) because that, by definition, will only be invoked when dealing with an operand of a different type.

This concludes our exploration of operator overloading in Python.

Chapter Summary

We started this chapter by reviewing some restrictions Python imposes on operator overloading: no overloading of operators in built-in types, and overloading limited to existing operators, except for a few ones (`is`, `and`, `or`, `not`).

We got down to business with the unary operators, implementing `__neg__` and `__pos__`. Next came the infix operators, starting with `+`, supported by the `__add__` method. We saw that unary and infix operators are supposed to produce results by creating new objects, and should never change their operands. To support operations with other types, we return the `NotImplemented` special value—not an exception—allowing the interpreter to try again by swapping the operands and calling the reverse special method for that operator (e.g., `__radd__`). The algorithm Python uses to handle infix operators is summarized in the flowchart in Figure 16-1.

Mixing operand types requires detecting operands we can't handle. In this chapter, we did this in two ways: in the duck typing way, we just went ahead and tried the operation, catching a `TypeError` exception if it happened; later, in `__mul__` and `__matmul__`, we did it with an explicit `isinstance` test. There are pros and cons to these approaches: duck typing is more flexible, but explicit type checking is more predictable.

In general, libraries should leverage duck typing—opening the door for objects regardless of their types, as long as they support the necessary operations. However, Python's operator dispatch algorithm may produce misleading error messages or unexpected results when combined with duck typing. For this reason, the discipline of type checking using `isinstance` calls against ABCs is often useful when writing special methods for operator overloading. That's the technique dubbed *goose typing* by Alex Martelli—which we saw in "Goose typing". Goose typing is a good compromise between flexibility and safety, because existing or future user-defined types can be declared as actual or virtual subclasses of an ABC. In addition, if an ABC implements the `__subclasshook__`, then objects pass `isinstance` checks against that ABC by providing the required methods—no subclassing or registration required.

The next topic we covered was the rich comparison operators. We implemented `==` with `__eq__` and discovered that Python provides a handy implementation of `!=` in the `__ne__` inherited from the `object` base class. The way Python evaluates these operators along with `>`, `<`, `>=`, and `<=` is slightly different, with special logic for choosing the reverse method, and fallback handling for `==` and `!=` which never generate errors because Python compares the object IDs as a last resort.

In the last section, we focused on augmented assignment operators. We saw that Python handles them by default as a combination of plain operator followed by assignment, that is: `a += b` is evaluated exactly as `a = a + b`. That always creates a new object, so it works for mutable or immutable types. For mutable objects, we can implement in-place special methods such as `__iadd__` for `+=`, and alter the value of the left-hand operand. To show this at work, we left behind the immutable `Vector` class and worked on implementing a `BingoCage` subclass to support `+=` for adding items to the random pool, similar to the way the `list` built-in supports `+=` as a shortcut for the `list.extend()` method. While doing this, we discussed how `+` tends to be stricter than `+=` regarding the types it accepts. For sequence types, `+` usually requires that both operands are of the same type, while `+=` often accepts any iterable as the right-hand operand.

Further Reading

Guido van Rossum wrote a good defense of operator overloading in Why operators are useful. Trey Hunner blogged Tuple ordering and deep comparisons in Python arguing that the rich comparisons operators in Python are more flexible and powerful than programmers may realize when coming from other languages.

Operator overloading is one area of Python programming where `isinstance` tests are common. The best practice around such tests is *goose typing*, covered in "Goose typing". If you skipped that, make sure to read it.

The main reference for the operator special methods is the "Data Model" chapter. Another relevant reading in the Python documentation is "9.1.2.2.

Implementing the arithmetic operations” in the `numbers` module of The Python Standard Library.

A clever example of operator overloading appeared in the `pathlib` package, added in Python 3.4. Its `Path` class overloads the `/` operator to build filesystem paths from strings, as shown in this example from the documentation:

```
>>> p = Path('/etc')
>>> q = p / 'init.d' / 'reboot'
>>> q
PosixPath('/etc/init.d/reboot')
```

Another non-arithmetic example of operator overloading is in the Scapy library, used to “send, sniff, dissect and forge network packets”. In Scapy, the `/` operator builds packets by stacking fields from different network layers. See Stacking layers for details.

If you are about to implement comparison operators, study `functools.total_ordering`. That is class decorator that automatically generates methods for all rich comparison operators in any class that defines at least a couple of them. See the functools module docs.

If you are curious about operator method dispatching in languages with dynamic typing, two seminal readings are “A Simple Technique for Handling Multiple Polymorphism” by Dan Ingalls (member of the original Smalltalk team) and “Arithmetic and Double Dispatching in Smalltalk-80” by Kurt J. Hebel and Ralph Johnson (Johnson became famous as one of the authors of the original *Design Patterns* book). Both papers provide deep insight into the power of polymorphism in languages with dynamic typing, like Smalltalk, Python, and Ruby. Python does not use double dispatching for handling operators as described in those articles. The Python algorithm using forward and reverse operators is easier for user-defined classes to support than double dispatching, but requires special handling by the interpreter. In contrast, classic double dispatching is a general technique you can use in Python or any OO language beyond the specific context of infix operators, and in fact Ingalls, Hebel, and Johnson use very different examples to describe it.

The article “The C Family of Languages: Interview with Dennis Ritchie, Bjarne Stroustrup, and James Gosling” from which I quoted the epigraph in this chapter appeared in *Java Report*, 5(7), July 2000 and *C++ Report*, 12(7), July/August 2000, along with two other snippets I used in the **Soapbox** (next). If you are into programming language design, do yourself a favor and read that interview.

SOAPBOX

Operator Overloading: Pros and Cons

James Gosling, quoted at the start of this chapter, made the conscious decision to leave operator overloading out when he designed Java. In that same interview (“The C Family of Languages: Interview with Dennis Ritchie, Bjarne Stroustrup, and James Gosling”) he says:

> *Probably about 20 to 30 percent of the population think of operator overloading as the spawn of the devil; somebody has done something with operator overloading that has just really ticked them off, because they’ve used like + for list insertion and it makes life really, really confusing. A lot of that problem stems from the fact that there are only about half a dozen operators you can sensibly overload, and yet there are thousands or millions of operators that people would like to define—so you have to pick, and often the choices conflict with your sense of intuition.*

Guido van Rossum picked the middle way in supporting operator overloading: he did not leave the door open for users creating new arbitrary operators like `<=>` or `:-)`, which prevents a Tower of Babel of custom operators, and allows the Python parser to be simple. Python also does not let you overload the operators of the built-in types, another limitation that promotes readability and predictable performance.

Gosling goes on to say:

> *Then there’s a community of about 10 percent that have actually used operator overloading appropriately and who really care about it, and for whom it’s actually really important; this is almost exclusively people who do numerical work, where the notation is very important to appealing to people’s intuition, because they come into it with an intuition about what the + means, and the ability to say “a + b” where a and b are complex numbers or matrices or something really does make sense.*

The notation side of the issue cannot be underestimated. Here is an illustrative example from the realm of finances. In Python, you can compute compound interest using a formula written like this:

```
interest = principal * ((1 + rate) ** periods - 1)
```

That same notation works regardless of the numeric types involved. Thus, if you are doing serious financial work, you can make sure that `periods` is an `int`, while `rate`, `interest`, and `principal` are exact numbers—instances of the Python `decimal.Decimal` class — and that formula will work exactly as written.

But in Java, if you switch from `float` to `BigDecimal` to get arbitrary precision, you can't use infix operators anymore, because they only work with the primitive types. This is the same formula coded to work with `BigDecimal` numbers in Java:

```
BigDecimal interest = principal.multiply(BigDecimal.ONE.add(rate)
                        .pow(periods).subtract(BigDecimal.ONE));
```

It's clear that infix operators make formulas more readable, at least for most of us.[7] And operator overloading is necessary to support non-primitive types with infix operator notation. Having operator overloading in a high-level, easy-to-use language was probably a key reason for the amazing penetration of Python in scientific computing in recent years.

Of course, there are benefits to disallowing operator overloading in a language. It is arguably a sound decision for lower-level systems languages where performance and safety are paramount. The much newer Go language followed the lead of Java in this regard and does not support operator overloading.

But overloaded operators, when used sensibly, do make code easier to read and write. It's a great feature to have in a modern high-level language.

A Glimpse at Lazy Evaluation

If you look closely at the traceback in Example 16-9, you'll see evidence of the *lazy* evaluation of generator expressions. Example 16-20 is that same traceback, now with callouts.

Example 16-20. Same as Example 16-9

```
>>> v1 + 'ABC'
Traceback (most recent call last):
```

```
  File "<stdin>", line 1, in <module>
  File "vector_v6.py", line 329, in __add__
    return Vector(a + b for a, b in pairs)  ❶
  File "vector_v6.py", line 243, in __init__
    self._components = array(self.typecode, components)  ❷
  File "vector_v6.py", line 329, in <genexpr>
    return Vector(a + b for a, b in pairs)  ❸
TypeError: unsupported operand type(s) for +: 'float' and 'str'
```

❶ The `Vector` call gets a generator expression as its `components` argument. No problem at this stage.

❷ The `components` genexp is passed to the `array` constructor. Within the `array` constructor, Python tries to iterate over the genexp, causing the evaluation of the first item `a + b`. That's when the `TypeError` occurs.

❸ The exception propagates to the `Vector` constructor call, where it is reported.

This shows how the generator expression is evaluated at the latest possible moment, and not where it is defined in the source code.

In contrast, if the `Vector` constructor was invoked as `Vector([a + b for a, b in pairs])`, then the exception would happen right there, because the list comprehension tried to build a `list` to be passed as the argument to the `Vector()` call. The body of `Vector.__init__` would not be reached at all.

Chapter 17 will cover generator expressions in detail, but I did not want to let this accidental demonstration of their lazy nature go unnoticed.

---

1 Source: "The C Family of Languages: Interview with Dennis Ritchie, Bjarne Stroustrup, and James Gosling".

2 The remaining ABCs in Python's standard library are still valuable for goose typing and static typing. The issue with the `numbers` ABCs is explained in "The numbers ABCs and numeric protocols".

3 The Python documentation uses both terms. The "Data Model" chapter uses "reflected," but "9.1.2.2. Implementing the arithmetic operations" in the `numbers` module docs mention "forward" and "reverse" methods, and I find this terminology better, because "forward" and "reversed" clearly name each of the directions, while "reflected" doesn't have an obvious opposite.

4 See "Soapbox" for an discussion of the problem.

5 The logic for `object.__eq__` and `object.__ne__` is in function `object_richcompare` in Objects/typeobject.c in the CPython source code.

6 The `iter` built-in function will be covered in the next chapter. Here I could have used `tuple(other)`, and it would work, but at the cost of building a new `tuple` when all the `.load(…)` method needs is to iterate over its argument.

7 My friend Mario Domenech Goulart, a core developer of the CHICKEN Scheme compiler, will probably disagree with this.

Chapter 17. Iterables, Iterators, and Generators

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 17th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *When I see patterns in my programs, I consider it a sign of trouble. The shape of a program should reflect only the problem it needs to solve. Any other regularity in the code is a sign, to me at least, that I'm using abstractions that aren't powerful enough—often that I'm generating by hand the expansions of some macro that I need to write.*[1]
>
> —Paul Graham, Lisp hacker and venture capitalist

Iteration is fundamental to data processing: programs mostly apply computations to data series, from pixels to nucleotides. If the data doesn't fit in memory, we need to fetch the items *lazily*— one at a time and on demand. That's what an iterator does. This chapter shows how the Iterator pattern is built into the Python language so you never need to code it by hand.

Python does not have macros like Lisp (Paul Graham's favorite language), so abstracting away the Iterator pattern required changing the language: the `yield` keyword was added in Python 2.2 (2001).[2] The `yield` keyword allows the construction of generator functions, which return iterators.

Python 3 uses generators in many places. Even the `range()` built-in now returns a generator-like object instead of full-blown lists like before. If you must build a `list` from `range`, you have to be explicit (e.g., `list(range(100))`).

Every collection in Python is *iterable*, and iterators are used internally to support:

- `for` loops
- Collection types construction and extension
- Looping over text files line by line
- List, dict, and set comprehensions
- Tuple unpacking
- Unpacking actual parameters with `*` in function calls

This chapter covers the following topics:

- How the `iter(…)` built-in function is used internally to handle iterable objects
- How to implement the classic Iterator pattern in Python
- How a generator function works in detail, with line-by-line descriptions
- How the classic Iterator can be replaced by a generator function or generator expression
- Leveraging the general-purpose generator functions in the standard library
- Using the new `yield from` statement to combine generators

- A case study: using generator functions in a database conversion utility designed to work with large datasets
- Why generators and coroutines look alike but are actually very different and should not be mixed

What's new in this chapter

The one major change was the introductory section on `yield from`, which grew from 1 to 6 pages. "Subgenerators with yield from" now includes both simpler experiments demonstrating the behavior of generators with `yield from`, and a practical application of that syntax to traverse a tree data structure, developed step-by-step.

We'll get started studying how the `iter(…)` built-in function makes sequences iterable.

A Sequence of Words

We'll start our exploration of iterables by implementing a `Sentence` class: you give its constructor a string with some text, and then you can iterate word by word. The first version will implement the sequence protocol, and it's iterable because all sequences are iterable—as we've seen since Chapter 1. Now we'll see exactly why.

Example 17-1 shows a `Sentence` class that extracts words from a text by index.

Example 17-1. sentence.py: A Sentence as a sequence of words

```
import re
import reprlib

RE_WORD = re.compile(r'\w+')


class Sentence:

    def __init__(self, text):
```

```
        self.text = text
        self.words = RE_WORD.findall(text)  ❶

    def __getitem__(self, index):
        return self.words[index]  ❷

    def __len__(self):  ❸
        return len(self.words)

    def __repr__(self):
        return 'Sentence(%s)' % reprlib.repr(self.text)  ❹
```

❶ `re.findall` returns a list with all nonoverlapping matches of the regular expression, as a list of strings.

❷ `self.words` holds the result of `.findall`, so we simply return the word at the given index.

❸ To complete the sequence protocol, we implement `__len__`—but it is not needed to make an iterable object.

❹ `reprlib.repr` is a utility function to generate abbreviated string representations of data structures that can be very large.[3]

By default, `reprlib.repr` limits the generated string to 30 characters. See the console session in Example 17-2 to see how `Sentence` is used.

Example 17-2. Testing iteration on a Sentence instance

```
>>> s = Sentence('"The time has come," the Walrus said,')  ❶
>>> s
Sentence('"The time ha... Walrus said,')  ❷
>>> for word in s:  ❸
...     print(word)
The
time
has
come
the
Walrus
said
>>> list(s)  ❹
['The', 'time', 'has', 'come', 'the', 'Walrus', 'said']
```

❶ A sentence is created from a string.

❷ Note the output of `__repr__` using `...` generated by `reprlib.repr`.

❸ `Sentence` instances are iterable; we'll see why in a moment.

❹ Being iterable, `Sentence` objects can be used as input to build lists and other iterable types.

In the following pages, we'll develop other `Sentence` classes that pass the tests in Example 17-2. However, the implementation in Example 17-1 is different from all the others because it's also a sequence, so you can get words by index:

```
>>> s[0]
'The'
>>> s[5]
'Walrus'
>>> s[-1]
'said'
```

Every Python programmer knows that sequences are iterable. Now we'll see precisely why.

Why Sequences Are Iterable: The `iter` Function

Whenever the interpreter needs to iterate over an object `x`, it automatically calls `iter(x)`.

The `iter` built-in function:

1. Checks whether the object implements `__iter__`, and calls that to obtain an iterator.

2. If `__iter__` is not implemented, but `__getitem__` is implemented, Python creates an iterator that attempts to fetch items in order, starting from index 0 (zero).

3. If that fails, Python raises `TypeError`, usually saying "*C* object is not iterable," where `C` is the class of the target object.

That is why any Python sequence is iterable: they all implement `__getitem__`. In fact, the standard sequences also implement `__iter__`, and yours should too, because the special handling of `__getitem__` exists for backward compatibility reasons and may be gone in the future (although it is not deprecated as I write this).

As mentioned in "Python Digs Sequences", this is an extreme form of duck typing: an object is considered iterable not only when it implements the special method `__iter__`, but also when it implements `__getitem__`, as long as `__getitem__` accepts `int` keys starting from `0`.

In the goose-typing approach, the definition for an iterable is simpler but not as flexible: an object is considered iterable if it implements the `__iter__` method. No subclassing or registration is required, because `abc.Iterable` implements the `__subclasshook__`, as seen in "Structural typing with ABCs". Here is a demonstration:

```
>>> class Foo:
...     def __iter__(self):
...         pass
...
>>> from collections import abc
>>> issubclass(Foo, abc.Iterable)
True
>>> f = Foo()
>>> isinstance(f, abc.Iterable)
True
```

However, note that our initial `Sentence` class does not pass the `issubclass(Sentence, abc.Iterable)` test, even though it is iterable in practice.

> **TIP**
>
> As of Python 3.9, the most accurate way to check whether an object `x` is iterable is to call `iter(x)` and handle a `TypeError` exception if it isn't. This is more accurate than using `isinstance(x, abc.Iterable)`, because `iter(x)` also considers the legacy `__getitem__` method, while the `Iterable` ABC does not.

Explicitly checking whether an object is iterable may not be worthwhile if right after the check you are going to iterate over the object. After all, when the iteration is attempted on a noniterable, the exception Python raises is clear enough: `TypeError: 'C' object is not iterable`. If you can do better than just raising `TypeError`, then do so in a `try/except` block instead of doing an explicit check. The explicit check may make sense if you are holding on to the object to iterate over it later; in this case, catching the error early may be useful.

The next section makes explicit the relationship between iterables and iterators.

Iterables Versus Iterators

From the explanation in "Why Sequences Are Iterable: The `iter` Function" we can extrapolate a definition:

iterable

Any object from which the `iter` built-in function can obtain an iterator. Objects implementing an `__iter__` method returning an *iterator* are iterable. Sequences are always iterable; as are objects implementing a `__getitem__` method that takes 0-based indexes.

It's important to be clear about the relationship between iterables and iterators: Python obtains iterators from iterables.

Here is a simple `for` loop iterating over a `str`. The `str` `'ABC'` is the iterable here. You don't see it, but there is an iterator behind the curtain:

```
>>> s = 'ABC'
>>> for char in s:
...     print(char)
...
A
B
C
```

If there was no `for` statement and we had to emulate the `for` machinery by hand with a `while` loop, this is what we'd have to write:

```
>>> s = 'ABC'
>>> it = iter(s)  ❶
>>> while True:
...     try:
...         print(next(it))  ❷
...     except StopIteration:  ❸
...         del it  ❹
...         break  ❺
...
A
B
C
```

❶ Build an iterator `it` from the iterable.

❷ Repeatedly call `next` on the iterator to obtain the next item.

❸ The iterator raises `StopIteration` when there are no further items.

❹ Release reference to `it`—the iterator object is discarded.

❺ Exit the loop.

`StopIteration` signals that the iterator is exhausted. This exception is handled internally in `for` loops and other iteration contexts like list comprehensions, tuple unpacking, etc.

The standard interface for an iterator has two methods:

`__next__`

Returns the next available item, raising `StopIteration` when there are no more items.

`__iter__`

Returns `self`; this allows iterators to be used where an iterable is expected, for example, in a `for` loop.

This is formalized in the `collections.abc.Iterator` ABC, which defines the `__next__` abstract method, and subclasses `Iterable`—where the abstract `__iter__` method is defined. See Figure 17-1.

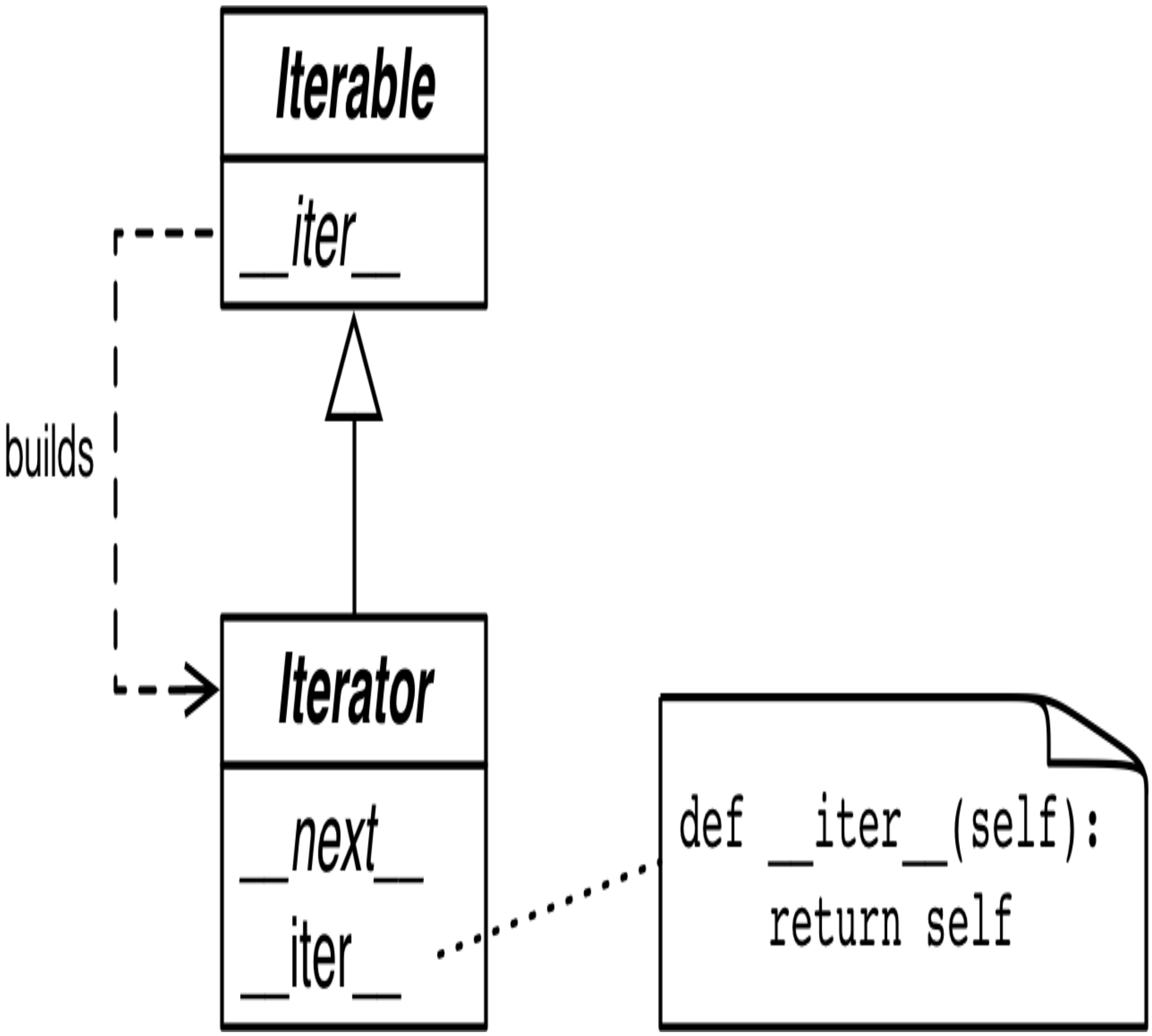

Figure 17-1. The Iterable and Iterator ABCs. Methods in italic are abstract. A concrete Iterable.__iter__ should return a new Iterator instance. A concrete Iterator must implement __next__. The Iterator.__iter__ method just returns the instance itself.

The `Iterator` ABC implements `__iter__` by doing `return self`. This allows an iterator to be used wherever an iterable is required. The source code for `abc.Iterator` is in Example 17-3.

Example 17-3. abc.Iterator class; extracted from Lib/_collections_abc.py

```
class Iterator(Iterable):

    __slots__ = ()

    @abstractmethod
    def __next__(self):
        'Return the next item from the iterator. When exhausted,
raise StopIteration'
```

```
        raise StopIteration

    def __iter__(self):
        return self

    @classmethod
    def __subclasshook__(cls, C):
        if cls is Iterator:
            if (any("__next__" in B.__dict__ for B in C.__mro__)
and
                any("__iter__" in B.__dict__ for B in C.__mro__)):
                return True
        return NotImplemented
```

> **WARNING**
>
> The `Iterator` ABC abstract method is `it.__next__()` in Python 3 and `it.next()` in Python 2. As usual, you should avoid calling special methods directly. Just use the `next(it)`: this built-in function does the right thing in Python 2 and 3.

The *Lib/types.py* module source code in Python 3.9 has a comment that says:

```
# Iterators in Python aren't a matter of type but of protocol.  A
large
# and changing number of builtin types implement *some* flavor of
# iterator.  Don't check the type!  Use hasattr to check for both
# "__iter__" and "__next__" attributes instead.
```

In fact, that’s exactly what the `__subclasshook__` method of the `abc.Iterator` ABC does (see Example 17-3).

> **TIP**
>
> Taking into account the advice from *Lib/types.py* and the logic implemented in *Lib/_collections_abc.py*, the best way to check if an object `x` is an iterator is to call `isinstance(x, abc.Iterator)`. Thanks to `Iterator.__subclasshook__`, this test works even if the class of `x` is not a real or virtual subclass of `Iterator`.

Back to our `Sentence` class from Example 17-1, you can clearly see how the iterator is built by `iter(…)` and consumed by `next(…)` using the Python console:

```
>>> s3 = Sentence('Pig and Pepper')  ❶
>>> it = iter(s3)  ❷
>>> it  # doctest: +ELLIPSIS
<iterator object at 0x...>
>>> next(it)  ❸
'Pig'
>>> next(it)
'and'
>>> next(it)
'Pepper'
>>> next(it)  ❹
Traceback (most recent call last):
  ...
StopIteration
>>> list(it)  ❺
[]
>>> list(iter(s3))  ❻
['Pig', 'and', 'Pepper']
```

❶ Create a sentence `s3` with three words.

❷ Obtain an iterator from `s3`.

❸ `next(it)` fetches the next word.

❹ There are no more words, so the iterator raises a `StopIteration` exception.

❺ Once exhausted, an iterator becomes useless.

❻ To go over the sentence again, a new iterator must be built.

Because the only methods required of an iterator are `__next__` and `__iter__`, there is no way to check whether there are remaining items, other than to call `next()` and catch `StopIteration`. Also, it's not possible to “reset” an iterator. If you need to start over, you need to call `iter(…)` on the iterable that built the iterator in the first place. Calling `iter(…)` on the iterator itself won’t help, because—as mentioned—`Iterator.__iter__` is implemented by returning `self`, so this will not reset a depleted iterator.

To wrap up this section, here is a definition for *iterator*:

iterator

> Any object that implements the `__next__` no-argument method that returns the next item in a series or raises `StopIteration` when there are no more items. Python iterators also implement the `__iter__` method so they are *iterable* as well.

The first version of `Sentence` from Example 17-1 was iterable thanks to the special treatment the `iter(…)` built-in gives to sequences. Next, we will implement `Sentence` variations that implement `__iter__` to return iterators.

Sentence classes with `__iter__`

The first variation of `Sentence` implements the standard iterable protocol.

Sentence Take #2: A Classic Iterator

The following `Sentence` class is built according to the classic Iterator design pattern according to the blueprint in the GoF book. Note that this is not idiomatic Python, as the next refactorings will make very clear. But it serves to make explicit the relationship between the iterable collection and the iterator object.

Example 17-4 shows an implementation of a `Sentence` that is iterable because it implements the `__iter__` special method, which builds and returns a `SentenceIterator`. This is how the Iterator design pattern is described in the original *Design Patterns* book.

We are doing it this way here just to make clear the crucial distinction between an iterable and an iterator and how they are connected.

Example 17-4. sentence_iter.py: Sentence implemented using the Iterator pattern

```
import re
import reprlib

RE_WORD = re.compile(r'\w+')


class Sentence:

    def __init__(self, text):
        self.text = text
        self.words = RE_WORD.findall(text)

    def __repr__(self):
        return f'Sentence({reprlib.repr(self.text)})'

    def __iter__(self):  ❶
        return SentenceIterator(self.words)  ❷


class SentenceIterator:

    def __init__(self, words):
        self.words = words  ❸
        self.index = 0  ❹

    def __next__(self):
        try:
            word = self.words[self.index]  ❺
        except IndexError:
            raise StopIteration()  ❻
        self.index += 1  ❼
        return word  ❽

    def __iter__(self):  ❾
        return self
```

❶ The `__iter__` method is the only addition to the previous `Sentence` implementation. This version has no `__getitem__`, to make it clear that the class is iterable because it implements `__iter__`.

❷ `__iter__` fulfills the iterable protocol by instantiating and returning an iterator.

❸ `SentenceIterator` holds a reference to the list of words.

❹ `self.index` determines the next word to fetch.

❺ Get the word at `self.index`.

❻ If there is no word at `self.index`, raise `StopIteration`.

❼ Increment `self.index`.

❽ Return the word.

❾ Implement `self.__iter__`.

The code in Example 17-4 passes the tests in Example 17-2.

Note that implementing `__iter__` in `SentenceIterator` is not actually needed for this example to work, but the it's the right thing to do: iterators are supposed to implement both `__next__` and `__iter__`, and doing so makes our iterator pass the `issubclass(SentenceIterator, abc.Iterator)` test. If we had subclassed `SentenceIterator` from `abc.Iterator`, we'd inherit the concrete `abc.Iterator.__iter__` method.

That is a lot of work (for us lazy Python programmers, anyway). Note how most code in `SentenceIterator` deals with managing the internal state of the iterator. Soon we'll see how to make it shorter. But first, a brief detour to address an implementation shortcut that may be tempting, but is just wrong.

Don’t make the iterable an iterator for itself

A common cause of errors in building iterables and iterators is to confuse the two. To be clear: iterables have an `__iter__` method that instantiates a new iterator every time. Iterators implement a `__next__` method that returns individual items, and an `__iter__` method that returns `self`.

Therefore, iterators are also iterable, but iterables are not iterators.

It may be tempting to implement `__next__` in addition to `__iter__` in the `Sentence` class, making each `Sentence` instance at the same time an iterable and iterator over itself. But this is a terrible idea. It’s also a common anti-pattern, according to Alex Martelli who has a lot of experience with Python code reviews.

The “Applicability” section[4] of the Iterator design pattern in the *GoF book* says:

> *Use the Iterator pattern*
>
> - *to access an aggregate object’s contents without exposing its internal representation.*
> - *to support multiple traversals of aggregate objects.*
> - *to provide a uniform interface for traversing different aggregate structures (that is, to support polymorphic iteration).*

To “support multiple traversals” it must be possible to obtain multiple independent iterators from the same iterable instance, and each iterator must keep its own internal state, so a proper implementation of the pattern requires each call to `iter(my_iterable)` to create a new, independent, iterator. That is why we need the `SentenceIterator` class in this example.

WARNING

Avoid making an iterable act as an iterator over itself. In other words, iterables must implement `__iter__`, but should not implement `__next__`.

On the other hand, iterators should always be iterable. An iterator's `__iter__` should just return `self`.

Now that the classic Iterator pattern is properly demonstrated, we can let it go. The next section presents a more idiomatic implementation of `Sentence`.

Sentence Take #3: A Generator Function

A Pythonic implementation of the same functionality uses a generator, avoiding all the work to implement the `SentenceIterator` class. A proper explanation of the generator comes right after Example 17-5.

Example 17-5. sentence_gen.py: Sentence implemented using a generator

```
import re
import reprlib

RE_WORD = re.compile(r'\w+')


class Sentence:

    def __init__(self, text):
        self.text = text
        self.words = RE_WORD.findall(text)

    def __repr__(self):
        return 'Sentence(%s)' % reprlib.repr(self.text)

    def __iter__(self):
        for word in self.words:  ❶
            yield word  ❷
        return  ❸

# done! ❹
```

1. Iterate over `self.words`.
2. Yield the current `word`.
3. This `return` is not needed; the function can just “fall-through” and return automatically. Either way, a generator function doesn’t raise `StopIteration`: it simply exits when it’s done producing values.[5]
4. No need for a separate iterator class!

Here again we have a different implementation of `Sentence` that passes the tests in Example 17-2.

Back in the `Sentence` code in Example 17-4, `__iter__` called the `SentenceIterator` constructor to build an iterator and return it. Now the iterator in Example 17-5 is in fact a generator object, built automatically when the `__iter__` method is called, because `__iter__` here is a generator function.

A full explanation of generators follows.

How a Generator Works

Any Python function that has the `yield` keyword in its body is a generator function: a function which, when called, returns a generator object. In other words, a generator function is a generator factory.

> **TIP**
>
> The only syntax distinguishing a plain function from a generator function is the fact that the latter has a `yield` keyword somewhere in its body. Some argued that a new keyword like `gen` should be used for generator functions instead of `def`, but Guido did not agree. His arguments are in PEP 255 — Simple Generators.[6]

Here is the simplest function useful to demonstrate the behavior of a generator:[7]

```
>>> def gen_123():  ❶
...     yield 1  ❷
...     yield 2
...     yield 3
...
>>> gen_123  # doctest: +ELLIPSIS
<function gen_123 at 0x...>  ❸
>>> gen_123()   # doctest: +ELLIPSIS
<generator object gen_123 at 0x...>  ❹
>>> for i in gen_123():  ❺
...     print(i)
1
2
3
>>> g = gen_123()  ❻
>>> next(g)  ❼
1
>>> next(g)
2
>>> next(g)
3
>>> next(g)  ❽
Traceback (most recent call last):
  ...
StopIteration
```

❶ Any Python function that contains the `yield` keyword is a generator function.

❷ Usually the body of a generator function has loop, but not necessarily; here I just repeat `yield` three times.

❸ Looking closely, we see `gen_123` is a function object.

❹ But when invoked, `gen_123()` returns a generator object.

❺ Generators are iterators that produce the values of the expressions passed to `yield`.

❻ For closer inspection, we assign the generator object to `g`.

❼ Because `g` is an iterator, calling `next(g)` fetches the next item produced by `yield`.

❽ When the body of the function completes, the generator object raises a `StopIteration`.

A generator function builds a generator object that wraps the body of the function. When we invoke `next(…)` on the generator object, execution advances to the next `yield` in the function body, and the `next(…)` call evaluates to the value yielded when the function body is suspended. Finally, when the function body returns, the enclosing generator object raises `StopIteration`, in accordance with the `Iterator` protocol.

> **TIP**
>
> I find it helpful to be strict when talking about the results obtained from a generator: I say that a generator *yields* or *produces* values. But it's confusing to say a generator "returns" values. Functions return values. Calling a generator function returns a generator. A generator yields or produces values. A generator doesn't "return" values in the usual way: the `return` statement in the body of a generator function causes `StopIteration` to be raised by the generator object.[8]

Example 17-6 makes the interaction between a `for` loop and the body of the function more explicit.

Example 17-6. A generator function that prints messages when it runs

```
>>> def gen_AB():  ❶
...     print('start')
...     yield 'A'          ❷
...     print('continue')
...     yield 'B'          ❸
...     print('end.')      ❹
...
>>> for c in gen_AB():     ❺
...     print('-->', c)     ❻
```

```
...
start     ❼
--> A    ❽
continue ❾
--> B    ❿
end.      ⓫
>>>   ⓬
```

❶ The generator function is defined like any function, but uses `yield`.

❷ The first implicit call to `next()` in the `for` loop at ❺ will print `'start'` and stop at the first `yield`, producing the value `'A'`.

❸ The second implicit call to `next()` in the `for` loop will print `'continue'` and stop at the second `yield`, producing the value `'B'`.

❹ The third call to `next()` will print `'end.'` and fall through the end of the function body, causing the generator object to raise `StopIteration`.

❺ To iterate, the `for` machinery does the equivalent of `g = iter(gen_AB())` to get a generator object, and then `next(g)` at each iteration.

❻ The loop block prints `-->` and the value returned by `next(g)`. But this output will be seen only after the output of the `print` calls inside the generator function.

❼ The string `'start'` appears as a result of `print('start')` in the generator function body.

❽ `yield 'A'` in the generator function body produces the value *A* consumed by the `for` loop, which gets assigned to the `c` variable and results in the output `--> A`.

❾

Iteration continues with a second call `next(g)`, advancing the generator function body from `yield 'A'` to `yield 'B'`. The text `continue` is output because of the second `print` in the generator function body.

10. `yield 'B'` produces the value *B* consumed by the `for` loop, which gets assigned to the `c` loop variable, so the loop prints `--> B`.

11. Iteration continues with a third call `next(it)`, advancing to the end of the body of the function. The text `end.` appears in the output because of the third `print` in the generator function body.

12. When the generator function body runs to the end, the generator object raises `StopIteration`. The `for` loop machinery catches that exception, and the loop terminates cleanly.

Now hopefully it's clear how `Sentence.__iter__` in Example 17-5 works: `__iter__` is a generator function which, when called, builds a generator object that implements the iterator interface, so the `SentenceIterator` class is no longer needed.

This second version of `Sentence` is much shorter than the first, but it's not as lazy as it could be. Nowadays, laziness is considered a good trait, at least in programming languages and APIs. A lazy implementation postpones producing values to the last possible moment. This saves memory and may avoid useless processing as well.

We'll build lazy `Sentence` classes next.

Lazy sentences

The final variations of `Sentence` are lazy, taking advantage of a lazy function from the `re` module.

Sentence Take #4: Lazy Generator

The `Iterator` interface is designed to be lazy: `next(my_iterator)` produces one item at a time. The opposite of lazy is eager: lazy evaluation and eager evaluation are actual technical terms in programming language theory.

Our `Sentence` implementations so far have not been lazy because the `__init__` eagerly builds a list of all words in the text, binding it to the `self.words` attribute. This will entail processing the entire text, and the list may use as much memory as the text itself (probably more; it depends on how many nonword characters are in the text). Most of this work will be in vain if the user only iterates over the first couple words.

Whenever you are using Python 3 and start wondering "Is there a lazy way of doing this?", often the answer is "Yes."

The `re.finditer` function is a lazy version of `re.findall` which, instead of a list, returns a generator producing `re.MatchObject` instances on demand. If there are many matches, `re.finditer` saves a lot of memory. Using it, our third version of `Sentence` is now lazy: it only produces the next word when it is needed. The code is in Example 17-7.

Example 17-7. sentence_gen2.py: Sentence implemented using a generator function calling the re.finditer generator function

```
import re
import reprlib

RE_WORD = re.compile(r'\w+')


class Sentence:

    def __init__(self, text):
        self.text = text  ❶

    def __repr__(self):
        return f'Sentence({reprlib.repr(self.text)})'

    def __iter__(self):
```

```
        for match in RE_WORD.finditer(self.text):  ❷
            yield match.group()  ❸
```

❶ No need to have a `words` list.

❷ `finditer` builds an iterator over the matches of `RE_WORD` on `self.text`, yielding `MatchObject` instances.

❸ `match.group()` extracts the actual matched text from the `MatchObject` instance.

Generators are an awesome shortcut, but the code can be made even shorter with a generator expression.

Sentence Take #5: Lazy Generator Expression

Simple generator functions like the one in the previous `Sentence` class (Example 17-7) can be replaced by a generator expression.

A generator expression can be understood as a lazy version of a list comprehension: it does not eagerly build a list, but returns a generator that will lazily produce the items on demand. In other words, if a list comprehension is a factory of lists, a generator expression is a factory of generators.

Example 17-8 is a quick demo of a generator expression, comparing it to a list comprehension.

Example 17-8. The gen_AB generator function is used by a list comprehension, then by a generator expression

```
>>> def gen_AB():  ❶
...     print('start')
...     yield 'A'
...     print('continue')
...     yield 'B'
...     print('end.')
...
>>> res1 = [x*3 for x in gen_AB()]  ❷
start
```

```
continue
end.
>>> for i in res1:  ❸
...     print('-->', i)
...
--> AAA
--> BBB
>>> res2 = (x*3 for x in gen_AB())  ❹
>>> res2  ❺
<generator object <genexpr> at 0x10063c240>
>>> for i in res2:  ❻
...     print('-->', i)
...
start
--> AAA
continue
--> BBB
end.
```

❶ This is the same `gen_AB` function from Example 17-6.

❷ The list comprehension eagerly iterates over the items yielded by the generator object produced by calling `gen_AB()`: `'A'` and `'B'`. Note the output in the next lines: `start`, `continue`, `end.`

❸ This `for` loop is iterating over the `res1` `list` produced by the list comprehension.

❹ The generator expression returns `res2`. The call to `gen_AB()` is made, but that call returns a generator, which is not consumed here.

❺ `res2` is a generator object.

❻ Only when the `for` loop iterates over `res2`, the body of `gen_AB` actually executes. Each iteration of the `for` loop implicitly calls `next(res2)`, advancing `gen_AB` to the next `yield`. Note the output of `gen_AB` with the output of the `print` in the `for` loop.

So, a generator expression produces a generator, and we can use it to further reduce the code in the `Sentence` class. See Example 17-9.

Example 17-9. sentence_genexp.py: Sentence implemented using a generator expression

```
import re
import reprlib

RE_WORD = re.compile(r'\w+')


class Sentence:

    def __init__(self, text):
        self.text = text

    def __repr__(self):
        return f'Sentence({reprlib.repr(self.text)})'

    def __iter__(self):
        return (match.group() for match in
RE_WORD.finditer(self.text))
```

The only difference from Example 17-7 is the `__iter__` method, which here is not a generator function (it has no `yield`) but uses a generator expression to build a generator and then returns it. The end result is the same: the caller of `__iter__` gets a generator object.

Generator expressions are syntactic sugar: they can always be replaced by generator functions, but sometimes are more convenient. The next section is about generator expression usage.

Generator Expressions: When to Use Them

I used several generator expressions when implementing the `Vector` class in Example 12-16. Each of the methods `__eq__`, `__hash__`, `__abs__`, `angle`, `angles`, `format`, `__add__`, and `__mul__` has a generator expression. In all those methods, a list comprehension would also work, at the cost of using more memory to store the intermediate list values.

In Example 17-9, we saw that a generator expression is a syntactic shortcut to create a generator without defining and calling a function. On the other hand, generator functions are much more flexible: you can code complex logic with multiple statements, and can even use them as *coroutines* (see Chapter 19).

For the simpler cases, a generator expression will do, and it's easier to read at a glance, as the `Vector` example shows.

My rule of thumb in choosing the syntax to use is simple: if the generator expression spans more than a couple of lines, I prefer to code a generator function for the sake of readability.

> **SYNTAX TIP**
>
> When a generator expression is passed as the single argument to a function or constructor, you don't need to write a set of parentheses for the function call and another to enclose the generator expression. A single pair will do, like in the `Vector` call from the `__mul__` method in Example 12-16, reproduced here. However, if there are more function arguments after the generator expression, you need to enclose it in parentheses to avoid a `SyntaxError`:
>
> ```
> def __mul__(self, scalar):
>     if isinstance(scalar, numbers.Real):
>         return Vector(n * scalar for n in self)
>     else:
>         return NotImplemented
> ```

The `Sentence` examples we've seen exemplify the use of generators playing the role of classic iterators: retrieving items from a collection. But generators can also be used to produce values independent of a data source. The next section shows an example of that.

Another Example: Arithmetic Progression Generator

The classic Iterator pattern is all about traversal: navigating some data structure. But a standard interface based on a method to fetch the next item in a series is also useful when the items are produced on the fly, instead of retrieved from a collection. For example, the `range` built-in generates a bounded arithmetic progression (AP) of integers, and the `itertools.count` function generates a boundless AP.

We'll cover `itertools.count` in the next section, but what if you need to generate a bounded AP of numbers of any type?

Example 17-10 shows a few console tests of an `ArithmeticProgression` class we will see in a moment. The signature of the constructor in Example 17-10 is `ArithmeticProgression(begin, step[, end])`. The `range()` function is similar to the `ArithmeticProgression` here, but its full signature is `range(start, stop[, step])`. I chose to implement a different signature because for an arithmetic progression the `step` is mandatory but `end` is optional. I also changed the argument names from `start/stop` to `begin/end` to make it very clear that I opted for a different signature. In each test in Example 17-10 I call `list()` on the result to inspect the generated values.

Example 17-10. Demonstration of an ArithmeticProgression class

```
>>> ap = ArithmeticProgression(0, 1, 3)
>>> list(ap)
[0, 1, 2]
>>> ap = ArithmeticProgression(1, .5, 3)
>>> list(ap)
[1.0, 1.5, 2.0, 2.5]
>>> ap = ArithmeticProgression(0, 1/3, 1)
>>> list(ap)
[0.0, 0.3333333333333333, 0.6666666666666666]
>>> from fractions import Fraction
>>> ap = ArithmeticProgression(0, Fraction(1, 3), 1)
>>> list(ap)
[Fraction(0, 1), Fraction(1, 3), Fraction(2, 3)]
>>> from decimal import Decimal
>>> ap = ArithmeticProgression(0, Decimal('.1'), .3)
>>> list(ap)
[Decimal('0.0'), Decimal('0.1'), Decimal('0.2')]
```

Note that type of the numbers in the resulting arithmetic progression follows the type of `begin` or `step`, according to the numeric coercion rules of Python arithmetic. In Example 17-10, you see lists of `int`, `float`, `Fraction`, and `Decimal` numbers.

Example 17-11 lists the implementation of the `ArithmeticProgression` class.

Example 17-11. The ArithmeticProgression class

```
class ArithmeticProgression:

    def __init__(self, begin, step, end=None):       ❶
        self.begin = begin
        self.step = step
        self.end = end  # None -> "infinite" series

    def __iter__(self):
        result_type = type(self.begin + self.step)   ❷
        result = result_type(self.begin)             ❸
        forever = self.end is None                   ❹
        index = 0
        while forever or result < self.end:          ❺
            yield result                             ❻
            index += 1
            result = self.begin + self.step * index  ❼
```

❶ `__init__` requires two arguments: `begin` and `step`. `end` is optional, if it's `None`, the series will be unbounded.

❷ Get the type of adding `self.begin` and `self.step`. For example, if one is `int` and the other is `float`, `result_type` will be `float`.

❸ This line produces a `result` value equal to `self.begin`, but coerced to the type of the subsequent additions.[9]

❹ For readability, the `forever` flag will be `True` if the `self.end` attribute is `None`, resulting in an unbounded series.

❺ This loop runs `forever` or until the result matches or exceeds `self.end`. When this loop exits, so does the function.

❻ The current `result` is produced.

❼ The next potential result is calculated. It may never be yielded, because the `while` loop may terminate.

In the last line of Example 17-11, instead of simply incrementing the `result` with `self.step` iteratively, I opted to use an `index` variable and calculate each `result` by adding `self.begin` to `self.step` multiplied by `index` to reduce the cumulative effect of errors when working with floats.

The `ArithmeticProgression` class from Example 17-11 works as intended, and is a clear example of the use of a generator function to implement the `__iter__` special method. However, if the whole point of a class is to build a generator by implementing `__iter__`, the class can be reduced to a generator function. A generator function is, after all, a generator factory.

Example 17-12 shows a generator function called `aritprog_gen` that does the same job as `ArithmeticProgression` but with less code. The tests in Example 17-10 all pass if you just call `aritprog_gen` instead of `ArithmeticProgression`.[10]

Example 17-12. The aritprog_gen generator function

```
def aritprog_gen(begin, step, end=None):
    result = type(begin + step)(begin)
    forever = end is None
    index = 0
    while forever or result < end:
        yield result
        index += 1
        result = begin + step * index
```

Example 17-12 is pretty cool, but always remember: there are plenty of ready-to-use generators in the standard library, and the next section will show an even cooler implementation using the `itertools` module.

Arithmetic Progression with itertools

The `itertools` module in Python 3.9 has 19 generator functions that can be combined in a variety of interesting ways.

For example, the `itertools.count` function returns a generator that produces numbers. Without arguments, it produces a series of integers starting with `0`. But you can provide optional `start` and `step` values to achieve a result very similar to our `aritprog_gen` functions:

```
>>> import itertools
>>> gen = itertools.count(1, .5)
>>> next(gen)
1
>>> next(gen)
1.5
>>> next(gen)
2.0
>>> next(gen)
2.5
```

However, `itertools.count` never stops, so if you call `list(count())`, Python will try to build a `list` larger than available memory and your machine will be very grumpy long before the call fails.

On the other hand, there is the `itertools.takewhile` function: it produces a generator that consumes another generator and stops when a given predicate evaluates to `False`. So we can combine the two and write this:

```
>>> gen = itertools.takewhile(lambda n: n < 3, itertools.count(1,
.5))
>>> list(gen)
[1, 1.5, 2.0, 2.5]
```

Leveraging `takewhile` and `count`, Example 17-13 is sweet and short.

Example 17-13. aritprog_v3.py: this works like the previous aritprog_gen functions

```
import itertools


def aritprog_gen(begin, step, end=None):
    first = type(begin + step)(begin)
    ap_gen = itertools.count(first, step)
    if end is not None:
        ap_gen = itertools.takewhile(lambda n: n < end, ap_gen)
    return ap_gen
```

Note that `aritprog_gen` is not a generator function in Example 17-13: it has no `yield` in its body. But it returns a generator, so it operates as a generator factory, just as a generator function does.

The point of Example 17-13 is: when implementing generators, know what is available in the standard library, otherwise there's a good chance you'll reinvent the wheel. That's why the next section covers several ready-to-use generator functions.

Generator Functions in the Standard Library

The standard library provides many generators, from plain-text file objects providing line-by-line iteration, to the awesome `os.walk` function, which yields filenames while traversing a directory tree, making recursive filesystem searches as simple as a `for` loop.

The `os.walk` generator function is impressive, but in this section I want to focus on general-purpose functions that take arbitrary iterables as arguments and return generators that produce selected, computed, or rearranged items. In the following tables, I summarize two dozen of them, from the built-in, `itertools`, and `functools` modules. For convenience, I grouped them by high-level functionality, regardless of where they are defined.

> **NOTE**
>
> Perhaps you know all the functions mentioned in this section, but some of them are underused, so a quick overview may be good to recall what's already available.

The first group are filtering generator functions: they yield a subset of items produced by the input iterable, without changing the items themselves. We used `itertools.takewhile` previously in this chapter, in "Arithmetic Progression with itertools". Like `takewhile`, most functions listed in Table 17-1 take a `predicate`, which is a one-argument Boolean function that will be applied to each item in the input to determine whether the item is included in the output.

Table 17-1. Filtering generator fun

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Module	Function	Description
`itertools`	`compress(it, selector_it)`	Consumes two iterables in parallel; yields items from `it` whenever the corresponding item in `selector_it` is truthy
`itertools`	`dropwhile(predicate, it)`	Consumes `it` skipping items while `predicate` computes truthy, then yields every remaining item (no further checks are made)
(built-in)	`filter(predicate, it)`	Applies `predicate` to each item of `iterable`, yielding the item if `predicate(item)` is truthy; if `predicate` is `None`, only truthy items are yielded
`itertools`	`filterfalse(predicate, it)`	Same as `filter`, with the `predicate` logic negated: yields items whenever `predicate` computes falsy
`itertools`	`islice(it, stop)` or `islice(it, start, stop, step=1)`	Yields items from a slice of `it`, similar to `s[:stop]` or `s[start:stop:step]` except `it` can be any iterable, and the operation is lazy
`itertools`	`takewhile(predicate, it)`	Yields items while `predicate` computes truthy, then stops and no further checks are made

The console listing in Example 17-14 shows the use of all functions in Table 17-1.

Example 17-14. Filtering generator functions examples

```
>>> def vowel(c):
...     return c.lower() in 'aeiou'
...
>>> list(filter(vowel, 'Aardvark'))
['A', 'a', 'a']
>>> import itertools
>>> list(itertools.filterfalse(vowel, 'Aardvark'))
['r', 'd', 'v', 'r', 'k']
>>> list(itertools.dropwhile(vowel, 'Aardvark'))
['r', 'd', 'v', 'a', 'r', 'k']
>>> list(itertools.takewhile(vowel, 'Aardvark'))
['A', 'a']
>>> list(itertools.compress('Aardvark', (1,0,1,1,0,1)))
['A', 'r', 'd', 'a']
>>> list(itertools.islice('Aardvark', 4))
['A', 'a', 'r', 'd']
>>> list(itertools.islice('Aardvark', 4, 7))
['v', 'a', 'r']
>>> list(itertools.islice('Aardvark', 1, 7, 2))
['a', 'd', 'a']
```

The next group are the mapping generators: they yield items computed from each individual item in the input iterable—or iterables, in the case of `map` and `starmap`.[11] The generators in Table 17-2 yield one result per item in the input iterables. If the input comes from more than one iterable, the output stops as soon as the first input iterable is exhausted.

Table 17-2. Mapping generator funct

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Module	Function	Description
`itertools`	`accumulate(it, [func])`	Yields accumulated sums; if `func` is provided, yields the result of applying it to the first pair of items, then to the first result and next item, etc.
(built-in)	`enumerate(iterable, start=0)`	Yields 2-tuples of the form `(index, item)`, where `index` is counted from `start`, and `item` is taken from the `iterable`
(built-in)	`map(func, it1, [it2, …, itN])`	Applies `func` to each item of `it`, yielding the result; if N iterables are given, `func` must take N arguments and the iterables will be consumed in parallel
`itertools`	`starmap(func, it)`	Applies `func` to each item of `it`, yielding the result; the input iterable should yield iterable items `iit`, and `func` is applied as `func(*iit)`

Example 17-15 demonstrates some uses of `itertools.accumulate`.

Example 17-15. itertools.accumulate generator function examples

```
>>> sample = [5, 4, 2, 8, 7, 6, 3, 0, 9, 1]
>>> import itertools
>>> list(itertools.accumulate(sample))  ❶
[5, 9, 11, 19, 26, 32, 35, 35, 44, 45]
>>> list(itertools.accumulate(sample, min))  ❷
[5, 4, 2, 2, 2, 2, 2, 0, 0, 0]
>>> list(itertools.accumulate(sample, max))  ❸
[5, 5, 5, 8, 8, 8, 8, 8, 9, 9]
>>> import operator
>>> list(itertools.accumulate(sample, operator.mul))  ❹
[5, 20, 40, 320, 2240, 13440, 40320, 0, 0, 0]
>>> list(itertools.accumulate(range(1, 11), operator.mul))
[1, 2, 6, 24, 120, 720, 5040, 40320, 362880, 3628800]  ❺
```

❶ Running sum.

❷ Running minimum.

❸ Running maximum.

❹ Running product.

❺ Factorials from `1!` to `10!`.

The remaining functions of Table 17-2 are shown in Example 17-16.

Example 17-16. Mapping generator function examples

```
>>> list(enumerate('albatroz', 1))  ❶
[(1, 'a'), (2, 'l'), (3, 'b'), (4, 'a'), (5, 't'), (6, 'r'), (7,
'o'), (8, 'z')]
>>> import operator
>>> list(map(operator.mul, range(11), range(11)))  ❷
[0, 1, 4, 9, 16, 25, 36, 49, 64, 81, 100]
>>> list(map(operator.mul, range(11), [2, 4, 8]))  ❸
[0, 4, 16]
>>> list(map(lambda a, b: (a, b), range(11), [2, 4, 8]))  ❹
[(0, 2), (1, 4), (2, 8)]
>>> import itertools
>>> list(itertools.starmap(operator.mul, enumerate('albatroz', 1)))
❺
['a', 'll', 'bbb', 'aaaa', 'ttttt', 'rrrrrr', 'ooooooo',
'zzzzzzzz']
>>> sample = [5, 4, 2, 8, 7, 6, 3, 0, 9, 1]
>>> list(itertools.starmap(lambda a, b: b/a,
...     enumerate(itertools.accumulate(sample), 1)))  ❻
[5.0, 4.5, 3.6666666666666665, 4.75, 5.2, 5.333333333333333,
5.0, 4.375, 4.888888888888889, 4.5]
```

❶ Number the letters in the word, starting from `1`.

❷ Squares of integers from `0` to `10`.

❸ Multiplying numbers from two iterables in parallel: results stop when the shortest iterable ends.

❹ This is what the `zip` built-in function does.

❺ Repeat each letter in the word according to its place in it, starting from `1`.

❻ Running average.

Next, we have the group of merging generators—all of these yield items from multiple input iterables. `chain` and `chain.from_iterable` consume the input iterables sequentially (one after the other), while `product`, `zip`, and `zip_longest` consume the input iterables in parallel. See Table 17-3.

Table 17-3. Generator functions tha

t merge multiple input iterables

Module	Function	Description
`itertools`	`chain(it1, …, itN)`	Yield all items from `it1`, then from `it2` etc., seamlessly

itertools	chain.from_iterable(it)	Yield all items from each iterable produced by `it`, one after the other, seamlessly; `it` should yield iterable items, for example, a list of iterables
itertools	product(it1, …, itN, repeat=1)	Cartesian product: yields N-tuples made by combining items from each input iterable like nested `for` loops could produce; `repeat` allows the input iterables to be consumed more than once
(built-in)	zip(it1, …, itN)	Yields N-tuples built from items taken from the iterables in parallel, silently stopping when the first iterable is exhausted
itertools	zip_longest(it1, …, itN, fillvalue=None)	Yields N-tuples built from items taken from the iterables in parallel, stopping only when the last iterable is exhausted, filling the blanks with the `fillvalue`

Example 17-17 shows the use of the `itertools.chain` and `zip` generator functions and their siblings. Recall that the `zip` function is named after the zip fastener or zipper (no relation with compression). Both `zip` and `itertools.zip_longest` were introduced in "The Awesome zip".

Example 17-17. Merging generator function examples

```
>>> list(itertools.chain('ABC', range(2)))  ❶
['A', 'B', 'C', 0, 1]
>>> list(itertools.chain(enumerate('ABC')))  ❷
[(0, 'A'), (1, 'B'), (2, 'C')]
>>> list(itertools.chain.from_iterable(enumerate('ABC')))  ❸
[0, 'A', 1, 'B', 2, 'C']
>>> list(zip('ABC', range(5)))  ❹
[('A', 0), ('B', 1), ('C', 2)]
>>> list(zip('ABC', range(5), [10, 20, 30, 40]))  ❺
[('A', 0, 10), ('B', 1, 20), ('C', 2, 30)]
>>> list(itertools.zip_longest('ABC', range(5)))  ❻
[('A', 0), ('B', 1), ('C', 2), (None, 3), (None, 4)]
>>> list(itertools.zip_longest('ABC', range(5), fillvalue='?'))  ❼
[('A', 0), ('B', 1), ('C', 2), ('?', 3), ('?', 4)]
```

❶ `chain` is usually called with two or more iterables.

❷ `chain` does nothing useful when called with a single iterable.

❸ But `chain.from_iterable` takes each item from the iterable, and chains them in sequence, as long as each item is itself iterable.

❹ `zip` is commonly used to merge two iterables into a series of two-tuples.

❺ Any number of iterables can be consumed by `zip` in parallel, but the generator stops as soon as the first iterable ends.

❻ `itertools.zip_longest` works like `zip`, except it consumes all input iterables to the end, padding output tuples with `None` as needed.

❼ The `fillvalue` keyword argument specifies a custom padding value.

The `itertools.product` generator is a lazy way of computing Cartesian products, which we built using list comprehensions with more than one `for` clause in "Cartesian Products". Generator expressions with multiple `for` clauses can also be used to produce Cartesian products lazily. Example 17-18 demonstrates `itertools.product`.

Example 17-18. itertools.product generator function examples

```
>>> list(itertools.product('ABC', range(2)))  ❶
[('A', 0), ('A', 1), ('B', 0), ('B', 1), ('C', 0), ('C', 1)]
>>> suits = 'spades hearts diamonds clubs'.split()
>>> list(itertools.product('AK', suits))  ❷
[('A', 'spades'), ('A', 'hearts'), ('A', 'diamonds'), ('A',
'clubs'),
('K', 'spades'), ('K', 'hearts'), ('K', 'diamonds'), ('K',
'clubs')]
>>> list(itertools.product('ABC'))  ❸
[('A',), ('B',), ('C',)]
>>> list(itertools.product('ABC', repeat=2))  ❹
[('A', 'A'), ('A', 'B'), ('A', 'C'), ('B', 'A'), ('B', 'B'),
('B', 'C'), ('C', 'A'), ('C', 'B'), ('C', 'C')]
>>> list(itertools.product(range(2), repeat=3))
```

```
[(0, 0, 0), (0, 0, 1), (0, 1, 0), (0, 1, 1), (1, 0, 0),
(1, 0, 1), (1, 1, 0), (1, 1, 1)]
>>> rows = itertools.product('AB', range(2), repeat=2)
>>> for row in rows: print(row)
...
('A', 0, 'A', 0)
('A', 0, 'A', 1)
('A', 0, 'B', 0)
('A', 0, 'B', 1)
('A', 1, 'A', 0)
('A', 1, 'A', 1)
('A', 1, 'B', 0)
('A', 1, 'B', 1)
('B', 0, 'A', 0)
('B', 0, 'A', 1)
('B', 0, 'B', 0)
('B', 0, 'B', 1)
('B', 1, 'A', 0)
('B', 1, 'A', 1)
('B', 1, 'B', 0)
('B', 1, 'B', 1)
```

❶ The Cartesian product of a `str` with three characters and a `range` with two integers yields six tuples (because `3 * 2` is `6`).

❷ The product of two card ranks (`'AK'`), and four suits is a series of eight tuples.

❸ Given a single iterable, `product` yields a series of one-tuples, not very useful.

❹ The `repeat=N` keyword argument tells product to consume each input iterable `N` times.

Some generator functions expand the input by yielding more than one value per input item. They are listed in Table 17-4.

Table 17-4. Generator functions that e *xpand each input item into multiple o*

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Module	Function	Description
`itertools`	`combinations(it, out_len)`	Yield combinations of `out_len` items from the items yielded by `it`
`itertools`	`combinations_with_replacement(it, out_len)`	Yield combinations of `out_len` items from the items yielded by `it`, including combinations with repeated items
`itertools`	`count(start=0, step=1)`	Yields numbers starting at `start`, incremented by `step`, indefinitely
`itertools`	`cycle(it)`	Yields items from `it` storing a copy of each, then yields the entire sequence repeatedly, indefinitely
`itertools`	`permutations(it, out_len=None)`	Yield permutations of `out_len` items from the items yielded by `it`; by default, `out_len` is `len(list(it))`
`itertools`	`repeat(item, [times])`	Yield the given item repeatedly, indefinitely unless a number of `times` is given

The `count` and `repeat` functions from `itertools` return generators that conjure items out of nothing: neither of them takes an iterable as input. We saw `itertools.count` in "Arithmetic Progression with itertools".

The `cycle` generator makes a backup of the input iterable and yields its items repeatedly. Example 17-19 illustrates the use of `count`, `repeat`, and `cycle`.

Example 17-19. count, cycle, and repeat

```
>>> ct = itertools.count()  ❶
>>> next(ct)  ❷
0
>>> next(ct), next(ct), next(ct)  ❸
(1, 2, 3)
>>> list(itertools.islice(itertools.count(1, .3), 3))  ❹
[1, 1.3, 1.6]
>>> cy = itertools.cycle('ABC')  ❺
>>> next(cy)
'A'
>>> list(itertools.islice(cy, 7))  ❻
['B', 'C', 'A', 'B', 'C', 'A', 'B']
>>> rp = itertools.repeat(7)  ❼
>>> next(rp), next(rp)
(7, 7)
>>> list(itertools.repeat(8, 4))  ❽
[8, 8, 8, 8]
>>> list(map(operator.mul, range(11), itertools.repeat(5)))  ❾
[0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50]
```

❶ Build a `count` generator `ct`.

❷ Retrieve the first item from `ct`.

❸ I can't build a `list` from `ct`, because `ct` never stops, so I fetch the next three items.

❹ I can build a `list` from a `count` generator if it is limited by `islice` or `takewhile`.

❺ Build a `cycle` generator from `'ABC'` and fetch its first item, `'A'`.

❻ A `list` can only be built if limited by `islice`; the next seven items are retrieved here.

❼ Build a `repeat` generator that will yield the number `7` forever.

❽ A `repeat` generator can be limited by passing the `times` argument: here the number `8` will be produced `4` times.

❾ A common use of `repeat`: providing a fixed argument in `map`; here it provides the `5` multiplier.

The `combinations`, `combinations_with_replacement`, and `permutations` generator functions—together with `product`—are called the *combinatorics generators* in the `itertools` documentation page. There is a close relationship between `itertools.product` and the remaining *combinatoric* functions as well, as Example 17-20 shows.

Example 17-20. Combinatoric generator functions yield multiple values per input item

```
>>> list(itertools.combinations('ABC', 2))  ❶
[('A', 'B'), ('A', 'C'), ('B', 'C')]
>>> list(itertools.combinations_with_replacement('ABC', 2))  ❷
[('A', 'A'), ('A', 'B'), ('A', 'C'), ('B', 'B'), ('B', 'C'), ('C',
'C')]
>>> list(itertools.permutations('ABC', 2))  ❸
[('A', 'B'), ('A', 'C'), ('B', 'A'), ('B', 'C'), ('C', 'A'), ('C',
'B')]
>>> list(itertools.product('ABC', repeat=2))  ❹
[('A', 'A'), ('A', 'B'), ('A', 'C'), ('B', 'A'), ('B', 'B'), ('B',
'C'),
('C', 'A'), ('C', 'B'), ('C', 'C')]
```

❶ All combinations of `len()==2` from the items in `'ABC'`; item ordering in the generated tuples is irrelevant (they could be sets).

❷ All combinations of `len()==2` from the items in `'ABC'`, including combinations with repeated items.

❸ All permutations of `len()==2` from the items in `'ABC'`; item ordering in the generated tuples is relevant.

❹ Cartesian product from `'ABC'` and `'ABC'` (that’s the effect of `repeat=2`).

The last group of generator functions we’ll cover in this section are designed to yield all items in the input iterables, but rearranged in some way. Here are two functions that return multiple generators: `itertools.groupby` and `itertools.tee`. The other generator function in this group, the `reversed` built-in, is the only one covered in this section that does not accept any iterable as input, but only sequences. This makes sense: because `reversed` will yield the items from last to first, it only works with a sequence with a known length. But it avoids the cost of making a reversed copy of the sequence by yielding each item as needed. I put the `itertools.product` function together with the *merging* generators in Table 17-3 because they all consume more than one iterable, while the generators in Table 17-5 all accept at most one input iterable.

Table 17-5. Rearranging generator f

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Module	Function	Description
`itertools`	`groupby(it, key=None)`	Yields 2-tuples of the form `(key, group)`, where `key` is the grouping criterion and `group` is a generator yielding the items in the group
(built-in)	`reversed(seq)`	Yields items from `seq` in reverse order, from last to first; `seq` must be a sequence or implement the `__reversed__` special method
`itertools`	`tee(it, n=2)`	Yields a tuple of *n* generators, each yielding the items of the input iterable independently

Example 17-21 demonstrates the use of `itertools.groupby` and the `reversed` built-in. Note that `itertools.groupby` assumes that the input iterable is sorted by the grouping criterion, or at least that the items are clustered by that criterion—even if not sorted.

Example 17-21. itertools.groupby

```
>>> list(itertools.groupby('LLLLAAGGG'))  ❶
[('L', <itertools._grouper object at 0x102227cc0>),
('A', <itertools._grouper object at 0x102227b38>),
('G', <itertools._grouper object at 0x102227b70>)]
>>> for char, group in itertools.groupby('LLLLAAAGG'):  ❷
...     print(char, '->', list(group))
...
L -> ['L', 'L', 'L', 'L']
A -> ['A', 'A',]
```

```
G -> ['G', 'G', 'G']
>>> animals = ['duck', 'eagle', 'rat', 'giraffe', 'bear',
...            'bat', 'dolphin', 'shark', 'lion']
>>> animals.sort(key=len)  ❸
>>> animals
['rat', 'bat', 'duck', 'bear', 'lion', 'eagle', 'shark',
'giraffe', 'dolphin']
>>> for length, group in itertools.groupby(animals, len):  ❹
...     print(length, '->', list(group))
...
3 -> ['rat', 'bat']
4 -> ['duck', 'bear', 'lion']
5 -> ['eagle', 'shark']
7 -> ['giraffe', 'dolphin']
>>> for length, group in itertools.groupby(reversed(animals), len):
❺
...     print(length, '->', list(group))
...
7 -> ['dolphin', 'giraffe']
5 -> ['shark', 'eagle']
4 -> ['lion', 'bear', 'duck']
3 -> ['bat', 'rat']
>>>
```

❶ `groupby` yields tuples of `(key, group_generator)`.

❷ Handling `groupby` generators involves nested iteration: in this case, the outer `for` loop and the inner `list` constructor.

❸ To use `groupby`, the input should be sorted; here the words are sorted by length.

❹ Again, loop over the `key` and `group` pair, to display the `key` and expand the `group` into a `list`.

❺ Here the `reverse` generator iterates over `animals` from right to left.

The last of the generator functions in this group is `iterator.tee`, which has a unique behavior: it yields multiple generators from a single input iterable, each yielding every item from the input. Those generators can be consumed independently, as shown in Example 17-22.

Example 17-22. itertools.tee yields multiple generators, each yielding every item of the input generator

```
>>> list(itertools.tee('ABC'))
[<itertools._tee object at 0x10222abc8>, <itertools._tee object at
0x10222ac08>]
>>> g1, g2 = itertools.tee('ABC')
>>> next(g1)
'A'
>>> next(g2)
'A'
>>> next(g2)
'B'
>>> list(g1)
['B', 'C']
>>> list(g2)
['C']
>>> list(zip(*itertools.tee('ABC')))
[('A', 'A'), ('B', 'B'), ('C', 'C')]
```

Note that several examples in this section used combinations of generator functions. This is a great feature of these functions: because they take generators as arguments and return generators, they can be combined in many different ways.

The `yield from` syntax provides a new way of combining generators. That's next.

Subgenerators with yield from

The `yield from` expression syntax was introduced in Python 3.3 to allow a generator to delegate work to a subgenerator.

Example 17-23 is a simple experiment with `yield from`:

Example 17-23. Test driving `yield from`.

```
>>> def sub_gen():
...     yield 1.1
...     yield 1.2
...
>>> def gen():
...     yield 1
...     yield from sub_gen()
```

```
...     yield 2
...
>>> for x in gen():
...     print(x)
...
1
1.1
1.2
2
```

In Example 17-23, the `for` loop is the *client code*, `gen` is the *delegating generator* and `sub_gen` is the *subgenerator*. Note that `yield from` pauses `gen`, then executes `sub_gen`. The values yielded by `sub_gen` pass through `gen` directly to the client `for` loop. Meanwhile, `gen` is suspended and cannot see the values passing through it. When `sub_gen` is done, `gen` resumes.

When used in an expression, the value of `yield from` is the return value of the subgenerator. Example 17-24 demonstrates.

Example 17-24. `yield from` gets the return value of the subgenerator.

```
>>> def sub_gen():
...     yield 1.1
...     yield 1.2
...     return 'Done!'
...
>>> def gen():
...     yield 1
...     result = yield from sub_gen()
...     print('<--', result)
...     yield 2
...
>>> for x in gen():
...     print(x)
...
1
1.1
1.2
<-- Done!
2
```

Now that we've seen the basics of `yield from`, let's study a couple of simple but practical examples of its use.

Reinventing chain.

Before `yield from` was introduced, when a generator needed to yield values produced from another generator, nested `for` loops were the only way.

Here is an example: the `itertools` module of the Python standard library has a `chain` generator that yields items from several iterables, iterating over the first, then the second and so on up to the last.[12] This is a homemade implementation of `chain` in Python, using nested `for` loops:

```
>>> def chain(*iterables):
...     for it in iterables:
...         for i in it:
...             yield i
...
>>> s = 'ABC'
>>> t = tuple(range(3))
>>> list(chain(s, t))
['A', 'B', 'C', 0, 1, 2]
```

The `chain` generator above is delegating to each iterable `it` in turn, by driving each `it` in the inner `for` loop. That inner loop can be replaced with a `yield from` expression, as shown in the next console listing:

```
>>> def chain(*iterables):
...     for i in iterables:
...         yield from i
...
>>> list(chain(s, t))
['A', 'B', 'C', 0, 1, 2]
```

The use of `yield from` in this example is correct, and the code reads better, but it seems like mere syntactic sugar. Now let's develop a more interesting example.

Traversing a tree

In this section we’ll use `yield from` in a script to traverse a tree structure. We will build it in baby steps.

The tree structure for this example is Python’s exception hierarchy. But the code can be easily adapted to show a directory tree or any other tree structure.

Starting from `BaseException` at level zero, the exception hierarchy is 5 levels deep (as of Python 3.9). Our first baby step is to show level zero.

Given a root class, the `tree` generator in Example 17-25 yields its name and stops:

Example 17-25. tree/step0/tree.py: yield the name of root class and stop.

```
def tree(cls):
    yield cls.__name__


def display(cls):
    for cls_name in tree(cls):
        print(cls_name)


if __name__ == '__main__':
    display(BaseException)
```

The output of Example 17-25 is just one line:

```
BaseException
```

The next baby step takes us to level 1. The `tree` generator will yield the name of the root class and the names of each direct subclass. The names of the subclasses are indented to reveal the hierarchy. This is the output we want:

```
$ python3 tree.py
BaseException
    Exception
    GeneratorExit
    SystemExit
    KeyboardInterrupt
```

Example 17-26 produces that output.

Example 17-26. tree/step1/tree.py: yield the name of root class and direct subclasses.

```
def tree(cls):
    yield cls.__name__, 0                            ❶
    for sub_cls in cls.__subclasses__():             ❷
        yield sub_cls.__name__, 1                    ❸


def display(cls):
    for cls_name, level in tree(cls):
        indent = ' ' * 4 * level                     ❹
        print(f'{indent}{cls_name}')


if __name__ == '__main__':
    display(BaseException)
```

❶ To support the indented output, yield the name of the class and its level in the hierarchy.

❷ Use the `__subclasses__` special method to get list of subclasses.[13]

❸ Yield name of subclass and level 1.

❹ Build indentation string of 4 spaces times `level`. At level zero, this will be an empty string.

In Example 17-27 we refactor to separate the special case of the root class from the subclasses, which are now handled in the `sub_tree` generator. At `yield from`, the `tree` generator is suspended and `sub_tree` takes over yielding values.

Example 17-27. tree/step2/tree.py: `tree` yields root class name, then delegates to `sub_tree`.

```
def tree(cls):
    yield cls.__name__, 0
    yield from sub_tree(cls)                ❶
```

```
def sub_tree(cls):
    for sub_cls in cls.__subclasses__():
        yield sub_cls.__name__, 1          ❷


def display(cls):
    for cls_name, level in tree(cls):
        indent = ' ' * 4 * level
        print(f'{indent}{cls_name}')


if __name__ == '__main__':
    display(BaseException)
```

❶ Delegate to `sub_tree` to yield the names of the subclasses.

❷ Yield name of subclass and level 1, directly to the printing `for` loop driving `tree`.

In keeping with our baby steps method, we'll write the simplest code we can imagine to reach level 2. For depth-first tree traversal, after yielding each node in level 1, we want to yield the children of that node in level 2, before resuming level 1. We can code this with a nested `for` loop, as in Example 17-28.

Example 17-28. tree/step3/tree.py: `sub_tree` traverses levels 1 and 2 depth-first.

```
def tree(cls):
    yield cls.__name__, 0
    yield from sub_tree(cls)


def sub_tree(cls):
    for sub_cls in cls.__subclasses__():
        yield sub_cls.__name__, 1
        for sub_sub_cls in sub_cls.__subclasses__():
            yield sub_sub_cls.__name__, 2


def display(cls):
    for cls_name, level in tree(cls):
```

```
        indent = ' ' * 4 * level
        print(f'{indent}{cls_name}')


if __name__ == '__main__':
    display(BaseException)
```

This is the result of running `step3/tree.py` from Example 17-28:

```
$ python3 tree.py
BaseException
    Exception
        TypeError
        StopAsyncIteration
        StopIteration
        ImportError
        OSError
        EOFError
        RuntimeError
        NameError
        AttributeError
        SyntaxError
        LookupError
        ValueError
        AssertionError
        ArithmeticError
        SystemError
        ReferenceError
        MemoryError
        BufferError
        Warning
    GeneratorExit
    SystemExit
    KeyboardInterrupt
```

You may already know where this is going, but I will stick to baby steps one more time: let’s reach level 3 by adding yet another nested `for` loop. The rest of the program is unchanged, so Example 17-29 shows only the `sub_tree` generator.

Example 17-29. `sub_tree` generator from `tree/step4/tree.py`.

```
def sub_tree(cls):
    for sub_cls in cls.__subclasses__():
        yield sub_cls.__name__, 1
```

```
        for sub_sub_cls in sub_cls.__subclasses__():
            yield sub_sub_cls.__name__, 2
            for sub_sub_sub_cls in sub_sub_cls.__subclasses__():
                yield sub_sub_sub_cls.__name__, 3
```

There is a clear pattern in Example 17-29. We do a `for` loop to get the subclasses of level N. Each time around the loop we yield a subclass and level N, then start another for loop to visit level N+1.

In "Reinventing `chain`." we saw how we can replace a nested `for` loop driving a generator with `yield from` on the same generator. We can apply that idea here, if we make `sub_tree` accept a `level` parameter, and `yield from` it recursively, passing the current subclass as the new root class with the next level number. See Example 17-30.

Example 17-30. tree/step5/tree.py: recursive `sub_tree` goes as far as memory allows.

```
def tree(cls):
    yield cls.__name__, 0
    yield from sub_tree(cls, 1)


def sub_tree(cls, level):
    for sub_cls in cls.__subclasses__():
        yield sub_cls.__name__, level
        yield from sub_tree(sub_cls, level+1)


def display(cls):
    for cls_name, level in tree(cls):
        indent = ' ' * 4 * level
        print(f'{indent}{cls_name}')


if __name__ == '__main__':
    display(BaseException)
```

Example 17-30 can traverse trees of any depth, limited only by Python's recursion limit. The default limit allows 1000 pending functions.

Any good tutorial about recursion will stress the importance of a base case to avoid infinite recursion. The body of a recursive function often has an `if` with one branch that does not make a recursive call—that's the base case. In

Example 17-30, `sub_tree` has no `if`, but there is an implicit conditional in the `for` loop: if `cls.__subclasses__()` returns an empty list, the body of the loop is not executed, therefore no recursive call happens. The base case is when the current class has no subclasses. In that case, `sub_tree` does yields nothing. It just returns.

Example 17-30 works as intended, but we can make it more elegant by recalling the pattern we observed in when we reached level 3 (Example 17-29): we yield a subclass with level N, then start a nested for loop to visit level N+1. In Example 17-30 we replaced that nested loop with `yield from`. Now we can merge `tree` and `sub_tree` into a single generator. Example 17-31 is the last step for this example.

Example 17-31. tree/step6/tree.py: recursive calls of `tree` pass an incremented `level` argument.

```
def tree(cls, level=0):
    yield cls.__name__, level
    for sub_cls in cls.__subclasses__():
        yield from tree(sub_cls, level+1)


def display(cls):
    for cls_name, level in tree(cls):
        indent = ' ' * 4 * level
        print(f'{indent}{cls_name}')


if __name__ == '__main__':
    display(BaseException)
```

At the start of "Subgenerators with yield from" we saw how `yield from` connects the subgenerator directly to the client code, bypassing the delegating generator. That connection becomes really important when generators are used as coroutines and not only produce but also consume values from the client code. Chapter 19 dives into coroutines, and has several pages explaining why `yield from` is much more than syntactic sugar.

After this first encounter with `yield from`, we'll go back to our review of iterable-savvy functions in the standard library.

Iterable Reducing Functions

The functions in Table 17-6 all take an iterable and return a single result. They are known as “reducing,” “folding,” or “accumulating” functions. Actually, every one of the built-ins listed here can be implemented with `functools.reduce`, but they exist as built-ins because they address some common use cases more easily. Also, in the case of `all` and `any`, there is an important optimization that can’t be done with `reduce`: these functions short-circuit (i.e., they stop consuming the iterator as soon as the result is determined). See the last test with `any` in Example 17-32.

Table 17-6. Built-in functions that rea *d iterables and return single values*

Module	Function	Description
(built-in)	`all(it)`	Returns `True` if all items in `it` are truthy, otherwise `Fa`

		`lse`; `all([])` returns `True`
(built-in)	`any(it)`	Returns `True` if any item in `it` is truthy, otherwise `False`; `any([])` returns `False`
(built-in)	`max(it, [key=,] [default=])`	Returns the maximum value of the items in `it`;[a] `key` is an ordering function, as in `sorted`; `default` is returned if the iterable is empty
(built-in)	`min(it, [key=,] [default=])`	Returns the minimum value of the items in `it`.[b] `key` is an ordering function, as in `sorted`; `default` is returned if the iterable is empty
`functools`	`reduce(func, it, [initial])`	Returns the result of applying `func` to the first pair of items, then to that result and the third item and so on; if given, `initial` forms the initial pair with the first item
(built-in)	`sum(it, start=0)`	The sum of all items in `it`, with the optional `start` value added (use `math.fsum` for better precision when adding floats)

a May also be called as `max(arg1, arg2, …, [key=?])`, in which case the maximum among the arguments is returned.

b May also be called as `min(arg1, arg2, …, [key=?])`, in which case the minimum among the arguments is returned.

The operation of `all` and `any` is exemplified in Example 17-32.

Example 17-32. Results of all and any for some sequences

```
>>> all([1, 2, 3])
True
>>> all([1, 0, 3])
False
>>> all([])
True
>>> any([1, 2, 3])
True
>>> any([1, 0, 3])
True
>>> any([0, 0.0])
False
>>> any([])
```

```
False
>>> g = (n for n in [0, 0.0, 7, 8])
>>> any(g)
True
>>> next(g)
8
```

A longer explanation about `functools.reduce` appeared in "Vector Take #4: Hashing and a Faster ==".

Another built-in that takes an iterable and returns something else is `sorted`. Unlike `reversed`, which is a generator function, `sorted` builds and returns an actual list. After all, every single item of the input iterable must be read so they can be sorted, and the sorting happens in a `list`, therefore `sorted` just returns that `list` after it's done. I mention `sorted` here because it does consume an arbitrary iterable.

Of course, `sorted` and the reducing functions only work with iterables that eventually stop. Otherwise, they will keep on collecting items and never return a result.

We'll now go back to the `iter()` built-in: it has a little-known feature that we haven't covered yet.

A Closer Look at the iter Function

As we've seen, Python calls `iter(x)` when it needs to iterate over an object `x`.

But `iter` has another trick: it can be called with two arguments to create an iterator from a regular function or any callable object. In this usage, the first argument must be a callable to be invoked repeatedly (with no arguments) to yield values, and the second argument is a sentinel: a marker value which, when returned by the callable, causes the iterator to raise `StopIteration` instead of yielding the sentinel.

The following example shows how to use `iter` to roll a six-sided dice until a `1` is rolled:

```
>>> def d6():
...     return randint(1, 6)
...
>>> d6_iter = iter(d6, 1)
>>> d6_iter
<callable_iterator object at 0x00000000029BE6A0>
>>> for roll in d6_iter:
...     print(roll)
...
4
3
6
3
```

Note that the `iter` function here returns a `callable_iterator`. The `for` loop in the example may run for a very long time, but it will never display `1`, because that is the sentinel value. As usual with iterators, the `d6_iter` object in the example becomes useless once exhausted. To start over, you must rebuild the iterator by invoking `iter(…)` again.

A simple example used to be found in the `iter` built-in function documentation: this snippet reads lines from a file until a blank line terminated with `\n` is found.

```
with open('mydata.txt') as fp:
    for line in iter(fp.readline, '\n'):
        process_line(line)
```

However, that example is problematic in practice. If no blank line with a single `\n` is present, the `for` loop will run forever because `fp.readline()` returns an empty string `''` when the end of file is reached.

Since I wrote *Fluent Python, First Edition*, that example was replaced in the `iter` entry with this new one, a block reader. The documentation explains:

> *One useful application of the second form of `iter()` is to build a block-reader. For example, reading fixed-width blocks from a binary database file until the end of file is reached:*

```python
from functools import partial

with open('mydata.db', 'rb') as f:
    read64 = partial(f.read, 64)
    for block in iter(read64, b''):
        process_block(block)
```

For clarity, I’ve added the `read64` assignment, which is not in the current example.

To close this chapter, I present a practical example of using generators to handle a large volume of data efficiently.

Case Study: Generators in a Database Conversion Utility

Years ago I worked at BIREME, a digital library run by PAHO/WHO (Pan-American Health Organization/World Health Organization) in São Paulo, Brazil. Among the bibliographic datasets created by BIREME are LILACS (Latin American and Caribbean Health Sciences index) and SciELO (Scientific Electronic Library Online), two comprehensive databases indexing the scientific and technical literature produced in the region.

Since the late 1980s, the database system used to manage LILACS is CDS/ISIS, a non-relational, document database created by UNESCO and eventually rewritten in C by BIREME to run on GNU/Linux servers. One of my jobs was to research alternatives for a possible migration of LILACS—and eventually the much larger SciELO—to a modern, open source, document database such as CouchDB or MongoDB.

As part of that research, I wrote a Python script, *isis2json.py*, that reads a CDS/ISIS file and writes a JSON file suitable for importing to CouchDB or MongoDB. Initially, the script read files in the ISO-2709 format exported by CDS/ISIS. The reading and writing had to be done incrementally because the full datasets were much bigger than main memory. That was easy enough: each iteration of the main `for` loop read one record from the *.iso* file, massaged it, and wrote it to the *.json* output.

However, for operational reasons, it was deemed necessary that *isis2json.py* supported another CDS/ISIS data format: the binary *.mst* files used in production at BIREME—to avoid the costly export to ISO-2709.

Now I had a problem: the libraries used to read ISO-2709 and *.mst* files had very different APIs. And the JSON writing loop was already complicated because the script accepted a variety of command-line options to restructure each output record. Reading data using two different APIs in the same `for` loop where the JSON was produced would be unwieldy.

The solution was to isolate the reading logic into a pair of generator functions: one for each supported input format. In the end, the *isis2json.py* script was split into four functions. You can see the main Python 2 script in [Link to Come], but the full source code with dependencies is in *fluentpython/isis2json* on GitHub.

Here is a high-level overview of how the script is structured:

`main`

The `main` function uses `argparse` to read command-line options that configure the structure of the output records. Based on the input filename extension, a suitable generator function is selected to read the data and yield the records, one by one.

`iter_iso_records`

This generator function reads *.iso* files (assumed to be in the ISO-2709 format). It takes two arguments: the filename and `isis_json_type`, one of the options related to the record structure. Each iteration of its `for` loop reads one record, creates an empty `dict`, populates it with field data, and yields the `dict`.

`iter_mst_records`

This other generator functions reads *.mst* files.[14] If you look at the source code for *isis2json.py*, you'll see that it's not as simple as `iter_iso_records`, but its interface and overall structure is the same: it takes a filename and an `isis_json_type` argument and enters a `for` loop, which builds and yields one `dict` per iteration, representing a single record.

`write_json`

This function performs the actual writing of the JSON records, one at a time. It takes numerous arguments, but the first one—`input_gen`—is a reference to a generator function: either `iter_iso_records` or `iter_mst_records`. The main `for` loop in `write_json` iterates over the dictionaries yielded by the selected `input_gen` generator, massages it in several ways as determined by the command-line options, and appends the JSON record to the output file.

By leveraging generator functions, I was able to decouple the reading logic from the writing logic. Of course, the simplest way to decouple them would be to read all records to memory, then write them to disk. But that was not a viable option because of the size of the datasets. Using generators, the reading and writing is interleaved, so the script can process files of any size.

Now if *isis2json.py* needs to support an additional input format—say, MARCXML, a DTD used by the U.S. Library of Congress to represent ISO-2709 data—it will be easy to add a third generator function to implement the reading logic, without changing anything in the complicated `write_json` function.

This is not rocket science, but it’s a real example where generators provided a flexible solution to processing databases as a stream of records, keeping memory usage low regardless of the amount of data. Anyone who manages large datasets finds many opportunities for using generators in practice.

The next section addresses an aspect of generators that we’ll actually skip for now. Read on to understand why.

Generators as Coroutines

About five years after generator functions with the `yield` keyword were introduced in Python 2.2, PEP 342 — Coroutines via Enhanced Generators was implemented in Python 2.5. This proposal added extra methods and functionality to generator objects, most notably the `.send()` method.

Like `.__next__()`, `.send()` causes the generator to advance to the next `yield`, but it also allows the client using the generator to send data into it: whatever argument is passed to `.send()` becomes the value of the corresponding `yield` expression inside the generator function body. In other words, `.send()` allows two-way data exchange between the client code and the generator—in contrast with `.__next__()`, which only lets the client receive data from the generator.

This is such a major "enhancement" that it actually changes the nature of generators: when used in this way, they become *coroutines*. David Beazley—probably the most prolific writer and speaker about coroutines in the Python community—warned in a famous PyCon US 2009 tutorial:

> - *Generators produce data for iteration*
> - *Coroutines are consumers of data*
> - *To keep your brain from exploding, you don't mix the two concepts together*
> - *Coroutines are not related to iteration*
> - *Note: There is a use of having yield produce a value in a coroutine, but it's not tied to iteration.*[15]
>
> —David Beazley, A Curious Course on Coroutines and Concurrency

I will follow Dave's advice and close this chapter—which is really about iteration techniques—without touching `send` and the other features that make generators usable as coroutines. Coroutines will be covered in Chapter 19.

Generic Iterable Types

XXX

```
class typing.Iterable(Generic[T_co]):
    ...
class typing.Iterator(Iterable[T_co]):
    ...
```

Chapter Summary

Iteration is so deeply embedded in the language that I like to say that Python groks iterators.[16] The integration of the Iterator pattern in the semantics of Python is a prime example of how design patterns are not equally applicable in all programming languages. In Python, a classic iterator implemented "by hand" as in Example 17-4 has no practical use, except as a didactic example.

In this chapter, we built a few versions of a class to iterate over individual words in text files that may be very long. Thanks to the use of generators, the successive refactorings of the `Sentence` class become shorter and easier to read—when you know how they work.

We then coded a generator of arithmetic progressions and showed how to leverage the `itertools` module to make it simpler. An overview of 24 general-purpose generator functions in the standard library followed.

Following that, we looked at the `iter` built-in function: first, to see how it returns an iterator when called as `iter(o)`, and then to study how it builds an iterator from any function when called as `iter(func, sentinel)`.

For practical context, I described the implementation of a database conversion utility using generator functions to decouple the reading to the writing logic, enabling efficient handling of large datasets and making it easy to support more than one data input format.

Also mentioned in this chapter were the `yield from` syntax, new in Python 3.3, and coroutines. Both topics were just introduced here; they get more coverage later in the book.

Further Reading

A detailed technical explanation of generators appears in The Python Language Reference in 6.2.9. Yield expressions. The PEP where generator functions were defined is PEP 255 — Simple Generators.

The `itertools` module documentation is excellent because of all the examples included. Although the functions in that module are implemented in C, the documentation shows how many of them would be written in Python, often by leveraging other functions in the module. The usage examples are also great: for instance, there is a snippet showing how to use the `accumulate` function to amortize a loan with interest, given a list of payments over time. There is also an Itertools Recipes section with additional high-performance functions that use the `itertools` functions as building blocks.

Beyond Python's standard library, I recommend the More Itertools package, which follows the fine `itertools` tradition in providing powerful generators with plenty of examples and some useful recipes.

Chapter 4, "Iterators and Generators," of *Python Cookbook, 3E* (O'Reilly), by David Beazley and Brian K. Jones, has 16 recipes covering this subject from many different angles, focusing on practical applications. It includes some illuminating recipes with `yield from`.

Sebastian Rittau—a top contributor of *typeshed*—explains why iterators should be interable, as he noted in 2006 that Java: Iterators are not Iterable.

The `yield from` syntax is explained with examples in *What's New in Python 3.3*, section PEP 380: Syntax for Delegating to a Subgenerator. We'll also cover it in detail in "Using yield from" and "The Meaning of yield from" in Chapter 19.

If you are interested in document databases and would like to learn more about the context of "Case Study: Generators in a Database Conversion Utility", the Code4Lib Journal—which covers the intersection between libraries and technology—published my paper "From ISIS to CouchDB: Databases and Data Models for Bibliographic Records". One section of the paper describes the *isis2json.py* script. The rest of it explains why and how the semi-structured data model implemented by document databases like CouchDB and MongoDB are more suitable for cooperative bibliographic data collection than the relational model.

SOAPBOX

Generator Function Syntax: More Sugar Would Be Nice

> *Designers need to ensure that controls and displays for different purposes are significantly different from one another.*
>
> —Donald Norman, The Design of Everyday Things

Source code plays the role of "controls and displays" in programming languages. I think Python is exceptionally well designed; its source code is often as readable as pseudocode. But nothing is perfect. Guido van Rossum should have followed Donald Norman's advice (previously quoted) and introduced another keyword for defining generator expressions, instead of reusing `def`. The "BDFL Pronouncements" section of PEP 255 — Simple Generators actually argues:

> *A "yield" statement buried in the body is not enough warning that the semantics are so different.*

But Guido avoids introducing new keywords, because they may break existing code. The Python 3 breakage was a one-off event—I believe that because I started using Python 1.5 and when Python 2 came along, most programs did not break. Anyway, Guido did not find that argument convincing, and I don't anticipate major breaking changes in future versions of Python, so we are stuck with `def` doing double-duty for functions and generators.

Reusing the function syntax for generators has other bad consequences. In the paper and experimental work "Python, the Full Monty: A Tested Semantics for the Python Programming Language," Politz[17] et al. show this trivial example of a generator function (section 4.1 of the paper):

```
def f(): x=0
    while True:
        x += 1
        yield x
```

The authors then make the point that we can't abstract the process of yielding with a function call (Example 17-33).

Example 17-33. "[This] seems to perform a simple abstraction over the process of yielding" (Politz et al.)

```
def f():
    def do_yield(n):
        yield n
    x = 0
    while True:
        x += 1
        do_yield(x)
```

If we call `f()` in Example 17-33, we get an infinite loop, and not a generator, because the `yield` keyword only makes the immediately enclosing function a generator function. The call `do_yield(x)` returns a generator object which is immediately discarded, and the body of `do_yield` never runs.

Although generator functions look like functions, we cannot delegate to another generator function with a simple function call. As a point of comparison, the Lua language does not impose this limitation. A Lua coroutine can call other functions and any of them can yield to the original caller.

The new `yield from` syntax was introduced to allow a Python generator or coroutine to delegate work to another, without requiring the workaround of an inner `for` loop. Example 17-33 can be "fixed" by prefixing the function call with `yield from`, as in Example 17-34.

Example 17-34. This actually abstracts over the process of yielding

```
def f():
    def do_yield(n):
        yield n
    x = 0
    while True:
        x += 1
        yield from do_yield(x)
```

Reusing `def` for declaring generators was a usability mistake, and the problem was compounded in Python 2.5 with coroutines, which are also coded as functions with `yield`. In the case of coroutines, the `yield` just happens to appear—usually—on the right-hand side of an assignment, because it receives the argument of the `.send()` call from the client. As David Beazley says:

> *Despite some similarities, generators and coroutines are basically two different concepts.*[18]

Fortunately, when Guido accepted PEP 492 by Yury Selivanov, the `async` and `await` keywords were introduced to support coroutines, which are now declared with `async def`. I celebrated that decision, but it did cause breakage: when I wrote the first edition of *Fluent Python*, the `asyncio` package had a very important function named `async`. It was renamed to `ensure_future`, breaking many of the `asyncio` examples in the book. The `asyncio` API was provisional at the time, so I can't blame them. And I really like the new keywords. We'll cover them in Chapter 19 and Chapter 22.

However, PEP 492 did not fix the issue of using a plain `def` to declare generators. It can be argued that, because those features were made to work with little additional syntax, extra syntax would be merely "syntactic sugar." I happen to like syntactic sugar when it makes features that are different look different. The lack of syntactic sugar is the main reason why Lisp code is hard to read: every language construct in Lisp looks like a function call.

Terminology matters

Over the years, Python's official documentation has been inconsistent about the words "generator" and "iterator", using them as near synonyms in some places, but meaning different things in other places. Sometime after I wrote the first edition of *Fluent Python*, Python's Glossary was updated with new, clearly distinct definitions for those words and related terms. As I write this in February 2020, this is the definition of *generator* from the Python Glossary:

generator

A function which returns a generator iterator. It looks like a normal function except that it contains `yield` expressions for producing a series of values usable in a `for` loop or that can be retrieved one at a time with the `next()` function.

Usually refers to a generator function, but may refer to a generator iterator in some contexts. In cases where the intended meaning isn't clear, using the full terms avoids ambiguity.

—Python Glossary

I like that definition. The next Glossary entry is good as well:

generator iterator

An object created by a generator function.

Each yield temporarily suspends processing, remembering the location execution state (including local variables and pending try-statements). When the generator iterator resumes, it picks up where it left off (in contrast to functions which start fresh on every invocation).

—Python Glossary

Generator iterator would be a good term to describe the object returned by a generator, but the Python runtime has not changed to adopt this new term:

```
>>> def gen():
...     yield 1
...
>>> gen()
<generator object gen at 0x10bb3d120>
```

As long as Python itself uses the term *generator object* in that way, I am afraid *generator iterator* will not catch on, and the terminology will remain inconsistent. I did not adopt *generator iterator* in this second edition. I am sticking with *generator object*. But the Glossary has encouraged me to use the unqualified word *generator* when writing about generator functions.

After *generator iterator*, the next definition in the Glossary is for *generator expression*. It says:

> ***generator iterator***
>
> *An expression that returns an iterator. It looks like a normal expression followed by a `for` clause defining a loop variable, range, and an optional `if` clause. The combined expression generates values for an enclosing function:*
>
> ```
> >>> sum(i * i for i in range(10))  # sum of squares 0, 1,
> 4, ... 81
> 285
> ```
>
> —Python Glossary

That definition uses the word *iterator* to describe the object returned by a generator expression. I don't see the point of naming such objects differently from those returned by generator functions. Python agrees with me: it also calls that a *generator object*.

```
>>> (i*i for i in range(10))
<generator object <genexpr> at 0x10bb3d190>
```

Finally, the definition for *iterator* in the Glossary starts with these words:

> ***iterator***
>
> *An object representing a stream of data. Repeated calls to the iterator's `__next__()` method (or passing it to the built-in function `next()`) return successive items in the stream. When no more data are available a `StopIteration` exception is raised instead. […]*
>
> —Python Glossary

The entry is longer than that, but that's the most important part. I like it. This definition encompasses classic iterators with a user-defined `__next__` method as well as generator objects returned by generator functions or generator expressions. The main point is: generator objects are iterators that Python builds for you.

The Minimalistic Iterator Interface in Python

In the "Implementation" section of the Iterator pattern,[19] the *Gang of Four* wrote:

> *The minimal interface to Iterator consists of the operations First, Next, IsDone, and CurrentItem.*

However, that very sentence has a footnote which reads:

> *We can make this interface even smaller by merging Next, IsDone, and CurrentItem into a single operation that advances to the next object and returns it. If the traversal is finished, then this operation returns a special value (0, for instance) that marks the end of the iteration.*

This is close to what we have in Python: the single method `__next__` does the job. But instead of using a sentinel, which could be overlooked by mistake, the `StopIteration` exception signals the end of the iteration. Simple and correct: that's the Python way.

---

1 From "Revenge of the Nerds", a blog post.

2 Python 2.2 users could use `yield` with the directive `from __future__ import generators`; `yield` became available by default in Python 2.3.

3 We first used `reprlib` in "Vector Take #1: Vector2d Compatible".

4 Gamma et. al., *Design Patterns: Elements of Reusable Object-Oriented Software*, p. 259.

5 When reviewing this code, Alex Martelli suggested the body of this method could simply be `return iter(self.words)`. He is correct, of course: the result of calling `__iter__` would also be an iterator, as it should be. However, I used a `for` loop with `yield` here to introduce the syntax of a generator function, which will be covered in detail in the next section.

6 Sometimes I add a `gen` prefix or suffix when naming generator functions, but this is not a common practice. And you can't do that if you're implementing an iterable, of course: the necessary special method must be named `__iter__`.

7 Thanks to David Kwast for suggesting this example.

8 Prior to Python 3.3, it was an error to provide a value with the `return` statement in a generator function. Now that is legal, but the `return` still causes a `StopIteration` exception to be raised. The caller can retrieve the return value from the exception object. However, this is only relevant when using a generator function as a coroutine, as we'll see in "Returning a Value from a Coroutine".

9 In Python 2, there was a `coerce()` built-in function but it's gone in Python 3, deemed unnecessary because the numeric coercion rules are implicit in the arithmetic operator methods. So the best way I could think of to coerce the initial value to be of the same type as the rest of the series was to perform the addition and use its type to convert the result. I asked about this in the Python-list and got an excellent response from Steven D'Aprano.

10 The *14-it-generator/* directory in the *Fluent Python* code repository includes doctests and a script, *aritprog_runner.py*, which runs the tests against all variations of the *aritprog*.py* scripts.

11 Here the term "mapping" is unrelated to dictionaries, but has to do with the `map` built-in.

12 The `itertools.chain` from the standard library is written in C.

13 We saw this method earlier in [Link to Come], Chapter 13.

14 The library used to read the complex *.mst* binary is actually written in Java, so this functionality is only available when *isis2json.py* is executed with the Jython interpreter, version 2.5 or newer. For further details, see the *README.rst* file in the repository. The dependencies are imported inside the generator functions that need them, so the script can run even if only one of the external libraries is available.

15 Slide 33, "Keeping It Straight," in "A Curious Course on Coroutines and Concurrency".

16 According to the Jargon file, to *grok* is not merely to learn something, but to absorb it so "it becomes part of you, part of your identity."

17 Joe Gibbs Politz, Alejandro Martinez, Matthew Milano, Sumner Warren, Daniel Patterson, Junsong Li, Anand Chitipothu, and Shriram Krishnamurthi, "Python: The Full Monty," SIGPLAN Not. 48, 10 (October 2013), 217-232.

18 Slide 31, "A Curious Course on Coroutines and Concurrency".

19 Gamma et. al., *Design Patterns: Elements of Reusable Object-Oriented Software*, p. 261.

Chapter 18. Context Managers and else Blocks

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 18th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Context managers may end up being almost as important as the subroutine itself. We've only scratched the surface with them. […] Basic has a `with` statement, there are `with` statements in lots of languages. But they don't do the same thing, they all do something very shallow, they save you from repeated dotted [attribute] lookups, they don't do setup and tear down. Just because it's the same name don't think it's the same thing. The `with` statement is a very big deal.*[1]
>
> —Raymond Hettinger, Eloquent Python evangelist

In this chapter, we will discuss control flow features that are not so common in other languages, and for this reason tend to be overlooked or underused in Python. They are:

- The `with` statement and context managers.
- The `else` clause in `for`, `while`, and `try` statements.

- Pattern matching with `match/case`.

The `with` statement sets up a temporary context and reliably tears it down, under the control of a context manager object. This prevents errors and reduces boilerplate code, making APIs at the same time safer and easier to use. Python programmers are finding lots of uses for `with` blocks beyond automatic file closing.

XXX

The `else` clause is completely unrelated to `with`. But this is [Link to Come]—Control Flow. I couldn't find another place for covering `else`, and I wouldn't have a one-page chapter about it, so here it is.

Pattern matching appeared in several previous chapters, but here you'll see a more extensive example in "Pattern Matching: a Case Study".

What's new in this chapter

The only updates are in "The contextlib Utilities", mentioning features of the `contextlib` module added since Python 3.5.

Let's review the smaller topic to get to the real substance of this chapter.

Do This, Then That: else Blocks Beyond if

This is no secret, but it is an underappreciated language feature: the `else` clause can be used not only in `if` statements but also in `for`, `while`, and `try` statements.

The semantics of `for/else`, `while/else`, and `try/else` are closely related, but very different from `if/else`. Initially the word `else` actually hindered my understanding of these features, but eventually I got used to it.

Here are the rules:

`for`

The `else` block will run only if and when the `for` loop runs to completion (i.e., not if the `for` is aborted with a `break`).

`while`

The `else` block will run only if and when the `while` loop exits because the condition became *falsy* (i.e., not if the `while` is aborted with a `break`).

`try`

The `else` block will only run if no exception is raised in the `try` block. The official docs also state: “Exceptions in the `else` clause are not handled by the preceding `except` clauses.”

In all cases, the `else` clause is also skipped if an exception or a `return`, `break`, or `continue` statement causes control to jump out of the main block of the compound statement.

> **NOTE**
>
> I think `else` is a very poor choice for the keyword in all cases except `if`. It implies an excluding alternative, like “Run this loop, otherwise do that,” but the semantics for `else` in loops is the opposite: “Run this loop, then do that.” This suggests `then` as a better keyword—which would also make sense in the `try` context: “Try this, then do that.” However, adding a new keyword is a breaking change to the language—not an easy decision to make.

Using `else` with these statements often makes the code easier to read and saves the trouble of setting up control flags or coding extra `if` statements.

The use of `else` in loops generally follows the pattern of this snippet:

```
for item in my_list:
    if item.flavor == 'banana':
        break
```

```python
else:
    raise ValueError('No banana flavor found!')
```

In the case of `try/except` blocks, `else` may seem redundant at first. After all, the `after_call()` in the following snippet will run only if the `dangerous_call()` does not raise an exception, correct?

```python
try:
    dangerous_call()
    after_call()
except OSError:
    log('OSError...')
```

However, doing so puts the `after_call()` inside the `try` block for no good reason. For clarity and correctness, the body of a `try` block should only have the statements that may generate the expected exceptions. This is much better:

```python
try:
    dangerous_call()
except OSError:
    log('OSError...')
else:
    after_call()
```

Now it's clear that the `try` block is guarding against possible errors in `dangerous_call()` and not in `after_call()`. It's also more obvious that `after_call()` will only execute if no exceptions are raised in the `try` block.

In Python, `try/except` is commonly used for control flow, and not just for error handling. There's even an acronym/slogan for that documented in the official Python glossary:

EAFP

> *Easier to ask for forgiveness than permission. This common Python coding style assumes the existence of valid keys or attributes and catches exceptions if the assumption proves false. This clean and fast style is characterized by the presence of many try and except statements. The technique contrasts with the LBYL style common to many other languages such as C.*

The glossary then defines LBYL:

LBYL

> *Look before you leap. This coding style explicitly tests for pre-conditions before making calls or lookups. This style contrasts with the EAFP approach and is characterized by the presence of many if statements. In a multi-threaded environment, the LBYL approach can risk introducing a race condition between "the looking" and "the leaping". For example, the code, if key in mapping: return mapping[key] can fail if another thread removes key from mapping after the test, but before the lookup. This issue can be solved with locks or by using the EAFP approach.*

Given the EAFP style, it makes even more sense to know and use well `else` blocks in `try/except` statements.

Now let's address the main topic of this chapter: the powerful `with` statement.

Context Managers and with Blocks

Context manager objects exist to control a `with` statement, just like iterators exist to control a `for` statement.

The `with` statement was designed to simplify the `try/finally` pattern, which guarantees that some operation is performed after a block of code, even if the block is aborted because of an exception, a `return` or `sys.exit()` call. The code in the `finally` clause usually releases a critical resource or restores some previous state that was temporarily changed.

The context manager interface consists of the `__enter__` and `__exit__` methods. At the start of the `with`, `__enter__` is invoked on the context manager object. The role of the `finally` clause is played by a call to `__exit__` on the context manager object at the end of the `with` block.

The most common example is making sure a file object is closed. See Example 18-1 for a detailed demonstration of using `with` to close a file.

Example 18-1. Demonstration of a file object as a context manager

```
>>> with open('mirror.py') as fp:  ❶
...     src = fp.read(60)  ❷
...
>>> len(src)
60
>>> fp  ❸
<_io.TextIOWrapper name='mirror.py' mode='r' encoding='UTF-8'>
>>> fp.closed, fp.encoding  ❹
(True, 'UTF-8')
>>> fp.read(60)  ❺
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
ValueError: I/O operation on closed file.
```

❶ `fp` is bound to the opened file because the file's `__enter__` method returns `self`.

❷ Read some data from `fp`.

❸ The `fp` variable is still available.[2]

❹ You can read the attributes of the `fp` object.

❺ But you can't perform I/O with `fp` because at the end of the `with` block, the `TextIOWrapper.__exit__` method is called and closes the file.

The first callout in Example 18-1 makes a subtle but crucial point: the context manager object is the result of evaluating the expression after `with`, but the value bound to the target variable (in the `as` clause) is the result of calling `__enter__` on the context manager object.

It just happens that in Example 18-1, the `open()` function returns an instance of `TextIOWrapper`, and its `__enter__` method returns `self`. But the `__enter__` method may also return some other object instead of the context manager.

When control flow exits the `with` block in any way, the `__exit__` method is invoked on the context manager object, not on whatever is returned by `__enter__`.

The `as` clause of the `with` statement is optional. In the case of `open`, you'll always need it to get a reference to the file, but some context managers return `None` because they have no useful object to give back to the user.

Example 18-2 shows the operation of a perfectly frivolous context manager designed to highlight the distinction between the context manager and the object returned by its `__enter__` method.

Example 18-2. Test driving the LookingGlass context manager class

```
>>> from mirror import LookingGlass
>>> with LookingGlass() as what:  ❶
...     print('Alice, Kitty and Snowdrop')  ❷
...     print(what)
...
pordwonS dna yttiK ,ecilA  ❸
YKCOWREBBAJ
>>> what  ❹
'JABBERWOCKY'
>>> print('Back to normal.')  ❺
Back to normal.
```

❶

The context manager is an instance of `LookingGlass`; Python calls `__enter__` on the context manager and the result is bound to `what`.

❷ Print a `str`, then the value of the target variable `what`.

❸ The output of each `print` comes out backward.

❹ Now the `with` block is over. We can see that the value returned by `__enter__`, held in `what`, is the string `'JABBERWOCKY'`.

❺ Program output is no longer backward.

Example 18-3 shows the implementation of `LookingGlass`.

Example 18-3. mirror.py: code for the LookingGlass context manager class

```
class LookingGlass:

    def __enter__(self):  ❶
        import sys
        self.original_write = sys.stdout.write  ❷
        sys.stdout.write = self.reverse_write  ❸
        return 'JABBERWOCKY'  ❹

    def reverse_write(self, text):  ❺
        self.original_write(text[::-1])

    def __exit__(self, exc_type, exc_value, traceback):  ❻
        import sys  ❼
        sys.stdout.write = self.original_write  ❽
        if exc_type is ZeroDivisionError:  ❾
            print('Please DO NOT divide by zero!')
            return True  ❿
        ⓫
```

❶ Python invokes `__enter__` with no arguments besides `self`.

❷ Hold the original `sys.stdout.write` method in an instance attribute for later use.

❸

Monkey-patch `sys.stdout.write`, replacing it with our own method.

❹ Return the `'JABBERWOCKY'` string just so we have something to put in the target variable `what`.

❺ Our replacement to `sys.stdout.write` reverses the `text` argument and calls the original implementation.

❻ Python calls `__exit__` with `None, None, None` if all went well; if an exception is raised, the three arguments get the exception data, as described next.

❼ It's cheap to import modules again because Python caches them.

❽ Restore the original method to `sys.stdout.write`.

❾ If the exception is not `None` and its type is `ZeroDivisionError`, print a message…

❿ …and return `True` to tell the interpreter that the exception was handled.

⓫ If `__exit__` returns `None` or anything but `True`, any exception raised in the `with` block will be propagated.

> **TIP**
>
> When real applications take over standard output, they often want to replace `sys.stdout` with another file-like object for a while, then switch back to the original. The `contextlib.redirect_stdout` context manager does exactly that: just pass it the file-like object that will stand in for `sys.stdout`.

The interpreter calls the `__enter__` method with no arguments—beyond the implicit `self`. The three arguments passed to `__exit__` are:

`exc_type`

The exception class (e.g., `ZeroDivisionError`).

`exc_value`

The exception instance. Sometimes, parameters passed to the exception constructor—such as the error message—can be found in `exc_value.args`.

`traceback`

A `traceback` object.[3]

For a detailed look at how a context manager works, see Example 18-4, where `LookingGlass` is used outside of a `with` block, so we can manually call its `__enter__` and `__exit__` methods.

Example 18-4. Exercising LookingGlass without a with block

```
>>> from mirror import LookingGlass
>>> manager = LookingGlass()  ❶
>>> manager
<mirror.LookingGlass object at 0x2a578ac>
>>> monster = manager.__enter__()  ❷
>>> monster == 'JABBERWOCKY'  ❸
eurT
>>> monster
'YKCOWREBBAJ'
>>> manager
>ca875a2x0 ta tcejbo ssalGgnikooL.rorrim<
>>> manager.__exit__(None, None, None)  ❹
>>> monster
'JABBERWOCKY'
```

❶ Instantiate and inspect the `manager` instance.

❷ Call the context manager `__enter__()` method and store result in `monster`.

❸ Monster is the string `'JABBERWOCKY'`. The `True` identifier appears reversed because all output via `stdout` goes through the `write` method we patched in `__enter__`.

❹ Call `manager.__exit__` to restore previous `stdout.write`.

Context managers are a fairly novel feature and slowly but surely the Python community is finding new, creative uses for them. Some examples from the standard library are:

- Managing transactions in the `sqlite3` module; see "12.6.7.3. Using the connection as a context manager".
- Holding locks, conditions, and semaphores in `threading` code; see "17.1.10. Using locks, conditions, and semaphores in the `with` statement".
- Setting up environments for arithmetic operations with `Decimal` objects; see the `decimal.localcontext` documentation.
- Applying temporary patches to objects for testing; see the `unittest.mock.patch` function.

The standard library also includes the `contextlib` utilities, covered next.

The contextlib Utilities

Before rolling your own context manager classes, take a look at "`contextlib` — Utilities for `with`-statement contexts" in *The Python Standard Library*. Maybe what you are about to build already exists, or there is a class or some callable that will make your job easier.

Besides the `redirect_stdout` context manager mentioned in Example 18-3, `redirect_stderr` was added in Python 3.5—it does the same as the former, but for output directed to `stderr`.

The `contextlib` package also includes:

`closing`

A function to build context managers out of objects that provide a `close()` method but don't implement the `__enter__`/`__exit__` interface.

`suppress`

A context manager to temporarily ignore exceptions given as arguments.

`nullcontext`

A context manager wrapper that does nothing, to simplify conditional logic around objects that may or may not implement a suitable context manager (since Python 3.7).

The `contextlib` module provides classes and a decorator that are more widely applicable than those above:

`@contextmanager`

A decorator that lets you build a context manager from a simple generator function, instead of creating a class and implementing the interface. See "Using @contextmanager".

`AbstractContextManager`

An ABC that formalizes the context manager interface, and makes it a bit easier to create context manager classes by subclassing (since Python 3.6).

`ContextDecorator`

A base class for defining class-based context managers that can also be used as function decorators, running the entire function within a managed context.

`ExitStack`

> A context manager that lets you enter a variable number of context managers. When the `with` block ends, `ExitStack` calls the stacked context managers' `__exit__` methods in LIFO order (last entered, first exited). Use this class when you don't know beforehand how many context managers you need to enter in your `with` block; for example, when opening all files from an arbitrary list of files at the same time.

With Python 3.7, `contextlib` added `AbstractAsyncContextManager`, `@asynccontextmanager`, and `AsyncExitStack`. They are similar to the equivalent utilities without the `async` part of the name, but designed for use with the new `async with` statement, covered in Chapter 22.

The most widely used of these utilities is surely the `@contextmanager` decorator, so it deserves more attention. That decorator is also intriguing because it shows a use for the `yield` statement unrelated to iteration. This paves the way to the concept of a coroutine, the theme of the next chapter.

Using @contextmanager

The `@contextmanager` decorator reduces the boilerplate of creating a context manager: instead of writing a whole class with `__enter__/__exit__` methods, you just implement a generator with a single `yield` that should produce whatever you want the `__enter__` method to return.

In a generator decorated with `@contextmanager`, `yield` splits the body of the function in two parts: everything before the `yield` will be executed at the beginning of the `with` block when the interpreter calls `__enter__`; the code after `yield` will run when `__exit__` is called at the end of the block.

Here is an example. Example 18-5 replaces the `LookingGlass` class from Example 18-3 with a generator function.

Example 18-5. mirror_gen.py: a context manager implemented with a generator

```
import contextlib


@contextlib.contextmanager  ❶
def looking_glass():
    import sys
    original_write = sys.stdout.write  ❷

    def reverse_write(text):  ❸
        original_write(text[::-1])

    sys.stdout.write = reverse_write  ❹
    yield 'JABBERWOCKY'  ❺
    sys.stdout.write = original_write  ❻
```

❶ Apply the `contextmanager` decorator.

❷ Preserve original `sys.stdout.write` method.

❸ Define custom `reverse_write` function; `original_write` will be available in the closure.

❹ Replace `sys.stdout.write` with `reverse_write`.

❺ Yield the value that will be bound to the target variable in the `as` clause of the `with` statement. This function pauses at this point while the body of the `with` executes.

❻ When control exits the `with` block in any way, execution continues after the `yield`; here the original `sys.stdout.write` is restored.

Example 18-6 shows the `looking_glass` function in operation.

Example 18-6. Test driving the looking_glass context manager function

```
>>> from mirror_gen import looking_glass
>>> with looking_glass() as what:  ❶
...      print('Alice, Kitty and Snowdrop')
...      print(what)
```

```
...
pordwonS dna yttiK ,ecilA
YKCOWREBBAJ
>>> what
'JABBERWOCKY'
```

❶ The only difference from Example 18-2 is the name of the context manager: `looking_glass` instead of `LookingGlass`.

Essentially the `contextlib.contextmanager` decorator wraps the function in a class that implements the `__enter__` and `__exit__` methods.[4]

The `__enter__` method of that class:

1. Invokes the generator function and holds on to the generator object —let's call it `gen`.
2. Calls `next(gen)` to make it run to the `yield` keyword.
3. Returns the value yielded by `next(gen)`, so it can be bound to a target variable in the with/as form.

When the `with` block terminates, the `__exit__` method:

1. Checks an exception was passed as `exc_type`; if so, `gen.throw(exception)` is invoked, causing the exception to be raised in the `yield` line inside the generator function body.
2. Otherwise, `next(gen)` is called, resuming the execution of the generator function body after the `yield`.

Example 18-5 has a serious flaw: if an exception is raised in the body of the `with` block, the Python interpreter will catch it and raise it again in the `yield` expression inside `looking_glass`. But there is no error handling there, so the `looking_glass` function will abort without ever restoring the original `sys.stdout.write` method, leaving the system in an invalid state.

Example 18-7 adds special handling of the `ZeroDivisionError` exception, making it functionally equivalent to the class-based Example 18-3.

Example 18-7. mirror_gen_exc.py: generator-based context manager implementing exception handling—same external behavior as Example 18-3

```
import contextlib


@contextlib.contextmanager
def looking_glass():
    import sys
    original_write = sys.stdout.write

    def reverse_write(text):
        original_write(text[::-1])

    sys.stdout.write = reverse_write
    msg = ''  ❶
    try:
        yield 'JABBERWOCKY'
    except ZeroDivisionError:  ❷
        msg = 'Please DO NOT divide by zero!'
    finally:
        sys.stdout.write = original_write  ❸
        if msg:
            print(msg)  ❹
```

❶ Create a variable for a possible error message; this is the first change in relation to Example 18-5.

❷ Handle `ZeroDivisionError` by setting an error message.

❸ Undo monkey-patching of `sys.stdout.write`.

❹ Display error message, if it was set.

Recall that the `__exit__` method tells the interpreter that it has handled the exception by returning `True`; in that case, the interpreter suppresses the exception. On the other hand, if `__exit__` does not explicitly return a value, the interpreter gets the usual `None`, and propagates the exception. With `@contextmanager`, the default behavior is inverted: the `__exit__` method provided by the decorator assumes any exception sent into the generator is handled and should be suppressed.[5] You must explicitly re-raise an exception in the decorated function if you don't want `@contextmanager` to suppress it.[6]

> **TIP**
>
> Having a `try/finally` (or a `with` block) around the `yield` is an unavoidable price of using `@contextmanager`, because you never know what the users of your context manager are going to do inside their `with` block.[7]

An interesting real-life example of `@contextmanager` outside of the standard library is Martijn Pieters' in-place file rewriting context manager. Example 18-8 shows how it's used.

Example 18-8. A context manager for rewriting files in place

```
import csv

with inplace(csvfilename, 'r', newline='') as (infh, outfh):
    reader = csv.reader(infh)
    writer = csv.writer(outfh)

    for row in reader:
        row += ['new', 'columns']
        writer.writerow(row)
```

The `inplace` function is a context manager that gives you two handles—`infh` and `outfh` in the example—to the same file, allowing your code to read and write to it at the same time. It's easier to use than the standard library's `fileinput.input` function (which also provides a context manager, by the way).

If you want to study Martijn's `inplace` source code (listed in the post), find the `yield` keyword: everything before it deals with setting up the context, which entails creating a backup file, then opening and yielding references to the readable and writable file handles that will be returned by the `__enter__` call. The `__exit__` processing after the `yield` closes the file handles and restores the file from the backup if something went wrong.

Note that the use of `yield` in a generator used with the `@contextmanager` decorator has nothing to do with iteration. In the examples shown in this section, the generator function is operating more like a coroutine: a procedure that runs up to a point, then suspends to let the client code run until the client wants the coroutine to proceed with its job. Chapter 19 is all about coroutines.

Pattern Matching: a Case Study

XXX missing introduction

Before looking at the Python code, let's learn the bare minimum of Scheme so you can make sense of this case study—in case you haven't studied Scheme or Lisp before.

Scheme Syntax

Everything in Scheme is an expression—there is no distinction between expressions and statements, like we have in Python.

Scheme has no infix operators. Expressions with arithmetic and logic operators all use prefix notation like `(+ x 13)`. The same syntax is used for function calls—e.g. `(gcd x 13)`—and special forms—e.g. `(define x 13)`, which we'd write as `x = 13` in Python.[8]

Here is a simple example in Scheme:

Example 18-9. Greatest common divisor in Scheme. The last result of this code is 9, the GCD of 18 and 45.

```
(define (mod m n)
    (- m (* n (// m n))))

(define (gcd m n)
```

```
    (if (= n 0)
        m
        (gcd n (mod m n))))

(gcd 18 45)
```

Example 18-9 shows two function definitions—`mod` and `gcd`—and a call to `gcd`. Here is the same code in Python (quicker than an English explanation):

Example 18-10. Same as Example 18-9, written in Python.

```
def mod(m, n):
    return m - (m // n * n)

def gcd(m, n):
    if n == 0:
        return m
    else:
        return gcd(m, mod(m, n))

gcd(18, 45)  # returns 9
```

At its core, Scheme has no iterative control flow forms like `while` or `for`. Iteration is always implemented with recursion, as you saw in Example 18-9. Scheme implementations are required to implement tail call optimization (TCO) to make iteration through recursion efficient and practical. Norvig's *lispy.py* interpreter has TCO, but his simpler *lis.py* does not.

The Parser

The first part of Norvig's code is a parser that reads a string of Scheme source code, splits it into syntactic tokens, and returns a Python object representing the code.

Here are some examples from a doctest:

Example 18-11. `parse` takes a string and returns numbers, symbols, and/or lists.

```
>>> parse('1.5')  ❶
1.5
>>> parse('set!')  ❷
'set!'
```

```
>>> parse('(gcd 18 44)')  ❸
['gcd', 18, 44]
>>> parse('(- m (* n (// m n)))')  ❹
['-', 'm', ['*', 'n', ['//', 'm', 'n']]]
```

❶ A token that looks like a number is parsed as a number—`float` or `int`.

❷ Anything else that doesn't start with `'('` is parsed as a *symbol*—a `str` to be used as an identifier.

❸ Expressions inside `'('` and `')'` are parsed as lists of numbers or symbols or…

❹ …nested lists that may contain numbers, symbols, and more nested lists.

The simplest tokens—numbers and symbols—are called *atoms*. Using Python terminology, the output of `parse` is an AST (Abstract Syntax Tree): the nested lists form a tree-like structure, where the outermost list is the trunk, the inner lists are the branches, and the atoms are the leaves.

An Expression Evaluator

Now we are ready to see the beauty of pattern matching applied to interpreting Scheme expressions. The `evaluate` function in Example 18-12 is the most important part of the interpreter.

Example 18-12. `evaluate` takes an expression from `parse` and computes its value.

```
def evaluate(exp: Expression, env: Environment) -> Any:
    "Evaluate an expression in an environment."
    match exp:
        case int(x) | float(x):
            return x
        case Symbol(var):
            return env[var]
        case []:
            return []
        case ['quote', exp]:
```

```
            return exp
        case ['if', test, consequence, alternative]:
            if evaluate(test, env):
                return evaluate(consequence, env)
            else:
                return evaluate(alternative, env)
        case ['define', Symbol(var), value_exp]:
            env[var] = evaluate(value_exp, env)
        case ['define', [Symbol(name), *parms], *body]:
            env[name] = Procedure(parms, body, env)
        case ['lambda', [*parms], *body]:
            return Procedure(parms, body, env)
        case [op, *args]:
            proc = evaluate(op, env)
            values = [evaluate(arg, env) for arg in args]
            return proc(*values)
        case _:
            raise SyntaxError(repr(exp))
```

The two arguments of `evaluate` are:

`exp`

numbers, symbols or lists returned by `parse`;

`env`

an envirnoment—a mapping of names to values.

When the interpreter makes the initial call to `evaluate`, `env` gets a `dict` with dozens of names mapped to Python functions. This is a small sample of items in the initial environment:

```
{
    '+': op.add,
    '-': op.sub,
    'abs': abs,
    'append': lambda *args: list(itertools.chain(*args)),
    'length': len,
    'number?': lambda x: isinstance(x, (int, float)),
}
```

The body of `evaluate` is a single `match` statement with an expression `exp` as the subject. The 10 `case` patterns express the syntax and semantics of Scheme with amazing clarity.

Let's study each case in turn. On top of each `case`, I added a sample of Scheme code that would produce a subject `exp` matching that pattern, and a Python object that could be the value of that expression.

```
# 1.5
case int(x) | float(x):  ❶
    return x
```

❶ If subject is an `int` or `float`, just return it.

```
# count
case Symbol(var):  ❷
    return env[var]
```

❷ If subject is a `Symbol` (a `str` used as an identifier), get its value from `env` and return it.

Now, the sequence patterns:

```
# ()
case []:  ❸
    return []
```

❸ If subject is an empty list, return it.

```
# (quote (1.1 is not 1))
case ['quote', exp]:  ❹
    return exp
```

❹ If subject is a list starting with `'quote'`, followed by one `exp`, then return `exp` without evaluating it. Given the Scheme code in the comment, the Python object returned would be `[1.1, 'is', 'not', 1]`.

```
# (if (> n 0) n (- 0 n))
case ['if', test, consequence, alternative]:  ❺
    if evaluate(test, env):
        return evaluate(consequence, env)
    else:
        return evaluate(alternative, env)
```

❺ If subject is a list starting with `'if'` followed by three expressions, then evaluate `test`; if true, evaluate `consequence` and return it; otherwise, evaluete `alternative` and return it.

```
# (define half (/ 1 2))
case ['define', Symbol(var), value_exp]:  ❻
    env[var] = evaluate(value_exp, env)
```

❻ If subject is a list starting with `'define'`, followed by a symbol `var` and an expression, then evaluate the expression and add its value to `env`, using the `var` as key.

The next case also matches a sequence starting with `define`, but with a different structure.

```
# (define (double x) (* x 2))
case ['define', [Symbol(name), *parms], body]:  ❼
    env[name] = Procedure(parms, body, env)
```

❼ If subject is a list starting with `'define'` and two other items, the first being a list starting with a symbol `name`, followed by 0 or more parameter names, the second being an expression `body`, then create a new `Procedure` with those parameters, `body`, and the current environment, and add it to the `env` using `name` as the key.

The previous case is a named function definition. The next is an anonymous function definition.

```
# (lambda (a b) (* (/ a b) 100))
case ['lambda', [*parms], body]:  ❽
    return Procedure(parms, body, env)
```

❽ If subject is a list starting with `'lambda'` and two other items, the first being a list of parameter names, the second being an expression `body`, then create a new `Procedure` with those parameters, `body`, and the current environment, and return it.

Now we get to a function call.

```
# (gcd 210 84)
case [op, *args]:  ❾
    proc = evaluate(op, env)
    values = [evaluate(arg, env) for arg in args]
    return proc(*values)
```

❾ If subject is a list with one or more items, then evaluate the first to obtain a function `proc`, evaluate each of the remaining items to build a list of argument values, then call `proc` with the values as separate arguments.

```
case _:  ❿
    raise SyntaxError(repr(exp))
```

❿ If subject did not match any previous pattern, it matches the wildcard _. Raise `SyntaxError`.

To wrapt up the coverage of pattern matching in this chapter, let’s talk about OR-patterns.

OR-patterns

NOTE

An OR-pattern can be built from any other patterns, not only class patterns.

In Example 2-11 we saw part of Peter Norvig's *lis.py* `evaluate` function refactored to use `match/case`. Here are the first `case` clauses of that function, which I previously ommitted:

Example 18-13. Pattern matching with `match/case`—requires Python ≥ 3.10.

```
def evaluate(exp, env):
    "Evaluate an expression in an environment."
    match exp:
        case int(x) | float(x):  ❶
            return x
        case Symbol(var):  ❷
            return env[var]
        case ...:  # sequence patterns omitted
            ...
        case _:
            raise SyntaxError(repr(exp))
```

❶ Match if subject is an instance of `int` or `float`.

❷ Match is subject is an instance of `Symbol`—which is an alias for `str` in *lis.py*.

A series of patterns separated by `|` is an OR-pattern: it succeeds if any of the subpatterns succeed. All subpatterns must use the same variables. This restriction is necessary to ensure that the `case` body can rely on all the variables if there is a match.

WARNING

In the context of a `case` clause, the `|` operator has a special meaning. It does not trigger the `__or__` special method which handles expressions like `a | b` in other contexts, where it is overloaded to perform operations such as set union or integer bitwise-or.

Example 18-13 illustrates the simplest form of class pattern, exemplified by `int(x)`, which matches if `isinstance(x, int)` returns `True`.

XXX

Chapter Summary

This chapter started easily enough with discussion of `else` blocks in `for`, `while`, and `try` statements. Once you get used to the peculiar meaning of the `else` clause in these statements, I believe `else` can clarify your intentions.

We then covered context managers and the meaning of the `with` statement, quickly moving beyond its common use to automatically close opened files. We implemented a custom context manager: the `LookingGlass` class with the `__enter__/__exit__` methods, and saw how to handle exceptions in the `__exit__` method. A key point that Raymond Hettinger made in his PyCon US 2013 keynote is that `with` is not just for resource management, but it's a tool for factoring out common setup and teardown code, or any pair of operations that need to be done before and after another procedure (slide 21, What Makes Python Awesome?).

Finally, we reviewed functions in the `contextlib` standard library module. One of them, the `@contextmanager` decorator, makes it possible to implement a context manager using a simple generator with one `yield`—a leaner solution than coding a class with at least two methods. We reimplemented the `LookingGlass` as a `looking_glass` generator function, and discussed how to do exception handling when using `@contextmanager`.

The `@contextmanager` decorator is an elegant and practical tool that brings together three distinctive Python features: a function decorator, a generator, and the `with` statement.

Further Reading

Chapter 8, "Compound Statements," in *The Python Language Reference* says pretty much everything there is to say about `else` clauses in `if`, `for`, `while`, and `try` statements. Regarding Pythonic usage of `try/except`, with or without `else`, Raymond Hettinger has a brilliant answer to the question “Is it a good practice to use try-except-else in Python?” in StackOverflow. Alex Martelli’s *Python in a Nutshell, 2E* (O’Reilly), has a chapter about exceptions with an excellent discussion of the EAFP style, crediting computing pioneer Grace Hopper for coining the phrase “It’s easier to ask forgiveness than permission.”

The *Python Standard Library*, Chapter 4, “Built-in Types,” has a section devoted to Context Manager Types. The `__enter__/__exit__` special methods are also documented in *The Python Language Reference* in “3.3.8. With Statement Context Managers”. Context managers were introduced in PEP 343 — The “with” Statement. This PEP is not easy reading because it spends a lot of time covering corner cases and arguing against alternative proposals. That’s the nature of PEPs.

Raymond Hettinger highlighted the `with` statement as a “winning language feature” in his PyCon US 2013 keynote. He also showed some interesting applications of context managers in his talk “Transforming Code into Beautiful, Idiomatic Python” at the same conference.

Jeff Preshing’ blog post “The Python `with` Statement by Example” is interesting for the examples using context managers with the `pycairo` graphics library.

Beazley and Jones devised context managers for very different purposes in their *Python Cookbook, 3E* (O’Reilly). “Recipe 8.3. Making Objects Support the Context-Management Protocol” implements a `LazyConnection` class whose instances are context managers that open and close network connections automatically in `with` blocks. “Recipe 9.22. Defining Context Managers the Easy Way” introduces a context manager for timing code, and another for making transactional changes to a `list` object: within the `with` block, a working copy of the `list` instance is made, and all changes are applied to that working copy. Only when the `with` block completes without an exception, the working copy replaces the original list. Simple and ingenious.

SOAPBOX

Factoring Out the Bread

In his PyCon US 2013 keynote, "What Makes Python Awesome," Raymond Hettinger says when he first saw the `with` statement proposal he thought it was "a little bit arcane." Initially, I had a similar reaction. PEPs are often hard to read, and PEP 343 is typical in that regard.

Then—Hettinger told us—he had an insight: subroutines are the most important invention in the history of computer languages. If you have sequences of operations like A;B;C and P;B;Q, you can factor out B in a subroutine. It's like factoring out the filling in a sandwich: using tuna with different breads. But what if you want to factor out the bread, to make sandwiches with wheat bread, using a different filling each time? That's what the `with` statement offers. It's the complement of the subroutine. Hettinger went on to say:

> *The `with` statement is a very big deal. I encourage you to go out and take this tip of the iceberg and drill deeper. You can probably do profound things with the `with` statement. The best uses of it have not been discovered yet. I expect that if you make good use of it, it will be copied into other languages and all future languages will have it. You can be part of discovering something almost as profound as the invention of the subroutine itself.*

Hettinger admits he is overselling the `with` statement. Nevertheless, it is a very useful feature. When he used the sandwich analogy to explain how `with` is the complement to the subroutine, many possibilities opened up in my mind.

If you need to convince anyone that Python is awesome, you should watch Hettinger's keynote. The bit about context managers is from 23:00 to 26:15. But the entire keynote is excellent.

1 PyCon US 2013 keynote: "What Makes Python Awesome"; the part about `with` starts at 23:00 and ends at 26:15.

2 `with` blocks don't define a new scope, as functions and modules do.

3 The three arguments received by `self` are exactly what you get if you call `sys.exc_info()` in the `finally` block of a `try/finally` statement. This makes sense, considering that the `with` statement is meant to replace most uses of `try/finally`, and calling `sys.exc_info()` was often necessary to determine what clean-up action would be required.

4 The actual class is named `_GeneratorContextManager`. If you want to see exactly how it works, read its source code in *Lib/contextlib.py* in the Python 3.4 distribution.

5 The exception is sent into the generator using the `throw` method, covered in "Coroutine Termination and Exception Handling".

6 This convention was adopted because when context managers were created, generators could not `return` values, only `yield`. They now can, as explained in "Returning a Value from a Coroutine". As you'll see, returning a value from a generator does involve an exception.

7 This tip is quoted literally from a comment by Leonardo Rochael, one of the tech reviewers for this book. Nicely said, Leo!

8 People complain about the overuse of parenthesis, but the main readability problem of Lisp and its dialects is using the same `(foo ...)` syntax for function calls and special forms like `(define ...)`, `(if ...)`, and macros that don't behave at all like function calls.

Chapter 19. Classic Coroutines

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 19th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *There are many implementations of coroutines; even in Python there are several. […] Starting in Python 3.5, coroutines are a native feature of the language itself; however, understanding coroutines as they were first implemented in Python 3.4, using pre-existing language facilities, is the foundation to tackle Python 3.5's native coroutines.*[1]
>
> —A. Jesse Jiryu Davis and Guido van Rossum, A Web Crawler With asyncio Coroutines

We find two main senses for the verb "to yield" in dictionaries: to produce or to give way. Both senses apply in Python when we use the `yield` keyword in a generator. A line such as `yield item` produces a value that is received by the caller of `next(…)`, and it also gives way, suspending the execution of the generator so that the caller may proceed until it's ready to consume another value by invoking `next()` again. The caller pulls values from the generator.

A Python coroutine is essentially a generator driven by calls to its `.send(…)` method. In a coroutine, the essential meaning of "to yield" is to give way—to hand control to some other part of the program, and wait until notified to resume. The caller invokes `my_coroutine.send(datum)` to push data into the coroutine. The coroutine then resumes and gets `datum` as the value of the `yield` expression where it was suspended. In normal usage, a caller repeatedly pushes data into the coroutine in that way. In contrast with generators, coroutines are usually data consumers, not producers.

Regardless of the flow of data, `yield` is a control flow device that can be used to implement cooperative multitasking: each coroutine yields control to a central scheduler so that other coroutines can be activated.

Since version 3.5, Python has three kinds of coroutines:

classic coroutines

> A generator function that consumes data sent to it via `my_coro.send(data)` calls, and reads that data by using `yield` in an expression. Classic coroutines can delegate to other classic coroutines using `yield from`.

generator-based coroutines

> A generator function decorated with `@types.coroutine`, which makes it compatible with the new `await` keyword, introduced in Python 3.5.

native coroutines

> A coroutine defined with `async def`. You can delegate from a native coroutine to another native coroutine or to a generator-based coroutine using the `await` keyword, similar to how classic coroutines use `yield from`.

Native coroutines and generator-based coroutines are intended specifically for asynchronous I/O programming. As such, we'll get back to them in Chapter 22—Basic Asyncio.

This chapter is about *classic coroutines*. Although native coroutines evolved from classic coroutines, they don't replace them completely. Classic coroutines have some useful behaviors that native coroutines can't emulate—and vice-versa, native coroutines have features that are missing in classic coroutines.

Classic coroutines are the product of a series of enhancements to the simpler generator functions we've seen so far in the book. Following the evolution of coroutines in Python helps understand their features in stages of increasing functionality and complexity.

After a brief overview of how generators were enhanced to act as coroutines, we jump to the core of the chapter. Then we'll see:

- The behavior and states of a generator operating as a coroutine.
- Priming a coroutine automatically with a decorator.
- How the caller can control a coroutine through the `.close()` and `.throw(…)` methods of the generator object.
- How coroutines can return values upon termination.
- Usage and semantics of the new `yield from` syntax.
- A use case: coroutines for managing concurrent activities in a simulation.

> **NOTE**
>
> In this chapter I often use the word "coroutine" to refer to classic coroutines—a.k.a. generator-based coroutines— except when I am contrasting them with native coroutines.

What's new in this chapter

Since 2012 when `yield from` was implemented in Python 3.3, classic coroutines did not undergo major changes. Native coroutines—created with `async def`—are similar, but not a full replacement of classic coroutines. They are covered in Chapter 22.

Therefore, this chapter has no significant changes except for the occasional comparisons of classic versus native coroutines, as well as `yield from` versus `await`.

How Coroutines Evolved from Generators

A classic coroutine is syntactically like a generator: just a function with the `yield` keyword in its body. However, in a coroutine, `yield` usually appears on the right-hand side of an expression (e.g., `datum = yield`), and it may or may not produce a value—if there is no expression after the `yield` keyword, the generator yields `None`. The coroutine may receive data from the caller, which uses `coro.send(datum)` instead of `next(coro)` to drive the coroutine. Usually, the caller pushes values into the coroutine. It is even possible that no data goes in or out through the `yield` keyword. When you start thinking of `yield` primarily in terms of control flow, you have the mindset to understand why coroutines are useful for concurrent programming.

The infrastructure for coroutines appeared in PEP 342 — Coroutines via Enhanced Generators, implemented in Python 2.5 (2006): since then, the `yield` keyword can be used in an expression, and the `.send(value)` method was added to the generator API. This allows a generator to be used as a coroutine: a procedure that collaborates with the caller, yielding and receiving values from the caller.

In addition to `.send(…)`, PEP 342 also added `.throw(…)` and `.close()` methods that respectively allow the caller to throw an exception to be handled inside the generator, and to terminate it. These features are covered in the next section and in "Coroutine Termination and Exception Handling".

The latest evolutionary step for classic coroutines came with PEP 380 - Syntax for Delegating to a Subgenerator, implemented in Python 3.3

(2012). PEP 380 made two syntax changes to generator functions, to make them more useful as coroutines:

- A generator can now `return` a value; previously, providing a value to the `return` statement inside a generator raised a `SyntaxError`.
- The `yield from` syntax enables complex generators to be refactored into smaller, nested generators while avoiding a lot of boilerplate code previously required for a generator to delegate to subgenerators.

These changes will be addressed in "Returning a Value from a Coroutine" and "Using yield from".

After PEP 380 there have been no major changes to classic coroutines. PEP 492 introduced native coroutines, but that's a story for Chapter 22.

Let's follow the established tradition of *Fluent Python* and start with some very basic facts and examples, then move into increasingly mind-bending features.

Basic Behavior of a Generator Used as a Coroutine

Example 19-1 illustrates the behavior of a coroutine.

Example 19-1. Simplest possible demonstration of coroutine in action

```
>>> def simple_coroutine():  ❶
...     print('-> coroutine started')
...     x = yield  ❷
...     print('-> coroutine received:', x)
...
>>> my_coro = simple_coroutine()
>>> my_coro  ❸
<generator object simple_coroutine at 0x100c2be10>
>>> next(my_coro)  ❹
-> coroutine started
>>> my_coro.send(42)  ❺
-> coroutine received: 42
```

```
Traceback (most recent call last):  ❻
  ...
StopIteration
```

❶ A coroutine is defined as a generator function: with `yield` in its body.

❷ `yield` is used in an expression; when the coroutine is designed just to receive data from the client it yields `None`—this is implicit because there is no expression to the right of the `yield` keyword.

❸ As usual with generators, you call the function to get a generator object back.

❹ The first call is `next(…)` because the generator hasn't started so it's not waiting in a `yield` and we can't send it any data initially.

❺ This call makes the `yield` in the coroutine body evaluate to `42`; now the coroutine resumes and runs until the next `yield` or termination.

❻ In this case, control flows off the end of the coroutine body, which prompts the generator machinery to raise `StopIteration`, as usual.

A coroutine can be in one of four states. You can determine the current state using the `inspect.getgeneratorstate(…)` function, which returns one of these strings:

'GEN_CREATED'

Waiting to start execution.

'GEN_RUNNING'

Currently being executed by the interpreter.[2]

'GEN_SUSPENDED'

Currently suspended at a `yield` expression.

'GEN_CLOSED'

Execution has completed.

Because the argument to the `send` method will become the value of the pending `yield` expression, it follows that you can only make a call like `my_coro.send(42)` if the coroutine is currently suspended. But that's not the case if the coroutine has never been activated—when its state is `'GEN_CREATED'`. That's why the first activation of a coroutine is always done with `next(my_coro)`—you can also call `my_coro.send(None)`, and the effect is the same.

If you create a coroutine object and immediately try to send it a value that is not `None`, this is what happens:

```
>>> my_coro = simple_coroutine()
>>> my_coro.send(1729)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
TypeError: can't send non-None value to a just-started generator
```

Note the error message: it's quite clear.

The initial call `next(my_coro)` is often described as "priming" the coroutine (i.e., advancing it to the first `yield` to make it ready for use as a live coroutine).

To get a better feel for the behavior of a coroutine, an example that yields more than once is useful. See Example 19-2.

Example 19-2. A coroutine that yields twice

```
>>> def simple_coro2(a):
...     print('-> Started: a =', a)
...     b = yield a
...     print('-> Received: b =', b)
...     c = yield a + b
...     print('-> Received: c =', c)
...
>>> my_coro2 = simple_coro2(14)
>>> from inspect import getgeneratorstate
```

```
>>> getgeneratorstate(my_coro2)  ❶
'GEN_CREATED'
>>> next(my_coro2)  ❷
-> Started: a = 14
14
>>> getgeneratorstate(my_coro2)  ❸
'GEN_SUSPENDED'
>>> my_coro2.send(28)  ❹
-> Received: b = 28
42
>>> my_coro2.send(99)  ❺
-> Received: c = 99
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
StopIteration
>>> getgeneratorstate(my_coro2)  ❻
'GEN_CLOSED'
```

❶ `inspect.getgeneratorstate` reports `GEN_CREATED` (i.e., the coroutine has not started).

❷ Advance coroutine to first `yield`, printing `-> Started: a = 14` message then yielding value of `a` and suspending to wait for value to be assigned to `b`.

❸ `getgeneratorstate` reports `GEN_SUSPENDED` (i.e., the coroutine is paused at a `yield` expression).

❹ Send number `28` to suspended coroutine; the `yield` expression evaluates to `28` and that number is bound to `b`. The `-> Received: b = 28` message is displayed, the value of `a + b` is yielded (`42`), and the coroutine is suspended waiting for the value to be assigned to `c`.

❺ Send number `99` to suspended coroutine; the `yield` expression evaluates to `99` the number is bound to `c`. The `-> Received: c = 99` message is displayed, then the coroutine terminates, causing the generator object to raise `StopIteration`.

❻

`getgeneratorstate` reports `GEN_CLOSED` (i.e., the coroutine execution has completed).

It's crucial to understand that the execution of the coroutine is suspended exactly at the `yield` keyword. As mentioned before, in an assignment statement, the code to the right of the `=` is evaluated before the actual assignment happens. This means that in a line like `b = yield a`, the value of `b` will only be set when the coroutine is activated later by the client code. It takes some effort to get used to this fact, but understanding it is essential to make sense of the use of `yield` in asynchronous programming, as we'll see later.

Execution of the `simple_coro2` coroutine can be split in three phases, as shown in Figure 19-1:

1. `next(my_coro2)` prints first message and runs to yield `a`, yielding number `14`.

2. `my_coro2.send(28)` assigns `28` to `b`, prints second message, and runs to `yield a + b`, yielding number `42`.

3. `my_coro2.send(99)` assigns `99` to `c`, prints third message, and the coroutine terminates.

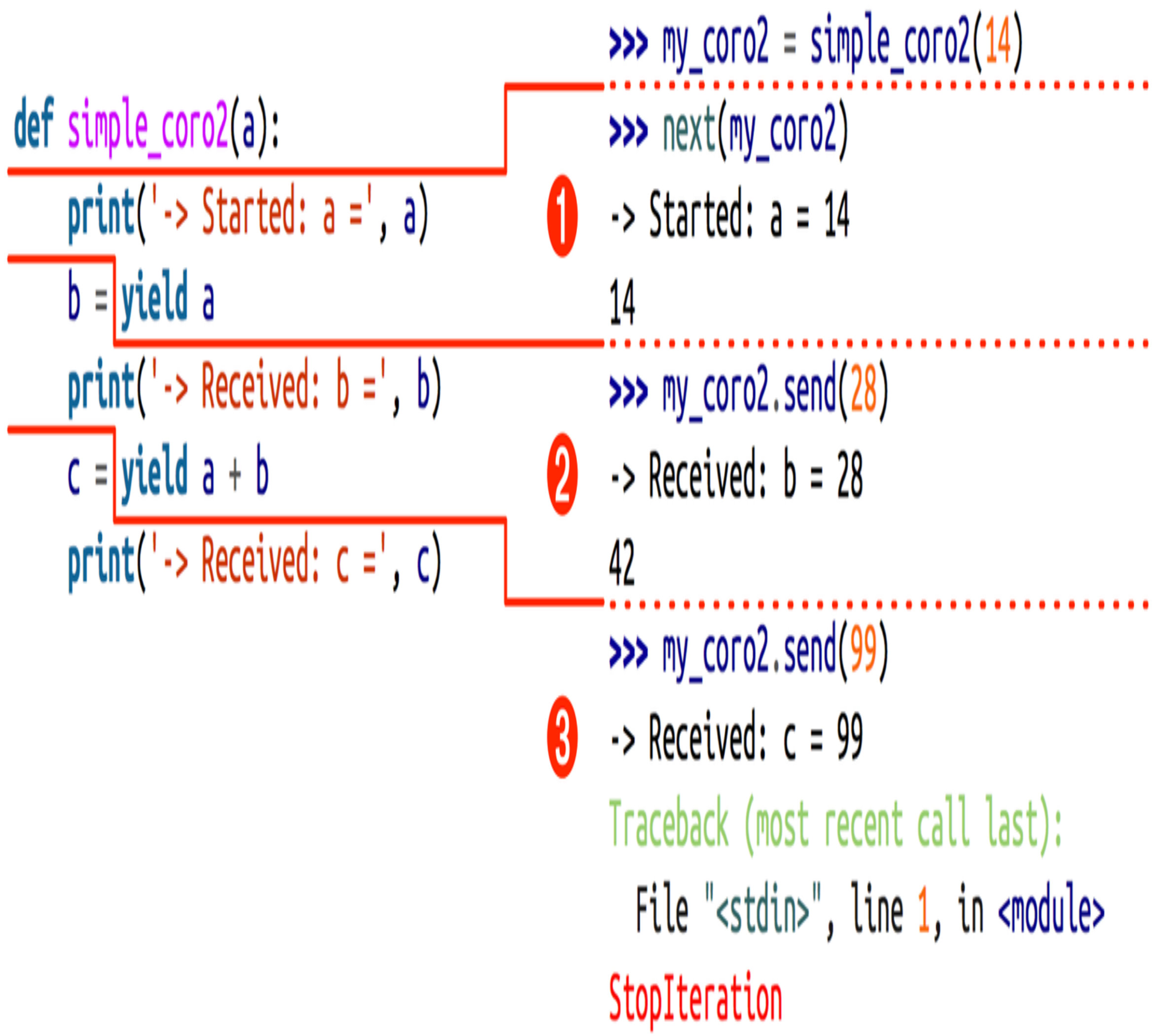


Figure 19-1. Three phases in the execution of the simple_coro2 coroutine (note that each phase ends in a yield expression, and the next phase starts in the very same line, when the value of the yield expression is assigned to a variable)

Now let’s consider a slightly more involved coroutine example.

Example: Coroutine to Compute a Running Average

While discussing closures in Chapter 9, we studied objects to compute a running average: Example 9-7 shows a plain class and Example 9-13 presents a higher-order function producing a closure to keep the `total` and count variables across invocations. Example 19-3 shows how to do the same with a coroutine.[3]

Example 19-3. coroaverager0.py: code for a running average coroutine

```
def averager():
    total = 0.0
    count = 0
    average = None
    while True:  ❶
        term = yield average  ❷
        total += term
        count += 1
        average = total/count
```

❶ This infinite loop means this coroutine will keep on accepting values and producing results as long as the caller sends them. This coroutine will only terminate when the caller calls `.close()` on it, or when it's garbage collected because there are no more references to it.

❷ The `yield` statement here suspends the coroutine, produces a result to the caller, and—later—gets a value sent by the caller to the coroutine, which resumes its infinite loop.

The advantage of using a coroutine is that `total` and `count` can be simple local variables: no instance attributes or closures are needed to keep the context between calls. Example 19-4 are doctests to show the `averager` coroutine in operation.

Example 19-4. coroaverager0.py: doctest for the running average coroutine in Example 19-3

```
    >>> coro_avg = averager()  ❶
    >>> next(coro_avg)  ❷
    >>> coro_avg.send(10)  ❸
    10.0
    >>> coro_avg.send(30)
    20.0
    >>> coro_avg.send(5)
    15.0
```

1. Create the coroutine object.

2. Prime it by calling `next`.

3. Now we are in business: each call to `.send(…)` yields the current average.

In the doctest (Example 19-4), the call `next(coro_avg)` makes the coroutine advance to the `yield`, yielding the initial value for `average`, which is `None`, so it does not appear on the console. At this point, the coroutine is suspended at the `yield`, waiting for a value to be sent. The line `coro_avg.send(10)` provides that value, causing the coroutine to activate, assigning it to `term`, updating the `total`, `count`, and `average` variables, and then starting another iteration in the `while` loop, which yields the `average` and waits for another term.

The attentive reader may be anxious to know how the execution of an `averager` instance (e.g., `coro_avg`) may be terminated, because its body is an infinite loop. We'll cover that in "Coroutine Termination and Exception Handling".

But before discussing coroutine termination, let's talk about getting them started. Priming a coroutine before use is a necessary but easy-to-forget chore. To avoid it, a special decorator can be applied to the coroutine. One such decorator is presented next.

Decorators for Coroutine Priming

You can't do much with a coroutine without priming it: we must always remember to call `next(my_coro)` before `my_coro.send(x)`. To make coroutine usage more convenient, a priming decorator is sometimes used. The `coroutine` decorator in Example 19-5 is an example.[4]

Example 19-5. coroutil.py: decorator for priming coroutine

```
from functools import wraps

def coroutine(func):
    """Decorator: primes `func` by advancing to first `yield`"""
    @wraps(func)
    def primer(*args, **kwargs):  ❶
        gen = func(*args, **kwargs)  ❷
        next(gen)  ❸
        return gen  ❹
    return primer
```

❶ The decorated generator function is replaced by this `primer` function which, when invoked, returns the primed generator.

❷ Call the decorated function to get a generator object.

❸ Prime the generator.

❹ Return it.

Example 19-6 shows the `@coroutine` decorator in use. Contrast with Example 19-3.

Example 19-6. coroaverager1.py: doctest and code for a running average coroutine using the @coroutine decorator from Example 19-5

```
"""
A coroutine to compute a running average

    >>> coro_avg = averager()  ❶
    >>> from inspect import getgeneratorstate
    >>> getgeneratorstate(coro_avg)  ❷
    'GEN_SUSPENDED'
    >>> coro_avg.send(10)  ❸
    10.0
    >>> coro_avg.send(30)
    20.0
    >>> coro_avg.send(5)
    15.0

"""

from coroutil import coroutine  ❹
```

```
@coroutine  ❺
def averager():  ❻
    total = 0.0
    count = 0
    average = None
    while True:
        term = yield average
        total += term
        count += 1
        average = total/count
```

❶ Call `averager()`, creating a generator object that is primed inside the `primer` function of the `coroutine` decorator.

❷ `getgeneratorstate` reports `GEN_SUSPENDED`, meaning that the coroutine is ready to receive a value.

❸ You can immediately start sending values to `coro_avg`: that's the point of the decorator.

❹ Import the `coroutine` decorator.

❺ Apply it to the `averager` function.

❻ The body of the function is exactly the same as Example 19-3.

Several frameworks provide special decorators designed to work with coroutines. Not all of them actually prime the coroutine—some provide other services, such as hooking it to an event loop. One example from the Tornado asynchronous networking library is the `tornado.gen` decorator.

The `yield from` syntax we'll see in "Using yield from" automatically primes the coroutine called by it, making it incompatible with decorators such as `@coroutine` from Example 19-5. The `asyncio.coroutine` decorator from the Python 3.4 standard library is designed to work with `yield from` so it does not prime the coroutine. We'll cover it in Chapter 22.

We’ll now focus on essential features of coroutines: the methods used to terminate and throw exceptions into them.

Coroutine Termination and Exception Handling

An unhandled exception within a coroutine propagates to the caller of the `next` or `send` that triggered it. Example 19-7 is an example using the decorated `averager` coroutine from Example 19-6.

Example 19-7. How an unhandled exception kills a coroutine

```
>>> from coroaverager1 import averager
>>> coro_avg = averager()
>>> coro_avg.send(40)  ❶
40.0
>>> coro_avg.send(50)
45.0
>>> coro_avg.send('spam')  ❷
Traceback (most recent call last):
  ...
TypeError: unsupported operand type(s) for +=: 'float' and 'str'
>>> coro_avg.send(60)  ❸
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
StopIteration
```

❶ Using the `@coroutine` decorated `averager` we can immediately start sending values.

❷ Sending a nonnumeric value causes an exception inside the coroutine.

❸ Because the exception was not handled in the coroutine, it terminated. Any attempt to reactivate it will raise `StopIteration`.

The cause of the error was the sending of a value `'spam'` that could not be added to the `total` variable in the coroutine.

Example 19-7 suggests one way of terminating coroutines: you can use `send` with some sentinel value that tells the coroutine to exit. Constant built-in singletons like `None` and `Ellipsis` are convenient sentinel values. `Ellipsis` has the advantage of being quite unusual in data streams. Another sentinel value I've seen used is `StopIteration`—the class itself, not an instance of it (and not raising it). In other words, using it like: `my_coro.send(StopIteration)`.

Since Python 2.5, generator objects have two methods that allow the client to explicitly send exceptions into the coroutine—`throw` and `close`:

`generator.throw(exc_type[, exc_value[, traceback]])`

> Causes the `yield` expression where the generator was paused to raise the exception given. If the exception is handled by the generator, flow advances to the next `yield`, and the value yielded becomes the value of the `generator.throw` call. If the exception is not handled by the generator, it propagates to the context of the caller.

`generator.close()`

> Causes the `yield` expression where the generator was paused to raise a `GeneratorExit` exception. No error is reported to the caller if the generator does not handle that exception or raises `StopIteration`—usually by running to completion. When receiving a `GeneratorExit`, the generator must not yield a value, otherwise a `RuntimeError` is raised. If any other exception is raised by the generator, it propagates to the caller.

> **TIP**
>
> The official documentation of the generator object methods is buried deep in *The Python Language Reference*, (see Generator-iterator methods).

Let's see how `close` and `throw` control a coroutine. Example 19-8 lists the `demo_exc_handling` function used in the following examples.

Example 19-8. coro_exc_demo.py: test code for studying exception handling in a coroutine

```
class DemoException(Exception):
    """An exception type for the demonstration."""

def demo_exc_handling():
    print('-> coroutine started')
    while True:
        try:
            x = yield
        except DemoException:  ❶
            print('*** DemoException handled. Continuing...')
        else:  ❷
            print(f'-> coroutine received: {x!r}')
    raise RuntimeError('This line should never run.')  ❸
```

❶ Special handling for `DemoException`.

❷ If no exception, display received value.

❸ This line will never be executed.

The last line in Example 19-8 is unreachable because the infinite loop can only be aborted with an unhandled exception, and that terminates the coroutine immediately.

Normal operation of `demo_exc_handling` is shown in Example 19-9.

Example 19-9. Activating and closing demo_exc_handling without an exception

```
    >>> exc_coro = demo_exc_handling()
    >>> next(exc_coro)
    -> coroutine started
    >>> exc_coro.send(11)
    -> coroutine received: 11
    >>> exc_coro.send(22)
    -> coroutine received: 22
    >>> exc_coro.close()
    >>> from inspect import getgeneratorstate
```

```
>>> getgeneratorstate(exc_coro)
'GEN_CLOSED'
```

If the `DemoException` is thrown into the coroutine, it's handled and the `demo_exc_handling` coroutine continues, as in Example 19-10.

Example 19-10. Throwing DemoException into demo_exc_handling does not break it

```
>>> exc_coro = demo_exc_handling()
>>> next(exc_coro)
-> coroutine started
>>> exc_coro.send(11)
-> coroutine received: 11
>>> exc_coro.throw(DemoException)
*** DemoException handled. Continuing...
>>> getgeneratorstate(exc_coro)
'GEN_SUSPENDED'
```

On the other hand, if an unhandled exception is thrown into the coroutine, it stops—its state becomes `'GEN_CLOSED'`. Example 19-11 demonstrates it.

Example 19-11. Coroutine terminates if it can't handle an exception thrown into it

```
>>> exc_coro = demo_exc_handling()
>>> next(exc_coro)
-> coroutine started
>>> exc_coro.send(11)
-> coroutine received: 11
>>> exc_coro.throw(ZeroDivisionError)
Traceback (most recent call last):
  ...
ZeroDivisionError
>>> getgeneratorstate(exc_coro)
'GEN_CLOSED'
```

If it's necessary that some cleanup code is run no matter how the coroutine ends, you need to wrap the relevant part of the coroutine body in a `try/finally` block, as in Example 19-12.

Example 19-12. coro_finally_demo.py: use of try/finally to perform actions on coroutine termination

```
class DemoException(Exception):
    """An exception type for the demonstration."""
```

```python
def demo_finally():
    print('-> coroutine started')
    try:
        while True:
            try:
                x = yield
            except DemoException:
                print('*** DemoException handled. Continuing...')
            else:
                print(f'-> coroutine received: {x!r}')
    finally:
        print('-> coroutine ending')
```

One of the main reasons why the `yield from` construct was added to Python 3.3 has to do with throwing exceptions into nested coroutines. The other reason was to enable coroutines to return values more conveniently. Read on to see how.

Returning a Value from a Coroutine

Example 19-13 shows a variation of the `averager` coroutine that returns a result. For didactic reasons, it does not yield the running average with each activation. This is to emphasize that some coroutines do not yield anything interesting, but are designed to return a value at the end, often the result of some accumulation.

The result returned by `averager` in Example 19-13 is a `namedtuple` with the number of terms averaged (`count`) and the `average`. I could have returned just the `average` value, but returning a tuple exposes another interesting piece of data that was accumulated: the `count` of terms.

Example 19-13. coroaverager2.py: code for an averager coroutine that returns a result

```python
from collections import namedtuple

Result = namedtuple('Result', 'count average')


def averager():
```

```
    total = 0.0
    count = 0
    average = None
    while True:
        term = yield
        if term is None:
            break  ❶
        total += term
        count += 1
        average = total/count
    return Result(count, average)  ❷
```

❶ In order to return a value, a coroutine must terminate normally; this is why this version of `averager` has a condition to break out of its accumulating loop.

❷ Return a `namedtuple` with the `count` and `average`. Before Python 3.3, it was a syntax error to return a value in a generator function.

To see how this new `averager` works, we can drive it from the console, as in Example 19-14.

Example 19-14. coroaverager2.py: doctest showing the behavior of averager

```
    >>> coro_avg = averager()
    >>> next(coro_avg)
    >>> coro_avg.send(10)  ❶
    >>> coro_avg.send(30)
    >>> coro_avg.send(6.5)
    >>> coro_avg.send(None)  ❷
    Traceback (most recent call last):
       ...
    StopIteration: Result(count=3, average=15.5)
```

❶ This version does not yield values.

❷ Sending `None` terminates the loop, causing the coroutine to end by returning the result. As usual, the generator object raises `StopIteration`. The `value` attribute of the exception carries the value returned.

Note that the value of the `return` expression is smuggled to the caller as an attribute of the `StopIteration` exception. This is a bit of a hack, but it preserves the existing behavior of generator objects: raising `StopIteration` when exhausted.

Example 19-15 shows how to retrieve the value returned by the coroutine.

Example 19-15. Catching StopIteration lets us get the value returned by averager

```
>>> coro_avg = averager()
>>> next(coro_avg)
>>> coro_avg.send(10)
>>> coro_avg.send(30)
>>> coro_avg.send(6.5)
>>> try:
...     coro_avg.send(None)
... except StopIteration as exc:
...     result = exc.value
...
>>> result
Result(count=3, average=15.5)
```

This roundabout way of getting the return value from a coroutine makes more sense when we realize it was defined as part of PEP 380, and the `yield from` construct handles it automatically by catching `StopIteration` internally. This is analogous to the use of `StopIteration` in `for` loops: the exception is handled by the loop machinery in a way that is transparent to the user. In the case of `yield from`, the interpreter not only consumes the `StopIteration`, but its `value` attribute becomes the value of the `yield from` expression itself. Unfortunately we can't test this interactively in the console, because it's a syntax error to use `yield from`—or `yield`, for that matter—outside of a function.[5]

The next section has an example where the `averager` coroutine is used with `yield from` to produce a result, as intended in PEP 380. So let's tackle `yield from`.

Using yield from

The first thing to know about `yield from` is that it is a completely new language construct. It does a lot more than `yield`. The newer `await` keyword is very similar to `yield from`, and its name conveys a crucial point: when a generator `gen` calls `yield from subgen()`, the `subgen` takes over and will yield values to the caller of `gen`; the caller will in effect drive `subgen` directly. Meanwhile `gen` will be blocked, waiting until `subgen` terminates.

However, `await` does not completely replace `yield from`. Each of them has its own use cases, and `await` is more strict about its context and target: `await` can only be used inside a native coroutine, and its target must be an *awaitable* object, which we will cover in Chapter 22. In contrast, `yield from` can be used in any function—which then becomes a generator—and its target can be any iterable. This super simple `yield from` example cannot be written with `async/await` syntax:

```
>>> def gen123():
...     yield from [1, 2, 3]
...
>>> tuple(gen123())
(1, 2, 3)
```

We've seen in Chapter 17 that `yield from` can be used as a shortcut to `yield` in a `for` loop. For example, this:

```
>>> def gen():
...     for c in 'AB':
...         yield c
...     for i in range(1, 3):
...         yield i
...
>>> list(gen())
['A', 'B', 1, 2]
```

Can be written as:

```
>>> def gen():
...     yield from 'AB'
...     yield from range(1, 3)
...
>>> list(gen())
['A', 'B', 1, 2]
```

When we first mentioned `yield from` in "Subgenerators with yield from", the code from Example 19-16 demonstrates a practical use for it—although the `itertools` module already provides an optimized `chain` generator written in C.

Example 19-16. Chaining iterables with yield from

```
>>> def chain(*iterables):
...     for it in iterables:
...         yield from it
...
>>> s = 'ABC'
>>> t = tuple(range(3))
>>> list(chain(s, t))
['A', 'B', 'C', 0, 1, 2]
```

Two slightly more complicated—but more useful—examples of `yield from` are the code in "Traversing a tree", and "Recipe 4.14. Flattening a Nested Sequence" in Beazley and Jones's *Python Cookbook, 3E* (source code available on GitHub).

The first thing the `yield from x` expression does with the `x` object is to call `iter(x)` to obtain an iterator from it. This means that `x` can be any iterable.

However, if replacing nested `for` loops yielding values was the only contribution of `yield from`, this language addition wouldn't have had a good chance of being accepted. The real nature of `yield from` cannot be demonstrated with simple iterables; it requires the mind-expanding use of nested generators. That's why PEP 380, which introduced `yield from`, is titled *Syntax for Delegating to a Subgenerator*.

The main feature of `yield from` is to open a bidirectional channel from the outermost caller to the innermost subgenerator, so that values can be sent and yielded back and forth directly from them, and exceptions can be thrown all the way in without adding a lot of exception handling boilerplate code in the intermediate coroutines. This is what enables coroutine delegation in a way that was not possible before.

The use of `yield from` requires a nontrivial arrangement of code. To talk about the required moving parts, PEP 380 uses some terms in a very specific way:

delegating generator

The generator function that contains the `yield from <iterable>` expression.

subgenerator

The generator obtained from the `<iterable>` part of the `yield from` expression. This is the "subgenerator" mentioned in the title of PEP 380: "Syntax for Delegating to a Subgenerator."

caller

PEP 380 uses the term "caller" to refer to the client code that calls the delegating generator. Depending on context, I use "client" instead of "caller," to distinguish from the delegating generator, which is also a "caller" (it calls the subgenerator).

> **TIP**
>
> PEP 380 often uses the word "iterator" to refer to the subgenerator. That's confusing because the delegating generator is also an iterator. So I prefer to use the term subgenerator, in line with the title of the PEP—"Syntax for Delegating to a Subgenerator." However, the subgenerator can be a simple iterator implementing only `__next__`, and `yield from` can handle that too, although it was created to support generators implementing `__next__`, `send`, `close`, and `throw`.

Example 19-17 provides more context to see `yield from` at work, and Figure 19-2 identifies the relevant parts of the example.[6]

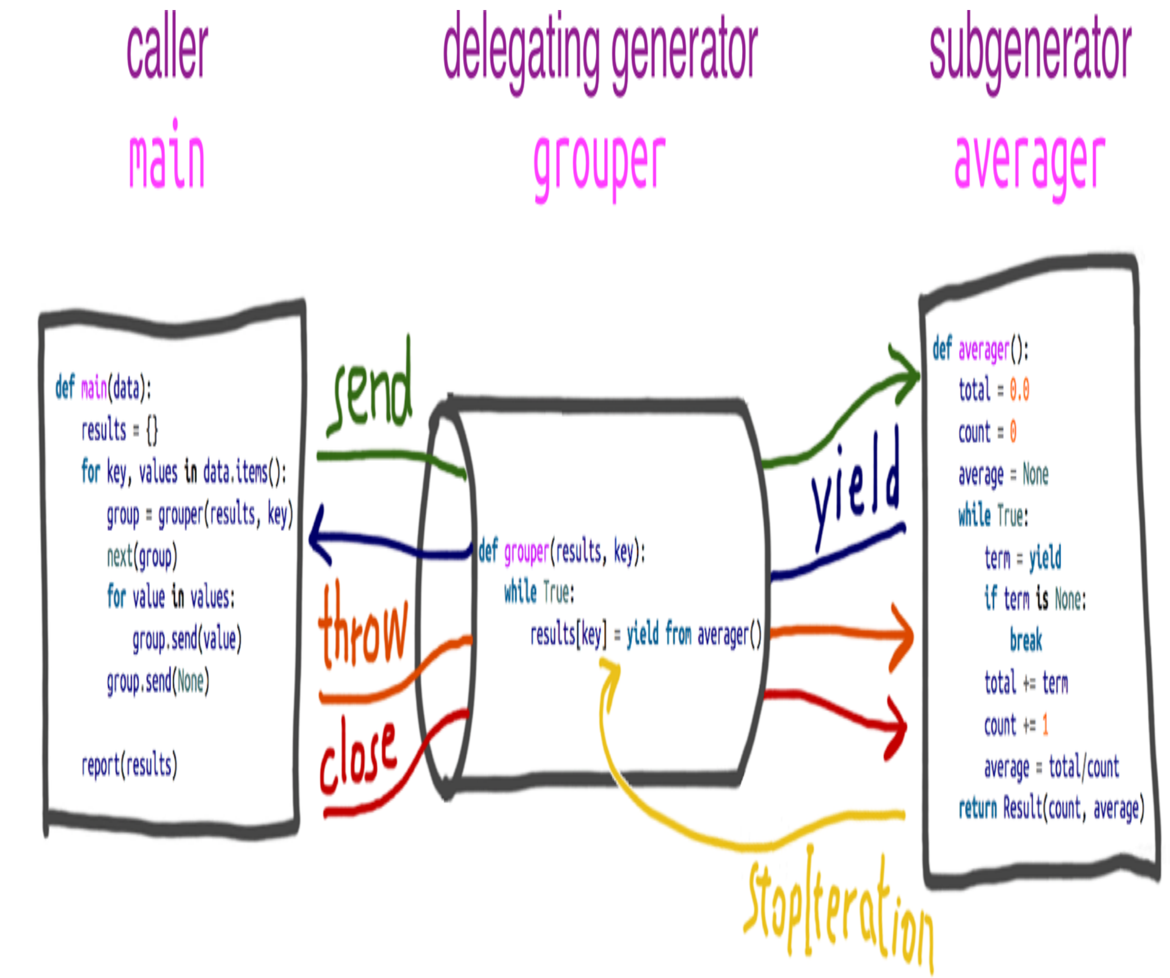


Figure 19-2. While the delegating generator is suspended at yield from, the caller sends data directly to the subgenerator, which yields data back to the caller. The delegating generator resumes when the subgenerator returns and the interpreter raises StopIteration with the returned value attached.

The *coroaverager3.py* script reads a `dict` with weights and heights from girls and boys in an imaginary seventh grade class. For example, the key `'boys;m'` maps to the heights of 9 boys, in meters; `'girls;kg'` are the weights of 10 girls in kilograms. The script feeds the data for each group into the `averager` coroutine we've seen before, and produces a report like this one:

```
$ python3 coroaverager3.py
 9 boys  averaging 40.42kg
 9 boys  averaging 1.39m
10 girls averaging 42.04kg
10 girls averaging 1.43m
```

The code in Example 19-17 is certainly not the most straightforward solution to the problem, but it serves to show `yield from` in action. This example is inspired by the one given in What’s New in Python 3.3.

Example 19-17. coroaverager3.py: using yield from to drive averager and report statistics

```
from collections import namedtuple

Result = namedtuple('Result', 'count average')


# the subgenerator
def averager():  ❶
    total = 0.0
    count = 0
    average = None
    while True:
        term = yield  ❷
        if term is None:  ❸
            break
        total += term
        count += 1
        average = total/count
    return Result(count, average)  ❹


# the delegating generator
def grouper(results, key):  ❺
    while True:  ❻
        results[key] = yield from averager()  ❼


# the client code, a.k.a. the caller
def main(data):  ❽
    results = {}
    for key, values in data.items():
        group = grouper(results, key)  ❾
        next(group)  ❿
        for value in values:
            group.send(value)  ⓫
        group.send(None)  # important! ⓬

    # print(results)  # uncomment to debug
    report(results)
```

```python
# output report
def report(results):
    for key, result in sorted(results.items()):
        group, unit = key.split(';')
        print(f'{result.count:2} {group:5}',
              f'averaging {result.average:.2f}{unit}')


data = {
    'girls;kg':
        [40.9, 38.5, 44.3, 42.2, 45.2, 41.7, 44.5, 38.0, 40.6,
44.5],
    'girls;m':
        [1.6, 1.51, 1.4, 1.3, 1.41, 1.39, 1.33, 1.46, 1.45, 1.43],
    'boys;kg':
        [39.0, 40.8, 43.2, 40.8, 43.1, 38.6, 41.4, 40.6, 36.3],
    'boys;m':
        [1.38, 1.5, 1.32, 1.25, 1.37, 1.48, 1.25, 1.49, 1.46],
}


if __name__ == '__main__':
    main(data)
```

❶ Same `averager` coroutine from Example 19-13. Here it is the subgenerator.

❷ Each value sent by the client code in `main` will be bound to `term` here.

❸ The crucial terminating condition. Without it, a `yield from` calling this coroutine will block forever.

❹ The returned `Result` will be the value of the `yield from` expression in `grouper`.

❺ `grouper` is the delegating generator.

❻ Each iteration in this loop creates a new instance of `averager`; each is a generator object operating as a coroutine.

❼

Whenever `grouper` is sent a value, it’s piped into the `averager` instance by the `yield from`. `grouper` will be suspended here as long as the `averager` instance is consuming values sent by the client. When an `averager` instance runs to the end, the value it returns is bound to `results[key]`. The `while` loop then proceeds to create another `averager` instance to consume more values.

❽ `main` is the client code, or “caller” in PEP 380 parlance. This is the function that drives everything.

❾ `group` is a generator object resulting from calling `grouper` with the `results` `dict` to collect the results, and a particular `key`. It will operate as a coroutine.

❿ Prime the coroutine.

⓫ Send each `value` into the `grouper`. That value ends up in the `term = yield` line of `averager`; `grouper` never has a chance to see it.

⓬ Sending `None` into `grouper` causes the current `averager` instance to terminate, and allows `grouper` to run again, which creates another `averager` for the next group of values.

The last callout in Example 19-17 with the comment `"important!"` highlights a crucial line of code: `group.send(None)`, which terminates one `averager` and starts the next. If you comment out that line, the script produces no output. Uncommenting the `print(results)` line near the end of `main` reveals that the `results` `dict` ends up empty.

> **NOTE**
>
> If you want to figure out for yourself why no results are collected, it will be a great way to exercise your understanding of how `yield from` works. The code for *coroaverager3.py* is in the Fluent Python code repository. The explanation is next.

Here is an overview of how Example 19-17 works, explaining what would happen if we omitted the call `group.send(None)` marked “important!” in `main`:

- Each iteration of the outer `for` loop creates a new `grouper` instance named `group`; this is the delegating generator.
- The call `next(group)` primes the `grouper` delegating generator, which enters its `while True` loop and suspends at the `yield from`, after calling the subgenerator `averager`.
- The inner `for` loop calls `group.send(value)`; this feeds the subgenerator `averager` directly. Meanwhile, the current `group` instance of `grouper` is suspended at the `yield from`.
- When the inner `for` loop ends, the `group` instance is still suspended at the `yield from`, so the assignment to `results[key]` in the body of `grouper` has not happened yet.
- Without the last `group.send(None)` in the outer `for` loop, the `averager` subgenerator never terminates, the delegating generator `group` is never reactivated, and the assignment to `results[key]` never happens.
- When execution loops back to the top of the outer `for` loop, a new `grouper` instance is created and bound to `group`. The previous `grouper` instance is garbage collected (together with its own unfinished `averager` subgenerator instance).

WARNING

The key takeaway from this experiment is: if a subgenerator never terminates, the delegating generator will be suspended forever at the `yield from`. This will not prevent your program from making progress because the `yield from` (like the simple `yield`) transfers control to the client code (i.e., the caller of the delegating generator). But it does mean that some task will be left unfinished.

Pipelines of coroutines

Example 19-17 demonstrates the simplest arrangement of `yield from`, with only one delegating generator and one subgenerator. Because the delegating generator works as a pipe, you can connect any number of them in a pipeline: one delegating generator uses `yield from` to call a subgenerator, which itself is a delegating generator calling another subgenerator with `yield from`, and so on. Eventually this chain must end in a simple generator that uses just `yield`, but it may also end in any iterable object, as in Example 19-16.

Every `yield from` chain must be driven by a client that calls `next(…)` or `.send(…)` on the outermost delegating generator. This call may be implicit, such as a `for` loop.

Now let's review the formal description of the `yield from` construct, as presented in PEP 380.

The Meaning of yield from

> **NOTE**
>
> This is one of the most challenging sections in the book. You may wonder whether it is worth your attention, given that most uses of `yield from` are in legacy asynchronous programming code, where it is now preferable to use `await` instead. But if you really want to understand how `async/wait` works under the hood, you need to understand `yield from`. The underlying machinery is the same. PEP 492–Coroutines with async and await syntax states that `await` "uses the `yield from` implementation with an extra step of validating its argument".[7] PEP 492 also assumes understanding of PEP 380, and does not go into the same level of detail about the behavior of `yield from` or `await`.

While developing PEP 380, Greg Ewing—the PEP author—was questioned about the complexity of the proposed semantics. One of his answers was "For humans, almost all the important information is contained in one paragraph near the top.” He then quoted part of the draft of PEP 380 which at the time read as follows:

> *“When the iterator is another generator, the effect is the same as if the body of the subgenerator were inlined at the point of the* `yield from` *expression. Furthermore, the subgenerator is allowed to execute a* `return` *statement with a value, and that value becomes the value of the* `yield from` *expression.”*[8]

Those soothing words are no longer part of the PEP—because they don’t cover all the corner cases. But they are OK as a first approximation.

We will tackle our study of `yield from` in two steps: first, its basic behavior, which covers many use cases. After that, we’ll see what happens when the subgenerator is terminated before it runs to completion, as well as other exceptional execution paths.

Basic behavior of yield from

The approved version of PEP 380 explains the behavior of `yield from` in six points in the Proposal section. Here I reproduce them almost exactly, except that I replaced every occurrence of the ambiguous word “iterator” with “subgenerator” and added a few clarifications. Let’s start with the four points that are illustrated by `coroaverager3.py` in Example 19-17:

- Any values that the subgenerator yields are passed directly to the caller of the delegating generator (i.e., the client code).
- Any values sent to the delegating generator using `send()` are passed directly to the subgenerator. If the sent value is `None`, the subgenerator’s `__next__()` method is called. If the sent value is not `None`, the subgenerator’s `send()` method is called. If the call raises `StopIteration`, the delegating generator is resumed. Any other exception is propagated to the delegating generator.
- `return expr` in a generator (or subgenerator) causes `StopIteration(expr)` to be raised upon exit from the

generator.

- The value of the `yield from` expression is the first argument to the `StopIteration` exception raised by the subgenerator when it terminates.

The other two points about `yield from` in PEP 380 have to do with exceptions and termination. We'll see them in "Exception handling in yield from". For now, let's study on the behaviour of `yield from` under "normal" operating conditions.

The detailed semantics of `yield from` are subtle. Greg Ewing did a great job putting them to words in English in PEP 380.

Ewing also documented the behavior of `yield from` using pseudocode (with Python syntax). I personally found it useful to spend some time studying the pseudocode in PEP 380. However, the pseudocode is 40 lines long and not easy to grasp at first.

A good way to approach that pseudocode is to simplify it to handle only the most basic and common uses of `yield from`.

Consider that `yield from` appears in a delegating generator. The client code drives the delegating generator, which drives the subgenerator. So, to simplify the logic involved, let's assume the client doesn't ever call `.throw(…)` or `.close()` on the delegating generator. Let's also assume the subgenerator never raises an exception until it terminates, when `StopIteration` is raised by the interpreter.

The `coroaverager3.py` script in Example 19-17 is an example where those simplifying assumptions hold. In fact, often the delegating generator is expected to run to completion. So let's see how `yield from` works in this happier, simpler world.

Take a look at Example 19-18, which is an expansion of this single statement, in the body of the delegating generator:

```
RESULT = yield from EXPR
```

Try to follow the logic in Example 19-18.

Example 19-18. Simplified pseudocode equivalent to the statement RESULT = yield from EXPR in the delegating generator (this covers the simplest case: .throw(…) and .close() are not supported; the only exception handled is StopIteration)

```
_i = iter(EXPR)  ❶
try:
    _y = next(_i)  ❷
except StopIteration as _e:
    _r = _e.value  ❸
else:
    while 1:  ❹
        _s = yield _y  ❺
        try:
            _y = _i.send(_s)  ❻
        except StopIteration as _e:  ❼
            _r = _e.value
            break

RESULT = _r  ❽
```

❶ The `EXPR` can be any iterable, because `iter()` is applied to get an iterator `_i` (this is the subgenerator).

❷ The subgenerator is primed; the result is stored to be the first yielded value `_y`.

❸ If `StopIteration` was raised, extract the `value` attribute from the exception and assign it to `_r`: this is the `RESULT` in the simplest case.

❹ While this loop is running, the delegating generator is blocked, operating just as a channel between the caller and the subgenerator.

❺ Yield the current item yielded from the subgenerator; wait for a value `_s` sent by the caller. Note that this is the only `yield` in this listing.

❻ Try to advance the subgenerator, forwarding the `_s` sent by the caller.

❼

If the subgenerator raised `StopIteration`, get the `value`, assign to `_r`, and exit the loop, resuming the delegating generator.

❽ `_r` is the `RESULT`: the value of the whole `yield from` expression.

In this simplified pseudocode, I preserved the variable names used in the pseudocode published in PEP 380. The variables are:

`_i` *(iterator)*

The subgenerator

`_y` *(yielded)*

A value yielded from the subgenerator

`_r` *(result)*

The eventual result (i.e., the value of the `yield from` expression when the subgenerator ends)

`_s` *(sent)*

A value sent by the caller to the delegating generator, which is forwarded to the subgenerator

`_e` *(exception)*

An exception (always an instance of `StopIteration` in this simplified pseudocode)

Besides not handling `.throw(…)` and `.close()`, the simplified pseudocode always uses `.send(…)` to forward `next()` or `.send(…)` calls by the client to the subgenerator. Don’t worry about these fine distinctions on a first reading. As mentioned, `coroaverager3.py` in Example 19-17 would run perfectly well if the `yield from` did only what is shown in the simplified pseudocode in Example 19-18.

The next section covers the behavior of `yield from` when the subgenerator ends prematurely, either because the client cancels it, or an unhandled exception is raised.

Exception handling in yield from

In "Basic behavior of yield from" we saw the first four points about `yield from` behavior from PEP 380, and pseudo-code describing that behavior. But the reality is more complicated, because of the need to handle `.throw(…)` and `.close()` calls from the client, which must be passed into the subgenerator. Here are the other points of the PEP 380 Proposal section, slightly edited:

- Exceptions other than `GeneratorExit` thrown into the delegating generator are passed to the `throw()` method of the subgenerator. If the call raises `StopIteration`, the delegating generator is resumed. Any other exception is propagated to the delegating generator.

- If a `GeneratorExit` exception is thrown into the delegating generator, or the `close()` method of the delegating generator is called, then the `close()` method of the subgenerator is called if it has one. If this call results in an exception, it is propagated to the delegating generator. Otherwise, `GeneratorExit` is raised in the delegating generator.

Also, the subgenerator may be a plain iterator that does not support `.throw(…)` or `.close()`, so this must be handled by the `yield from` logic. If the subgenerator does implement those methods, inside the subgenerator both methods cause exceptions to be raised, which must be handled by the `yield from` machinery as well. The subgenerator may also throw exceptions of its own, unprovoked by the caller, and this must also be dealt with in the `yield from` implementation. Finally, as an optimization, if the caller calls `next(…)` or `.send(None)`, both are forwarded as a `next(…)` call on the subgenerator; only if the caller sends a non-`None` value, the `.send(…)` method of the subgenerator is used.

For your convenience, I present here the complete pseudocode of the `yield from` expansion from PEP 380, with numbered annotations. Example 19-19 was copied verbatim; I only added the callout numbers.

Most of the logic of the `yield from` pseudocode is implemented in six `try/except` blocks nested up to four levels deep, so it's a bit hard to read. The only other control flow keywords used are one `while`, one `if`, and one `yield`. Find the `while`, the `yield`, the `next(…)`, and the `.send(…)` calls: they will help you get an idea of how the whole structure works.

Remember that all the code shown in Example 19-19 is an expansion of this single statement, in the body of a delegating generator:

```
RESULT = yield from EXPR
```

Example 19-19. Pseudocode equivalent to the statement RESULT = yield from EXPR in the delegating generator

```
_i = iter(EXPR)  ❶
try:
    _y = next(_i)  ❷
except StopIteration as _e:
    _r = _e.value  ❸
else:
    while 1:  ❹
        try:
            _s = yield _y  ❺
        except GeneratorExit as _e:  ❻
            try:
                _m = _i.close
            except AttributeError:
                pass
            else:
                _m()
            raise _e
        except BaseException as _e:  ❼
            _x = sys.exc_info()
            try:
                _m = _i.throw
```

```
                except AttributeError:
                    raise _e
                else:  ❽
                    try:
                        _y = _m(*_x)
                    except StopIteration as _e:
                        _r = _e.value
                        break
            else:  ❾
                try:  ❿
                    if _s is None:  ⓫
                        _y = next(_i)
                    else:
                        _y = _i.send(_s)
                except StopIteration as _e:  ⓬
                    _r = _e.value
                    break

RESULT = _r  ⓭
```

❶ The `EXPR` can be any iterable, because `iter()` is applied to get an iterator `_i` (this is the subgenerator).

❷ The subgenerator is primed; the result is stored to be the first yielded value `_y`.

❸ If `StopIteration` was raised, extract the `value` attribute from the exception and assign it to `_r`: this is the `RESULT` in the simplest case.

❹ While this loop is running, the delegating generator is blocked, operating just as a channel between the caller and the subgenerator.

❺ Yield the current item yielded from the subgenerator; wait for a value `_s` sent by the caller. This is the only `yield` in this listing.

❻ This deals with closing the delegating generator and the subgenerator. Because the subgenerator can be any iterator, it may not have a `close` method.

❼

This deals with exceptions thrown in by the caller using `.throw(…)`. Again, the subgenerator may be an iterator with no `throw` method to be called—in which case the exception is raised in the delegating generator.

❽ If the subgenerator has a `throw` method, call it with the exception passed from the caller. The subgenerator may handle the exception (and the loop continues); it may raise `StopIteration` (the `_r` result is extracted from it, and the loop ends); or it may raise the same or another exception, which is not handled here and propagates to the delegating generator.

❾ If no exception was received when yielding…

❿ Try to advance the subgenerator…

⓫ Call `next` on the subgenerator if the last value received from the caller was `None`, otherwise call `send`.

⓬ If the subgenerator raised `StopIteration`, get the `value`, assign to `_r`, and exit the loop, resuming the delegating generator.

⓭ `_r` is the `RESULT`: the value of the whole `yield from` expression.

Right at the top of Example 19-19, one important detail revealed by the pseudocode is that the subgenerator is primed (second callout in Example 19-19).[9] This means that auto-priming decorators such as that in "Decorators for Coroutine Priming" are incompatible with `yield from`.

In the same message I quoted in the opening of this section, Greg Ewing has this to say about the pseudocode expansion of `yield from`:

> *You're not meant to learn about it by reading the expansion—that's only there to pin down all the details for language lawyers.*

Focusing on the details of the pseudocode expansion may not be helpful—depending on your learning style. Studying real code that uses `yield from` is certainly more profitable than poring over the pseudocode of its implementation. However, almost all the `yield from` examples I've seen are tied to asynchronous programming with the `asyncio` module, so they depend on an active event loop to work—and most such code now uses `await` instead of `yield from`. There are a few links in "Further Reading" to interesting code using `yield from` without an event loop.

We'll now move on to a classic example of coroutine usage: programming simulations. This example does not showcase `yield from`, but it does reveal how coroutines are used to manage concurrent activities on a single thread.

Use Case: Coroutines for Discrete Event Simulation

> *Coroutines are a natural way of expressing many algorithms, such as simulations, games, asynchronous I/O, and other forms of event-driven programming or co-operative multitasking.*[10]
>
> —Guido van Rossum and Phillip J. Eby, PEP 342—Coroutines via Enhanced Generators

In this section, I will describe a very simple simulation implemented using just coroutines and standard library objects. Simulation is a classic application of coroutines in the computer science literature. Simula, the first OO language, introduced the concept of coroutines precisely to support simulations.

> **NOTE**
>
> The motivation for the following simulation example is not academic. Coroutines are the fundamental building block of the `asyncio` package. A simulation shows how to implement concurrent activities using coroutines instead of threads—and this will greatly help when we tackle `asyncio` in Chapter 22.

Before going into the example, a word about simulations.

About Discrete Event Simulations

A discrete event simulation (DES) is a type of simulation where a system is modeled as a sequence of events. In a DES, the simulation “clock” does not advance by fixed increments, but advances directly to the simulated time of the next modeled event. For example, if we are simulating the operation of a taxi cab from a high-level perspective, one event is picking up a passenger, the next is dropping the passenger off. It doesn’t matter if a trip takes 5 or 50 minutes: when the drop off event happens, the clock is updated to the end time of the trip in a single operation. In a DES, we can simulate a year of cab trips in less than a second. This is in contrast to a continuous simulation where the clock advances continuously by a fixed—and usually small—increment.

Intuitively, turn-based games are examples of discrete event simulations: the state of the game only changes when a player moves, and while a player is deciding the next move, the simulation clock is frozen. Real-time games, on the other hand, are continuous simulations where the simulation clock is running all the time, the state of the game is updated many times per second, and slow players are at a real disadvantage.

Both types of simulations can be written with multiple threads or a single thread using event-oriented programming techniques such as callbacks or coroutines driven by an event loop. It’s arguably more natural to implement a continuous simulation using threads to account for actions happening in parallel in real time. On the other hand, coroutines offer exactly the right abstraction for writing a DES. SimPy[11] is a DES package for Python that uses one coroutine to represent each process in the simulation.

> **TIP**
>
> In the field of simulation, the term *process* refers to the activities of an entity in the model, and not to an OS process. A simulation process may be implemented as an OS process, but usually a thread or a coroutine is used for that purpose.

If you are interested in simulations, SimPy is well worth studying. However, in this section, I will describe a very simple DES implemented using only standard library features. My goal is to help you develop an intuition about programming concurrent actions with coroutines. Understanding the next section will require careful study, but the reward will come as insights on how libraries such as `asyncio`, Twisted, and Tornado can manage many concurrent activities using a single thread of execution.

The Taxi Fleet Simulation

In our simulation program, *taxi_sim.py*, a number of taxi cabs are created. Each will make a fixed number of trips and then go home. A taxi leaves the garage and starts "prowling"—looking for a passenger. This lasts until a passenger is picked up, and a trip starts. When the passenger is dropped off, the taxi goes back to prowling.

The time elapsed during prowls and trips is generated using an exponential distribution. For a cleaner display, times are in whole minutes, but the simulation would work as well using `float` intervals.[12] Each change of state in each cab is reported as an event. Figure 19-3 shows a sample run of the program.

The most important thing to note in Figure 19-3 is the interleaving of the trips by the three taxis. I manually added the arrows to make it easier to see the taxi trips: each arrow starts when a passenger is picked up and ends when the passenger is dropped off. Intuitively, this demonstrates how coroutines can be used for managing concurrent activities.

Other things to note about Figure 19-3:

- Each taxi leaves the garage 5 minutes after the other.
- It took 2 minutes for taxi 0 to pick up the first passenger at `time=2`; 3 minutes for taxi 1 (`time=8`), and 5 minutes for taxi 2 (`time=15`).
- The cabbie in taxi 0 only makes two trips (purple arrows): the first starts at `time=2` and ends at `time=18`; the second starts at `time=28` and ends at `time=65`—the longest trip in this simulation run.
- Taxi 1 makes four trips (green arrows) then goes home at `time=110`.
- Taxi 2 makes six trips (red arrows) then goes home at `time=109`. His last trip lasts only one minute, starting at `time=97`.[13]
- While taxi 1 is making her first trip, starting at `time=8`, taxi 2 leaves the garage at `time=10` and completes two trips (short red arrows).
- In this sample run, all scheduled events completed in the default simulation time of 180 minutes; last event was at `time=110`.

```
$ python3 taxi_sim.py -s 3
taxi: 0  Event(time=0, proc=0, action='leave garage')
taxi: 0  Event(time=2, proc=0, action='pick up passenger')
taxi: 1     Event(time=5, proc=1, action='leave garage')
taxi: 1     Event(time=8, proc=1, action='pick up passenger')
taxi: 2        Event(time=10, proc=2, action='leave garage')
taxi: 2        Event(time=15, proc=2, action='pick up passenger')
taxi: 2        Event(time=17, proc=2, action='drop off passenger')
taxi: 0  Event(time=18, proc=0, action='drop off passenger')
taxi: 2        Event(time=18, proc=2, action='pick up passenger')
taxi: 2        Event(time=25, proc=2, action='drop off passenger')
taxi: 1     Event(time=27, proc=1, action='drop off passenger')
taxi: 2        Event(time=27, proc=2, action='pick up passenger')
taxi: 0  Event(time=28, proc=0, action='pick up passenger')
taxi: 2        Event(time=40, proc=2, action='drop off passenger')
taxi: 2        Event(time=44, proc=2, action='pick up passenger')
taxi: 1     Event(time=55, proc=1, action='pick up passenger')
taxi: 1     Event(time=59, proc=1, action='drop off passenger')
taxi: 0  Event(time=65, proc=0, action='drop off passenger')
taxi: 1     Event(time=65, proc=1, action='pick up passenger')
taxi: 2        Event(time=65, proc=2, action='drop off passenger')
taxi: 2        Event(time=72, proc=2, action='pick up passenger')
taxi: 0  Event(time=76, proc=0, action='going home')
taxi: 1     Event(time=80, proc=1, action='drop off passenger')
taxi: 1     Event(time=88, proc=1, action='pick up passenger')
taxi: 2        Event(time=95, proc=2, action='drop off passenger')
taxi: 2        Event(time=97, proc=2, action='pick up passenger')
taxi: 2        Event(time=98, proc=2, action='drop off passenger')
taxi: 1     Event(time=106, proc=1, action='drop off passenger')
taxi: 2        Event(time=109, proc=2, action='going home')
taxi: 1     Event(time=110, proc=1, action='going home')
*** end of events ***
```

Figure 19-3. Sample run of taxi_sim.py with three taxis. The -s 3 argument sets the random generator seed so program runs can be reproduced for debugging and demonstration. Colored arrows highlight taxi trips.

The simulation may also end with pending events. When that happens, the final message reads like this:

```
*** end of simulation time: 3 events pending ***
```

The full listing of *taxi_sim.py* is at [Link to Come]. In this chapter, we'll show only the parts that are relevant to our study of coroutines. The really important functions are only two: `taxi_process` (a coroutine), and the `Simulator.run` method where the main loop of the simulation is executed.

Example 19-20 shows the code for `taxi_process`. This coroutine uses two objects defined elsewhere: the `compute_delay` function, which returns a time interval in minutes, and the `Event` class, a named tuple defined like this:

```
Event = collections.namedtuple('Event', 'time proc action')
```

In an `Event` instance, `time` is the simulation time when the event will occur, `proc` is the identifier of the taxi process instance, and `action` is a string describing the activity.

Let's review `taxi_process` play by play in Example 19-20.

Example 19-20. taxi_sim.py: taxi_process coroutine that implements the activities of each taxi

```
def taxi_process(ident, trips, start_time=0):  ❶
    """Yield to simulator issuing event at each state change"""
    time = yield Event(start_time, ident, 'leave garage')  ❷
    for i in range(trips):  ❸
        time = yield Event(time, ident, 'pick up passenger')  ❹
        time = yield Event(time, ident, 'drop off passenger')  ❺

    yield Event(time, ident, 'going home')  ❻
    # end of taxi process ❼
```

❶ `taxi_process` will be called once per taxi, creating a generator object to represent its operations. `ident` is the number of the taxi (e.g., 0, 1, 2 in the sample run); `trips` is the number of trips this taxi will make before going home; `start_time` is when the taxi leaves the garage.

❷ The first `Event` yielded is `'leave garage'`. This suspends the coroutine, and lets the simulation main loop proceed to the next scheduled event. When it's time to reactivate this process, the main loop will `send` the current simulation time, which is assigned to `time`.

❸ This block will be repeated once for each trip.

❹ An `Event` signaling passenger pick up is yielded. The coroutine pauses here. When the time comes to reactivate this coroutine, the main loop will again `send` the current time.

❺ An `Event` signaling passenger drop off is yielded. The coroutine is suspended again, waiting for the main loop to send it the time of when it's reactivated.

❻ The `for` loop ends after the given number of trips, and a final `'going home'` event is yielded. The coroutine will suspend for the last time. When reactivated, it will be sent the time from the simulation main loop, but here I don't assign it to any variable because it will not be used.

❼ When the coroutine falls off the end, the generator object raises `StopIteration`.

You can "drive" a taxi yourself by calling `taxi_process` in the Python console.[14] Example 19-21 shows how.

Example 19-21. Driving the taxi_process coroutine

```
>>> from taxi_sim import taxi_process
>>> taxi = taxi_process(ident=13, trips=2, start_time=0)  ❶
>>> next(taxi)  ❷
Event(time=0, proc=13, action='leave garage')
>>> taxi.send(_.time + 7)  ❸
Event(time=7, proc=13, action='pick up passenger')  ❹
>>> taxi.send(_.time + 23)  ❺
Event(time=30, proc=13, action='drop off passenger')
>>> taxi.send(_.time + 5)  ❻
Event(time=35, proc=13, action='pick up passenger')
>>> taxi.send(_.time + 48)  ❼
Event(time=83, proc=13, action='drop off passenger')
>>> taxi.send(_.time + 1)
Event(time=84, proc=13, action='going home')  ❽
>>> taxi.send(_.time + 10)  ❾
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
StopIteration
```

❶ Create a generator object to represent a taxi with `ident=13` that will make two trips and start working at `t=0`.

❷ Prime the coroutine; it yields the initial event.

❸ We can now `send` it the current time. In the console, the _ variable is bound to the last result; here I add `7` to the time, which means the `taxi` will spend 7 minutes searching for the first passenger.

❹ This is yielded by the `for` loop at the start of the first trip.

❺ Sending `_.time + 23` means the trip with the first passenger will last 23 minutes.

❻ Then the `taxi` will prowl for 5 minutes.

❼ The last trip will take 48 minutes.

❽ After two complete trips, the loop ends and the `'going home'` event is yielded.

❾ The next attempt to `send` to the coroutine causes it to fall through the end. When it returns, the interpreter raises `StopIteration`.

Note that in Example 19-21 I am using the console to emulate the simulation main loop. I get the `.time` attribute of an `Event` yielded by the `taxi` coroutine, add an arbitrary number, and use the sum in the next `taxi.send` call to reactivate it. In the simulation, the taxi coroutines are driven by the main loop in the `Simulator.run` method. The simulation "clock" is held in the `sim_time` variable, and is updated by the time of each event yielded.

To instantiate the `Simulator` class, the `main` function of *taxi_sim.py* builds a `taxis` dictionary like this:

```
    taxis = {i: taxi_process(i, (i + 1) * 2, i * 
DEPARTURE_INTERVAL)
             for i in range(num_taxis)}
    sim = Simulator(taxis)
```

`DEPARTURE_INTERVAL` is 5; if `num_taxis` is `3` as in the sample run, the preceding lines will do the same as:

```
    taxis = {0: taxi_process(ident=0, trips=2, start_time=0),
             1: taxi_process(ident=1, trips=4, start_time=5),
             2: taxi_process(ident=2, trips=6, start_time=10)}
    sim = Simulator(taxis)
```

Therefore, the values of the `taxis` dictionary will be three distinct generator objects with different parameters. For instance, taxi 1 will make 4 trips and begin looking for passengers at `start_time=5`. This `dict` is the only argument required to build a `Simulator` instance.

The `Simulator.__init__` method is shown in Example 19-22. The main data structures of `Simulator` are:

`self.events`

A `PriorityQueue` to hold `Event` instances. A `PriorityQueue` lets you `put` items, then `get` them ordered by `item[0]`; i.e., the `time` attribute in the case of our `Event` `namedtuple` objects.

`self.procs`

A `dict` mapping each process number to an active process in the simulation—a generator object representing one taxi. This will be bound to a copy of `taxis` `dict` shown earlier.

Example 19-22. taxi_sim.py: Simulator class initializer

```
class Simulator:

    def __init__(self, procs_map):
        self.events = queue.PriorityQueue()  ❶
        self.procs = dict(procs_map)  ❷
```

❶ The `PriorityQueue` to hold the scheduled events, ordered by increasing time.

❷ We get the `procs_map` argument as a `dict` (or any mapping), but build a `dict` from it, to have a local copy because when the simulation runs, each taxi that goes home is removed from `self.procs`, and we don't want to change the object passed by the user.

Priority queues are a fundamental building block of discrete event simulations: events are created in any order, placed in the queue, and later retrieved in order according to the scheduled time of each one. For example, the first two events placed in the queue may be:

```
Event(time=14, proc=0, action='pick up passenger')
Event(time=11, proc=1, action='pick up passenger')
```

This means that taxi 0 will take 14 minutes to pick up the first passenger, while taxi 1—starting at `time=10`—will take 1 minute and pick up a passenger at `time=11`. If those two events are in the queue, the first event the main loop gets from the priority queue will be `Event(time=11, proc=1, action='pick up passenger')`.

Now let’s study the main algorithm of the simulation, the `Simulator.run` method. It’s invoked by the `main` function right after the `Simulator` is instantiated, like this:

```
sim = Simulator(taxis)
sim.run(end_time)
```

The listing with callouts for the `Simulator` class is in Example 19-23, but here is a high-level view of the algorithm implemented in `Simulator.run`:

1. Loop over processes representing taxis.
    a. Prime the coroutine for each taxi by calling `next()` on it. This will yield the first `Event` for each taxi.
    b. Put each event in the `self.events` queue of the `Simulator`.
2. Run the main loop of the simulation while `sim_time` < `end_time`.
    a. Check if `self.events` is empty; if so, break from the loop.
    b. Get the `current_event` from `self.events`. This will be the `Event` object with the lowest time in the `PriorityQueue`.
    c. Display the `Event`.
    d. Update the simulation time with the `time` attribute of the `current_event`.

e. Send the time to the coroutine identified by the `proc` attribute of the `current_event`. The coroutine will yield the `next_event`.

f. Schedule `next_event` by adding it to the `self.events` queue.

The complete `Simulator` class is Example 19-23.

Example 19-23. taxi_sim.py: Simulator, a bare-bones discrete event simulation class; focus on the run method

```
class Simulator:

    def __init__(self, procs_map):
        self.events = queue.PriorityQueue()
        self.procs = dict(procs_map)

    def run(self, end_time):  ❶
        """Schedule and display events until time is up"""
        # schedule the first event for each cab
        for _, proc in sorted(self.procs.items()):  ❷
            first_event = next(proc)  ❸
            self.events.put(first_event)  ❹

        # main loop of the simulation
        sim_time = 0  ❺
        while sim_time < end_time:  ❻
            if self.events.empty():  ❼
                print('*** end of events ***')
                break

            current_event = self.events.get()  ❽
            sim_time, proc_id, previous_action = current_event  ❾
            print('taxi:', proc_id, proc_id * '   ', current_event)
❿
            active_proc = self.procs[proc_id]  ⓫
            next_time = sim_time +
compute_duration(previous_action)  ⓬
            try:
                next_event = active_proc.send(next_time)  ⓭
            except StopIteration:
                del self.procs[proc_id]  ⓮
            else:
                self.events.put(next_event)  ⓯
        else:  ⓰
```

```
            msg = '*** end of simulation time: {} events pending
***'
            print(msg.format(self.events.qsize()))
```

❶ The simulation end_time is the only required argument for run.

❷ Use sorted to retrieve the self.procs items ordered by the key; we don't care about the key, so assign it to _.

❸ next(proc) primes each coroutine by advancing it to the first yield, so it's ready to be sent data. An Event is yielded.

❹ Add each event to the self.events PriorityQueue. The first event for each taxi is 'leave garage', as seen in the sample run (Example 19-20).

❺ Zero sim_time, the simulation clock.

❻ Main loop of the simulation: run while sim_time is less than the end_time.

❼ The main loop may also exit if there are no pending events in the queue.

❽ Get Event with the smallest time in the priority queue; this is the current_event.

❾ Unpack the Event data. This line updates the simulation clock, sim_time, to reflect the time when the event happened.[15]

❿ Display the Event, identifying the taxi and adding indentation according to the taxi ID.

⓫ Retrieve the coroutine for the active taxi from the self.procs dictionary.

⓬

Compute the next activation time by adding the `sim_time` and the result of calling `compute_duration(…)` with the previous action (e.g., `'pick up passenger'`, `'drop off passenger'`, etc.)

(13) Send the `time` to the taxi coroutine. The coroutine will yield the `next_event` or raise `StopIteration` when it’s finished.

(14) If `StopIteration` is raised, delete the coroutine from the `self.procs` dictionary.

(15) Otherwise, put the `next_event` in the queue.

(16) If the loop exits because the simulation time passed, display the number of events pending (which may be zero by coincidence, sometimes).

Linking back to Chapter 18, note that the `Simulator.run` method in Example 19-23 uses `else` blocks in two places that are not `if` statements:

- The main `while` loop has an `else` statement to report that the simulation ended because the `end_time` was reached—and not because there were no more events to process.
- The `try` statement at the bottom of the `while` loop tries to get a `next_event` by sending the `next_time` to the current taxi process, and if that is successful the `else` block puts the `next_event` into the `self.events` queue.

I believe the code in `Simulator.run` would be a bit harder to read without those `else` blocks.

The point of this example was to show a main loop processing events and driving coroutines by sending data to them. This is the basic idea behind `asyncio`, which we’ll study in Chapter 22.

Before closing the chapter, let’s discuss generic coroutine types.

NOTE

Feel free to skip the next section if coroutines, generic types and variance are too much for you right now. I personally found the combination a bit hard to digest.

Generic Type Hints for Classic Coroutines

Back in "Contravariant Types", I mentioned `typing.Generator` as one of the few standard library types with a contravariant type parameter. Now that we've studied classic coroutines, we are ready to make sense of this generic type.

For generators that only yield values and are never sent any value other than `None`, the recommended type for annotations is `Iterator[T_co]`.

Despite its name, `typing.Generator` is really used to annotate classic coroutines which not only yield values, but also accept values via `.send()` and also return values through the `StopIteration(value)` hack.

Here is how `typing.Generator` was declared in the *typing.py* module of Python 3.6:[16]

```
T_co = TypeVar('T_co', covariant=True)
V_co = TypeVar('V_co', covariant=True)
T_contra = TypeVar('T_contra', contravariant=True)

# many lines omitted

class Generator(Iterator[T_co], Generic[T_co, T_contra, V_co],
                extra=_G_base):
```

That generic type declaration means that a `Generator` type hint requires three type parameters, as in this example:

```
my_coro : Generator[YieldType, SendType, ReturnType]
```

From the type variables in the formal parameters, we see that `YieldType` and `ReturnType` are covariant, but `SendType` is contravariant.

To understand why, consider that `YieldType` and `ReturnType` are "output" types. Both describe data that comes out of the coroutine object—i.e. the generator object when used as a coroutine object.

It makes sense that these are covariant, because any code expecting a coroutine that yields floats can accept a coroutine that yields integers. That's why `Generator` is covariant on its `YieldType` parameter. The same reasoning applies to the `ReturnType` parameter—also covariant.

Using the notation introduced in "Covariant Types", the covariance of the first and third parameters is expressed by the parallel `:>` symbols:

```
                       float :> int
Generator[float, Any, float] :> Generator[int, Any, int]
```

`YieldType` and `ReturnType` are examples of the first rule of "Variance Rules of Thumb".

On the other hand, `SendType` is an "input" parameter: it is the type of the argument for the `send` method of the coroutine object. Code that wants to send floats to a coroutine cannot use a coroutine with `int` as the `SendType` because `int` is not a supertype of `float`. In other words, `float` is not *consistent-with* `int`. But it can use a coroutine with `complex` as the `SendType`, because `complex` is a supertype of `float`, therefore `float` is *consistent-with* `complex`.

The `:>` notation makes the contravariance of the second parameter visible:

```
                     float :> int
Generator[Any, float, Any] <: Generator[Any, int, Any]
```

This is an example of the second *Variance Rule of Thumb*.

With this merry discussion of variance, we are ready to wrap this chapter—one of the hardest in the book.

Chapter Summary

Guido van Rossum wrote there are three different styles of code you can write using generators:

> *There's the traditional "pull" style (iterators), "push" style (like the averaging example), and then there are "tasks" (Have you read Dave Beazley's coroutines tutorial yet?…).*[17]

Chapter 17 was devoted to iterators; this chapter introduced classic coroutines used in "push style" and also as very simple "tasks"—the taxi processes in the simulation example. Chapter 22 will be about native coroutines and asynchronous generators, which evolved from the generators and classic coroutines as described here.

The running average example demonstrated a common use for a classic coroutine: as an accumulator processing items sent to it. We saw how a decorator can be applied to prime a coroutine, making it more convenient to use in some cases. But keep in mind that priming decorators are not compatible with some uses of coroutines. In particular, `yield from subgenerator()` assumes the `subgenerator` is not primed, and primes it automatically.

Accumulator coroutines can yield back partial results with each `send` method call, but they become more useful when they can return values, a feature that was added in Python 3.3 with PEP 380. We saw how the statement `return the_result` in a generator now raises `StopIteration(the_result)`, allowing the caller to retrieve `the_result` from the `value` attribute of the exception. This is a rather cumbersome way to retrieve coroutine results, but it's handled automatically by the `yield from` syntax introduced in PEP 380.

The coverage of `yield from` started with trivial examples using simple iterables, then moved to an example highlighting the three main components of any significant use of `yield from`: the delegating generator (defined by the use of `yield from` in its body), the subgenerator activated by `yield from`, and the client code that actually drives the whole setup by sending values to the subgenerator through the pass-through channel established by `yield from` in the delegating generator. This section was wrapped up with a look at the formal definition of `yield from` behavior as described in PEP 380 using English and Python-like pseudocode.

We closed the chapter with the discrete event simulation example, showing how generators can be used as an alternative to threads and callbacks to support concurrency. Although simple, the taxi simulation gives a first glimpse at how event-driven frameworks like Tornado and `asyncio` use a main loop to drive coroutines executing concurrent activities with a single thread of execution. In event-oriented programming with coroutines, each concurrent activity is carried out by a coroutine that repeatedly yields control back to the main loop, allowing other coroutines to be activated and move forward. This is a form of cooperative multitasking: coroutines voluntarily and explicitly yield control to the central scheduler. In contrast, threads implement preemptive multitasking. The scheduler can suspend threads at any time—even halfway through a statement—to give way to other threads.

Further Reading

David Beazley is the ultimate authority on Python generators and coroutines. The *Python Cookbook, 3E* (O'Reilly) he coauthored with Brian Jones has numerous recipes with coroutines. Beazley's PyCon tutorials on the subject are famous for their depth and breadth. The first was at PyCon US 2008: "Generator Tricks for Systems Programmers". PyCon US 2009 saw the legendary "A Curious Course on Coroutines and Concurrency" (hard-to-find video links for all three parts: part 1, part 2, part 3). His tutorial from PyCon 2014 in Montréal was "Generators: The Final Frontier," in which he tackles more concurrency examples—so it's really more about topics in Chapter 22 of *Fluent Python*. Dave can't resist making brains explode in his classes, so in the last part of "The Final Frontier," coroutines replace the classic Visitor pattern in an arithmetic expression evaluator.

Coroutines allow new ways of organizing code, and just as recursion or polymorphism (dynamic dispatch), it takes some time getting used to their possibilities. An interesting example of classic algorithm rewritten with coroutines is in the post "Greedy algorithm with coroutines," by James Powell. You may also want to browse "Popular recipes tagged *coroutine*" in the ActiveState Code recipes database.

Paul Sokolovsky implemented `yield from` in Damien George's super lean MicroPython interpreter designed to run on microcontrollers. As he studied the feature, he created a great, detailed diagram to explain how `yield from` works, and shared it in the python-tulip mailing list. Sokolovsky was kind enough to allow me to copy the PDF to this book's site, where it has a more permanent URL.

As I write this, the vast majority of uses of `yield from` to be found are in `asyncio` itself or code that uses it. I spent a lot of time looking for examples of `yield from` that did not depend on `asyncio`. Greg Ewing—who penned PEP 380 and implemented `yield from` in CPython—published a few examples of its use: a `BinaryTree` class, a simple XML parser, and a task scheduler.

Brett Slatkin's *Effective Python, First Edition* (Addison-Wesley) has an excellent short chapter titled "Consider Coroutines to Run Many Functions Concurrently". That chapter is not in *Effective Python, Second Edition*, but fortunately it is still available online as a sample chapter. Slatkin presents the best example of driving coroutines with `yield from` I've seen: an implementation of John Conway's Game of Life in which coroutines are used to manage the state of each cell as the game runs. I refactored the code for the Game of Life example—separating the functions and classes that implement the game from the testing snippets used in Slatkin's book original code. I also rewrote the tests as doctests, so you can see the output of the various coroutines and classes without running the script. The refactored example is posted as a GitHub gist.

Other interesting examples of `yield from` without `asyncio` appear in a message to the Python Tutor list, "Comparing two CSV files using Python" by Peter Otten, and a Rock-Paper-Scissors game in Ian Ward's "Iterables, Iterators, and Generators" tutorial published as an iPython notebook.

Guido van Rossum sent a long message to the python-tulip Google Group titled "The difference between `yield` and `yield-from`" that is worth reading. Nick Coghlan posted a heavily commented version of the `yield from` expansion to Python-Dev on March 21, 2009; in the same message, he wrote:

> *Whether or not different people will find code using `yield from` difficult to understand or not will have more to do with their grasp of the concepts of cooperative multitasking in general more so than the underlying trickery involved in allowing truly nested generators.*

Experimenting with discrete event simulations is a great way to become comfortable with cooperative multitasking. Wikipedia's "Discrete event simulation" article is a good place to start.[18] A short tutorial about writing discrete event simulations by hand (no special libraries) is Ashish Gupta's "Writing a Discrete Event Simulation: Ten Easy Lessons." The code is in Java so it's class-based and uses no coroutines, but can easily be ported to Python. Regardless of the code, the tutorial is a good short introduction to the terminology and components of a discrete event simulation. Converting Gupta's examples to Python classes and then to classes leveraging coroutines is a good exercise.

For a ready-to-use library in Python, using coroutines, there is SimPy. Its online documentation explains:

> *SimPy is a process-based discrete-event simulation framework based on standard Python. Its event dispatcher is based on Python's generators and can also be used for asynchronous networking or to implement multi-agent systems (with both simulated and real communication).*

Coroutines are not so new in Python but they were pretty much tied to niche application domains before asynchronous networking frameworks started supporting them, starting with Tornado. The addition of `yield from` in Python 3.3 and `asyncio` in Python 3.4 raised awareness about classic coroutines until their main use case—asynchronous programming—was taken over by native coroutines in Python 3.5. Classic coroutines are not obsolete, but they are now back to niche applications. Differences between classic coroutines and native coroutines are the subject of Python native coroutines and send() on StackOverflow.

I still believe classic coroutines and `yield from` are worth studying if you want to understand how native coroutines and `await` actually support concurrency under the hood. Also, if you want to develop asynchronous libraries—as opposed to applications—you'll discover that the functions that do the actual work of I/O are generators and classic coroutines, even in `asyncio`. Unfortunately, once you watch David Beazley's tutorials and read his cookbook examples on the subject, there isn't a whole lot of content out there that goes deep into programming with classic coroutines.

SOAPBOX

Raise from lambda

In programming languages, keywords establish the basic rules of control flow and expression evaluation.

A keyword in a language is like a piece in a board game. In the language of Chess, the keywords are ♔, ♕, ♖, ♗, ♘, and ♙. In the game of Go, it's ●.

Chess players have six different types of pieces to implement their plans, whereas Go players seem to have only one type of piece. However, in the semantics of Go, adjacent pieces form larger, solid pieces of many different shapes, with emerging properties. Some arrangements of Go pieces are indestructible. Go is more expressive than Chess. In Go there are 361 possible opening moves, and an estimated 10¹⁷² legal positions; for Chess, the numbers are 20 opening moves and 10⁵⁰ positions.

Adding a new piece to Chess would be a radical change. Adding a new keyword in a programming language is also a radical change. So it makes sense for language designers to be wary of introducing keywords.

Table 19-1. Number of keywords in pr

o
g
r
a
m
m
i
n
g

l
a
n
g
u
a
g
e
s

Keywords	Language	Comment
5	Smalltalk-80	Famous for its minimalist syntax.
25	Go	The language, not the game.
32	C	That's ANSI C. C99 has 37 keywords, C11 has 44.
35	Python	Python 2.7 had 31 keywords; Python 1.5 had 28.
41	Ruby	Keywords may be used as identifiers (e.g., `class` is also a method name).
49	Java	As in C, the names of the primitive types (`char`, `float`, etc.) are reserved.
60	JavaScript	Includes all keywords from Java 1.0, many of which are unused.

65	PHP	Since PHP 5.3, seven keywords were introduced, including `goto`, `trait`, and `yield`.
85	C++	According to cppreference.com, C++11 added 10 keywords to the existing 75.
555	COBOL	I did not make this up. See this IBM ILE COBOL manual.
∞	Scheme	Anyone can define new keywords.

Python 3.0 added `nonlocal`, promoted `None`, `True`, and `False` to keyword status, and dropped `print` and `exec`. It's very uncommon for a language to drop keywords as it evolves. Table 19-1 lists some languages, ordered by number of keywords.

Scheme inherited from Lisp a syntactic macro facility that allows anyone to create special forms adding new control structures and evaluation rules to the language. The user-defined identifiers of those forms are called "syntactic keywords." The Scheme R5RS standard states "There are no reserved identifiers" (page 45 of the standard), but a typical implementation such as MIT/GNU Scheme comes with 34 syntactic keywords predefined, such as `if`, `lambda`, and `define-syntax`—the keyword that lets you conjure new keywords.

I now enjoy Elixir as much as I enjoy Python. Elixir has syntactic macros, on top of a basic syntax that is more readable than the s-expressions of Lisp and Scheme. Elixir frameworks and libraries such as Phoenix and Ecto extend the language syntax to build domain-specific languages. For example, this is a database query written in Elixir using an Ecto macro:

```
query = from u in User,
          where: u.age > 18 or is_nil(u.email),
          select: u
```

“The Value Of Syntax?” is an interesting discussion about extensible syntax and programming language usability. The forum, Lambda the Ultimate, is a watering hole for programming language geeks.

Python is like Chess. Scheme and Elixir are like Go (the game).

Now, back to Python syntax. Guido used to be rather conservative with keywords. It’s nice to have a small set of them, and adding new keywords potentially breaks a lot of code. But the use of `else` in loops reveals a recurring problem: the overloading of existing keywords when a new one would be a better choice. In the context of `for`, `while`, and `try`, a new `then` keyword would be preferable to abusing `else`.

In *Fluent Python, First Edition* I wrote: “The introduction of `yield from` is particularly worrying. Once again, I believe Python users would be best served by a new keyword.” As I write this five years later, I got so used to `yield from` that I don’t see any problem with it any more. Now we have `await` too, which works in a similar way but is used in different contexts.

I am glad Guido approved PEP 492 introducing not only `await`, but also `async` combined to existing keywords to add three new statements to the language: `async def`, `async for` and `async with`—all of which we will see in Chapter 22. Using `async def` to declare native coroutines interrupted the long history of overloading of `def`: it’s still used to define functions, generators, and classic coroutines—objects that are too different to share the same declaration syntax. I highly recommended “What Color Is Your Function?” by Bob Nystrom, a post related to this discussion in the context of JavaScript, Python, and other languages.

Chaining existing keywords to create new syntax—instead of adding sensible, descriptive keywords—avoids breaking code, but has its downsides. I fear one day we may be poring over the meaning of `raise from lambda`.

1 *500 Lines or Less*, edited by Michael DiBernardo, chapter A Web Crawler With asyncio Coroutines by A. Jesse Jiryu Davis and Guido van Rossum.

2 You'll only see this state in a multithreaded application—or if the generator object calls `getgeneratorstate` on itself, which is not useful.

3 This example is inspired by a snippet from Jacob Holm in the Python-ideas list, message titled "Yield-From: Finalization guarantees." Some variations appear later in the thread, and Holm further explains his thinking in message 003912.

4 There are several similar decorators published on the Web. This one is adapted from the ActiveState recipe Pipeline made of coroutines by Chaobin Tang, who in turn credits David Beazley.

5 There is an iPython extension called ipython-yf that enables evaluating `yield from` directly in the iPython console. It's used to test asynchronous code and works with `asyncio`. It was submitted as a patch to Python 3.5 but was not accepted. See Issue #22412: Towards an asyncio-enabled command line in the Python bug tracker.

6 The picture in Figure 19-2 was inspired by a diagram by Paul Sokolovsky.

7 From PEP 492, section Await Expression

8 Message to Python-Dev: "PEP 380 (yield from a subgenerator) comments" (March 21, 2009).

9 In a message to Python-ideas on April 5, 2009, Nick Coghlan questioned whether the implicit priming done by `yield from` was a good idea.

10 Opening sentence of the "Motivation" section in PEP 342.

11 See the official documentation for SimPy—not to be confused with the well-known but unrelated SymPy, a library for symbolic mathematics.

12 I am not an expert in taxi fleet operations, so don't take my numbers seriously. Exponential distributions are commonly used in DES. You'll see some very short trips. Just pretend it's a rainy day and some passengers are taking cabs just to go around the block—in an ideal city where there are cabs when it rains.

13 I was the passenger. I realized I forgot my wallet.

14 The verb "to drive" is commonly used to describe the operation of a coroutine: the client code drives the coroutine by sending it values. In Example 19-21, the client code is what you type in the console.

15 This is typical of a discrete event simulation: the simulation clock is not incremented by a fixed amount on each loop, but advances according to the duration of each event completed.

16 Since Python 3.7, `typing.Generator` and other types that correspond to ABCs in `collections.abc` were refactored with a wrapper around the corresponding ABC, so their generic parameters aren't visible in the *typing.py* source file. That's why I refer to Python 3.6 source code here.

17 Message to thread "Yield-From: Finalization guarantees" in the Python-ideas mailing list. The David Beazley tutorial Guido refers to is "A Curious Course on Coroutines and Concurrency".

18 Nowadays even tenured professors agree that Wikipedia is a good place to start studying pretty much any subject in computer science. Not true about other subjects, but for computer science, Wikipedia rocks.

Chapter 20. Concurrency Models in Python

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 20th chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Concurrency is about dealing with lots of things at once.*
>
> *Parallelism is about doing lots of things at once.*
>
> *Not the same, but related.*
>
> *One is about structure, one is about execution.*
>
> *Concurrency provides a way to structure a solution to solve a problem that may (but not necessarily) be parallelizable.*[1]
>
> —Rob Pike, Co-inventor of the Go language

This chapter is about how to make Python deal with "lots of things at once." This may involve concurrent or parallel programming—even academics who are keen on jargon disagree on how to use those terms.[2] I will adopt Rob Pike's informal definitions quoted above, but note that I've found academic papers and books that claim to be about parallel computing but mostly covered concurrency.

Parallelism is a special case of concurrency, in Pike's view. All parallel systems are concurrent, but not all concurrent systems are parallel. In the early 2000's we used single core machines that handled 100 processes concurrently on GNU Linux. A modern laptop with 4 CPU cores is routinely running more than 200 processes at any given time under normal, casual use. To execute 200 tasks in parallel you'd need 200 cores. So, in practice, most computing is concurrent and not parallel. The OS manages hundreds of processes, making sure each has an opportunity to make progress, even if the CPU itself can't do more than 4 things at once. That's why Rob Pike titled that talk "Concurrency Is Not Parallelism (It's Better)."

This chapter assumes no prior knowledge of concurrent or parallel programming. After a brief conceptual introduction, we will study simple examples to introduce and compare Python's core packages for concurrent programming: `threading`, `multiprocessing`, and `asyncio`.

The last 30% of the chapter is a high-level overview of third-party tools, libraries, application servers, and distributed task queues—all of which can enhance the performance and scalability of Python applications. These are all important topics, but beyond the scope of a book focused on core Python language features. Nevertheless, I felt it was important to address these themes in this second edition of *Fluent Python*, because Python's fitness for concurrent and parallel computing is not limited to what the standard library provides. That's why YouTube, DropBox, Instagram, Reddit, and others were able to achieve Web scale when they started, using Python as their primary language.

What's new in this chapter

This chapter is new in *Fluent Python*, *Second Edition*. The spinner examples in "A Concurrent Hello World" previously were in the chapter about `asyncio`. Here they are improved, and provide the first illustration of Python's three approaches to concurrency: threads, processes, and native coroutines.

The remaining content is new—except for a few paragraphs that originally appeared in the chapters on `concurrent.futures` and `asyncio`.

"The Big Picture" is different from the rest of the book: there are no code examples. The goal is to mention important tools that you may want to study to achieve high-performance concurrency and parallelism beyond what's possible with Python's standard library.

A Bit of Jargon

Let's make sure we are on the same page regarding some core concepts. Here are some terms I will use for the rest of this chapter and the next two.

concurrency

> The ability to handle multiple pending tasks, making progress one at a time or in parallel (not necessarily) so that they all eventually succeed or fail. A single-core CPU is capable of concurrency if it runs an OS scheduler that interleaves the execution of the pending tasks. Also known as multitasking.

parallelism

> The ability to execute multiple computations at the same time. This requires a multi-core CPU, a GPU, or multiple computers in cluster.

process

> An instance of a computer program while it is running, using memory and a slice of the CPU time. Modern operating systems are able to manage multiple processes concurrently, with each process isolated in its own private memory space. Processes communicate via pipes, sockets, or memory mapped files—all of which can only carry raw bytes, not live Python objects. A process can spawn sub-processes, each

called a child process. These are also isolated from each other and from the parent.

thread

An execution path within a single process. When a process starts, it uses a single thread: the main thread. Using operating system APIs, a process can create more threads that operate concurrently thanks to the operating system scheduler. Threads share the memory space of the process, which holds live Python objects. This allows easy communication between threads, but can also lead to corrupted data when more than one thread updates the same object concurrently.

contention

Dispute over a limited asset. Resource contention happens when multiple processes or threads try to access a shared resource—such as a lock or storage. There's also CPU contention, when compute-intensive processes or threads must wait for their share of CPU time.

lock

An object that threads can use to coordinate and synchronize their actions and avoid corrupting data. While updating a shared data structure, a thread should hold an associated lock. This makes other well-behaved threads wait until the lock is released before accessing the same data structure. The simplest type of lock is also known as a mutex (for mutual exclusion).

Now let's use some of that jargon to understand concurrency support in Python.

Processes, threads, and Python's Infamous GIL

Here is how the concepts we just saw apply to Python programming, in ten points.

1. Each instance of the Python interpreter is a process. You can start additional Python processes using the `multiprocessing` or `concurrent.futures` libraries. Python's `subprocess` library is designed to launch processes to run external programs, regardless of the languages used to write them.

2. The Python interpreter uses a single thread to run the user's program and the memory garbage collector. You can start additional Python threads using the `threading` or `concurrent.futures` libraries.

3. Access to reference counts and other internal interpreter state is controlled by a lock, the Global Interpreter Lock (GIL). Only one Python thread can hold the GIL at any time. This means that only one Python thread can execute at any time, regardless of the number of CPU cores.

4. To prevent a Python thread from holding the GIL indefinitely, Python's bytecode interpreter pauses the current Python thread every 5ms by default[3], releasing the GIL. The thread can then try to reacquire the GIL, but if there are other threads waiting for it, the OS scheduler may pick one of them to proceed.

5. When we write Python code, we have no control over the GIL. But a built-in function or an extension written in C—or any language that interfaces at the Python/C API level—can release the GIL while running time-consuming tasks.

6. Every Python standard library function that makes a syscall[4] releases the GIL. This includes all functions that perform disk I/O, network I/O, and `time.sleep()`. Many CPU-intensive functions in the NumPy/SciPy libraries, as well as the compressing/decompressing functions from the `zlib` and `bz2` modules also release the GIL.[5]

7. Extensions that integrate at the Python/C level can also launch other non-Python threads that are not affected by the GIL. Such

GIL-free threads generally cannot change Python objects, but they can read from and write to the memory underlying `array.array` or NumPy arrays, which support the buffer protocol.

8. The effect of the GIL on network programming with Python threads is relatively small, because the I/O functions release the GIL, and reading or writing to the network always implies high latency—compared to reading and writing to memory. Consequently, each individual thread spends a lot of time waiting anyway, so their execution can be interleaved without major impact on the overall throughput. That's why David Beazley says: "Python threads are great at doing nothing."[6]

9. Contention over the GIL slows down compute-intensive Python threads. Sequential, single-threaded code is simpler and faster for such tasks.

10. To run CPU-intensive Python code on multiple cores, you must use multiple Python processes.

Here is a good summary from the documentation of the `threading` module:[7]

> ***CPython implementation detail****: In CPython, due to the Global Interpreter Lock, only one thread can execute Python code at once (even though certain performance-oriented libraries might overcome this limitation). If you want your application to make better use of the computational resources of multi-core machines, you are advised to use multiprocessing or concurrent.futures.ProcessPoolExecutor. However, threading is still an appropriate model if you want to run multiple I/O-bound tasks simultaneously.*

The previous paragraph starts with "CPython implementation detail" because the GIL is not part of the Python language definition. The Jython implementation does not have a GIL. Unfortunately, Jython is lagging behind—it's still tracking Python 2.7. The highly performant PyPy interpreter also has a GIL in its 2.7 and 3.7 versions—the latest as of June, 2021.

Enough concepts for now. Let's see some code.

A Concurrent Hello World

During a discussion about threads and how to avoid the GIL, Python contributor Michele Simionato posted an example that is like a concurrent *Hello World*: the simplest program to demonstrate how Python can "walk and chew gum."

Simionato's program uses `multiprocessing`, but I adapted it to introduce `threading` and `asyncio` as well. Let's start with the `threading` version, which may look familiar if you've studied threads in Java or C.

Spinner with threading

The idea of the next few examples is simple: start a function that blocks for 3 seconds while animating characters in the terminal to let the user know that the program is "thinking" and not stalled.

An animated spinner is built by displaying each character in the string `"\|/-"` in the same screen position.[8] When the slow computation finishes, the line with the spinner is cleared and the result is shown: `Answer: 42`.

Figure 20-1 shows the output of two versions of the spinning example: first with threads, then with coroutines. If you're away from the computer, imagine the `\` in the last line is spinning.

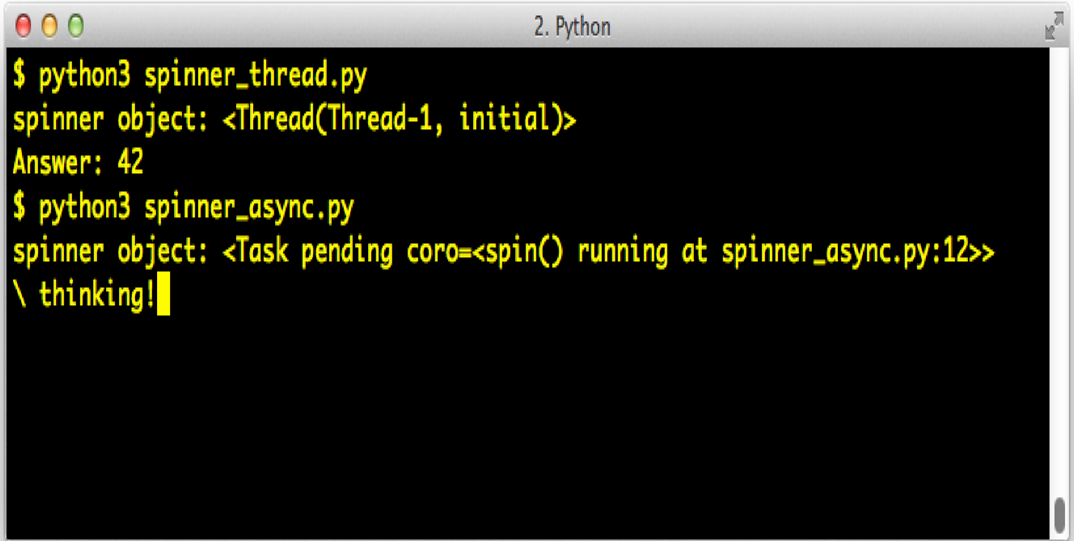


Figure 20-1. The scripts spinner_thread.py and spinner_async.py produce similar output: the repr of a spinner object and the text "Answer: 42". In the screenshot, spinner_async.py is still running, and the animated message "/ thinking!" is shown; that line will be replaced by "Answer: 42" after 3 seconds.

Let's review the *spinner_thread.py* script first. Example 20-1 lists the first two functions in the script, and Example 20-2 shows the rest.

Example 20-1. spinner_thread.py: the spin and slow functions.

```
import itertools
import time
from threading import Thread, Event

def spin(msg: str, done: Event) -> None:  ❶
    for char in itertools.cycle(r'\|/-'):  ❷
        status = f'\r{char} {msg}'  ❸
        print(status, end='', flush=True)
        if done.wait(.1):  ❹
            break  ❺
    blanks = ' ' * len(status)
    print(f'\r{blanks}\r', end='')  ❻

def slow() -> int:
    time.sleep(3)  ❼
    return 42
```

❶ This function will run in a separate thread. The `done` argument is an instance of `threading.Event`, a simple way to synchronize threads.

❷ This is an infinite loop because `itertools.cycle` yields one character at a time, cycling through the string forever.

❸ The trick for text-mode animation: move the cursor back to the start of the line with the carriage return ASCII control character (`'\r'`).

❹ The `Event.wait(timeout=None)` method returns `True` when the event is set by another thread; if the `timeout` elapses, it returns `False`. The .1s timeout sets the "frame rate" of the animation to 10FPS. If you want the spinner to go faster, use a smaller timeout.

❺ Exit the infinite loop.

❻ Clear the status line by overwriting with spaces and moving the cursor back to the beginning.

❼ `slow()` will be called by the main thread. Imagine this is a slow API call over the network. Calling `sleep` blocks the main thread, but the GIL is released so the spinner thread can proceed.

> **TIP**
>
> The first important insight of this example is that `time.sleep()` blocks the calling thread but releases the GIL, allowing other Python threads to run.

The `spin` and `slow` functions will execute concurrently. The main thread—the only thread when the program starts—will start a new thread to run `spin` and then call `slow`. By design, there is no API for terminating a thread in Python. You must send it a message to shut down.

The `threading.Event` class is Python's simplest signalling mechanism to coordinate threads. An `Event` instance has an internal boolean flag which starts as `False`. Calling `Event.set()` sets the flag to `True`. While the flag is false, if a thread calls `Event.wait()`, it is blocked until another thread calls `Event.set()`, at which time `Event.wait()` returns `True`. If a timeout in seconds is given to `Event.wait(s)`, this call returns `False` when the timeout elapses, or returns `True` as soon as `Event.set()` is called by another thread.

The `supervisor` function, listed in Example 20-2, uses an `Event` to signal the `spin` function to exit.

Example 20-2. spinner_thread.py: the supervisor and main functions.

```
def supervisor() -> int:  ❶
    done = Event()  ❷
    spinner = Thread(target=spin, args=('thinking!', done))  ❸
    print(f'spinner object: {spinner}')  ❹
    spinner.start()  ❺
    result = slow()  ❻
    done.set()  ❼
    spinner.join()  ❽
    return result

def main() -> None:
    result = supervisor()  ❾
    print(f'Answer: {result}')

if __name__ == '__main__':
    main()
```

❶ `supervisor` will return the result of `slow`.

❷ The `threading.Event` instance is the key to coordinate the activities of the main thread and the spinner thread, as explained below.

❸ To create a new `Thread`, provide a function as the `target` keyword argument, and positional arguments to the `target` as a tuple passed via `args`.

❹

Display the `spinner` object. The output is `<Thread(Thread-1, initial)>`, where `initial` is the state of the thread—meaning it has not started.

❺ Start the `spinner` thread.

❻ Call `slow`, which blocks the main thread. Meanwhile, the secondary thread is running the spinner animation.

❼ Set the `Event` flag to `True`; this will terminate the `for` loop inside the `spin` function.

❽ Wait until the `spinner` thread finishes.

❾ Run the `supervisor` function. I wrote separate `main` and `supervisor` functions to make this example look more like the `asyncio` version in Example 20-4.

When the main thread sets the `done` event, the `spinner` thread will eventually notice and exit cleanly.

Now let's take a look at a similar example using the `multiprocessing` package.

Spinner with multiprocessing

The `multiprocessing` package supports running concurrent tasks in separate Python processes instead of threads. When you create a `multiprocessing.Process` instance, a whole new Python interpreter is started as a child process in the background. Since each Python process has its own GIL, this allows your program to use all available CPU cores. We'll see practical effects in "A Homegrown Process Pool", but for this simple program it makes no real difference.

The point of this section is to introduce `multiprocessing` and show that its API emulates the `threading` API, making it easy to convert simple programs from threads to processes, as shown in *spinner_proc.py* (Example 20-3).

Example 20-3. spinner_proc.py: only the changed parts are shown. Everything else is the same as spinner_thread.py.

```
import itertools
import time
from multiprocessing import Process, Event  ❶
from multiprocessing import synchronize     ❷

def spin(msg: str, done: synchronize.Event) -> None:  ❸

# [snip] the rest of spin and slow functions are unchanged from
spinner_thread.py

def supervisor() -> int:
    done = Event()
    spinner = Process(target=spin,               ❹
                      args=('thinking!', done))
    print(f'spinner object: {spinner}')          ❺
    spinner.start()
    result = slow()
    done.set()
    spinner.join()
    return result

# [snip] main function is unchanged as well
```

❶ The basic `multiprocessing` API imitates the `threading` API, but type hints and *mypy* expose this difference: `multiprocessing.Event` is a function (not a class like `threading.Event`) which returns a `synchronize.Event` instance…

❷ …forcing us to import `multiprocessing.synchronize`…

❸ …to write this type hint.

❹ Basic usage of the `Process` class is similar to `Thread`.

❺

> The `spinner` object is displayed as `<Process name='Process-1' parent=14868 initial>`, were `14868` is the process id of the Python instance running `spinner_proc.py`.

The basic API of `threading` and `multiprocessing` are similar, but their implementation is very different and `multiprocessing` has a much larger API to handle the added complexity of multi-process programming. For example, one challenge when converting from threads to processes is how to communicate between processes that are isolated by the operating system and can't share Python objects. This means that objects crossing process boundaries have to be serialized and deserialized, which creates overhead. In Example 20-3 the only data that crosses the process boundary is the `Event` state, which is implemented with a low-level OS semaphore in the C code underlying the `multiprocessing` module.

> **NOTE**
>
> The semaphore is a fundamental building block that can be used to implement other synchronization mechanisms. Python provides different semaphore classes for use with threads, processes and coroutines. We'll see `asyncio.Semaphore` in "Using asyncio.as_completed and a semaphore" (Chapter 22).

Now let's see how the same behavior can be achieved with coroutines instead of threads or processes.

Spinner with asyncio

> **NOTE**
>
> Chapter 22 is entirely devoted to asynchronous programming with coroutines. This is just a high-level introduction to contrast this approach with the traditional threading and multiprocessing concurrency models. As such, we will overlook many details.

It is the job of OS schedulers to allocate CPU time to drive threads and processes. In contrast, coroutines are driven by an application-level event loop that manages a queue of pending coroutines, drives them one by one, monitors events triggered by I/O operations initiated by coroutines, and passes control back to the corresponding coroutine when each event happens. The event loop and the library coroutines and the user coroutines all execute in a single thread. Therefore, any time spent in a coroutine slows down the event loop—and all other coroutines.

> **NOTE**
>
> In the taxi simulator of Example 19-23, the `taxi_process` classic coroutines were driven by a main loop in the `Simulator.run` method. That main loop was an event loop, except that it handled simulation events like “drop off passenger” instead of system events triggered by I/O and timers. The event loop of `asyncio` is more complex than that simulation loop, but the idea is the same. So if you want to understand how concurrency with coroutines works, studying *taxi_sim.py* may be a good starting point.

The coroutine version of the spinner program is easier to understand if we start from the `main` function, then study the `supervisor`. That’s what Example 20-4 shows.

Example 20-4. spinner_async.py: the main function and supervisor coroutine

```
def main() -> None:  ❶
    result = asyncio.run(supervisor())  ❷
    print(f'Answer: {result}')

async def supervisor() -> int:  ❸
    spinner = asyncio.create_task(spin('thinking!'))  ❹
    print(f'spinner object: {spinner}')  ❺
    result = await slow()  ❻
    spinner.cancel()  ❼
    return result

if __name__ == '__main__':
    main()
```

❶ `main` is the only regular function in this program—the others are coroutines.

❷ The `asyncio.run` function starts the event loop to drive the coroutine that will eventually set the other coroutines in motion. The `main` function will stay blocked until `supervisor` returns. The return value of `supervisor` will be the return value of `asyncio.run`.

❸ Native coroutines are defined with `async def`.

❹ `asyncio.create_task` schedules the eventual execution of `spin`, immediately returning an instance of `asyncio.Task`.

❺ The `repr` of the `spinner` object looks like `<Task pending name='Task-2' coro=<spin() running at /path/to/spinner_async.py:11>>`.

❻ The `await` keyword calls `slow`, blocking `supervisor` until `slow` returns. The return value of `slow` will be assigned to `result`.

❼ The `Task.cancel` method raises a `CancelledError` exception inside the `spin` coroutine, as we'll see in Example 20-5.

Example 20-4 demonstrates the three main ways of running a coroutine:

`asyncio.run(coro())`

Called from a regular function to drive a coroutine object which usually is the entry point for all the asynchronous code in the program, like the `supervisor` in this example. This call blocks until the body of `coro` returns. The return value of the `run()` call is whatever the body of `coro` returns.

`asyncio.create_task(coro())`

Called from a coroutine to schedule another coroutine to execute eventually. This call does not suspend the current coroutine. It returns a `Task` instance, an object that wraps the coroutine object and provides methods to control and query its state.

`await coro()`

Called from a coroutine to transfer control to the coroutine object returned by `coro()`. This suspends the current coroutine until the body of `coro` returns. The value of the await expression is whatever body of `coro` returns.

> **NOTE**
>
> Remember: invoking a coroutine as `coro()` immediately returns a coroutine object, but does not run the body of the `coro` function. Driving the body of coroutines is the job of the event loop, which invokes the `.send()` method on the coroutine objects, just like we drove classic coroutines built from generators in Chapter 19.

Now let's study the `spin` and `slow` coroutines in Example 20-5.

Example 20-5. spinner_async.py: the spin and slow coroutines

```
import asyncio
import itertools

async def spin(msg: str) -> None:  ❶
    for char in itertools.cycle(r'\|/-'):
        status = f'\r{char} {msg}'
        print(status, flush=True, end='')
        try:
            await asyncio.sleep(.1)  ❷
        except asyncio.CancelledError:  ❸
            break
    blanks = ' ' * len(status)
    print(f'\r{blanks}\r', end='')

async def slow() -> int:
    await asyncio.sleep(3)  ❹
    return 42
```

❶ We don't need the `Event` argument that was used to signal that `slow` had completed its job in *spinner_thread.py* (Example 20-1).

❷ Use `await asyncio.sleep(.1)` instead of `time.sleep(.1)`, to pause without blocking other coroutines. See explanation after this example.

❸ `asyncio.CancelledError` is raised when the `cancel` method is called on the `Task` controlling this coroutine. Time to exit the loop.

❹ The `slow` coroutine also uses `await asyncio.sleep` instead of `time.sleep`.

Experiment: Break the Spinner for an Insight

Here is an experiment I recommend to understand how *spinner_async.py* works. Import the `time` module, then go to the `slow` coroutine and replace the line `await asyncio.sleep(3)` with a call to `time.sleep(3)`, like this:

Example 20-6. spinner_async.py: replacing `await asyncio.sleep(3)` with `time.sleep(3)`

```
async def slow() -> int:
    time.sleep(3)
    return 42
```

Watching the behavior is more memorable than reading about it. Go ahead, I'll wait.

When you run the experiment, this is what you see:

1. The spinner object is shown, similar to this: `<Task pending name='Task-2' coro=<spin() running at /path/to/spinner_async.py:12>>`.
2. The spinner never appears. The program hangs for 3 seconds.
3. "`Answer: 42`" is displayed and the program ends.

To understand what is happening, recall that Python code using `asyncio` has only one flow of execution, unless you've explicitly started additional threads or processes. That means only one coroutine executes at any point in time. Concurrency is achieved by control passing from one coroutine to another. Let's focus on what happens in the `supervisor` and `slow` coroutines during the proposed experiment:

Example 20-7. spinner_async_experiment.py: the supervisor and slow coroutines

```
async def slow() -> int:
    time.sleep(3)  ❹
    return 42

async def supervisor() -> int:
    spinner = asyncio.create_task(spin('thinking!'))  ❶
    print(f'spinner object: {spinner}')  ❷
    result = await slow()  ❸
    spinner.cancel()  ❺
    return result
```

❶ The `spinner` task is created, to eventually drive the execution of `spin`.

❷ The display shows the `Task` is "pending".

❸ The `await` expression transfers control to the `slow` coroutine.

❹ `time.sleep(3)` blocks for 3 seconds; nothing else can happen in the program, because the main thread is blocked—and it is the only thread. The operating system will continue with other activities. After 3 seconds, `sleep` unblocks, and `slow` returns.

❺ Right after `slow` returns, the `spinner` task is cancelled. The flow of control never reached the body of the `spin` coroutine.

The *spinner_async_experiment.py* teaches an important lesson:

WARNING

Never use `time.sleep(…)` in `asyncio` coroutines unless you want to pause your whole program. If a coroutine needs to spend some time doing nothing, it should `await asyncio.sleep(DELAY)`. This yields control back to the `asyncio` event loop, which can drive other pending coroutines.

Supervisors Side-by-side

The line count of *spinner_thread.py* and *spinner_async.py* is nearly the same. The `supervisor` functions are the heart of these examples. Let's compare them in detail. Example 20-8 lists only the `supervisor` from Example 20-2.

Example 20-8. spinner_thread.py: the threaded supervisor function

```
def supervisor() -> int:
    done = Event()
    spinner = Thread(target=spin,
                     args=('thinking!', done))
    print('spinner object:', spinner)
    spinner.start()
    result = slow()
    done.set()
    spinner.join()
    return result
```

For comparison, Example 20-9 shows the `supervisor` coroutine from Example 20-4.

Example 20-9. spinner_async.py: the asynchronous supervisor coroutine

```
async def supervisor() -> int:
    spinner = asyncio.create_task(spin('thinking!'))
    print('spinner object:', spinner)
    result = await slow()
    spinner.cancel()
    return result
```

Here is a summary of the differences and similarities to note between the two `supervisor` implementations:

- An `asyncio.Task` is roughly the equivalent of a `threading.Thread`.
- A `Task` drives a coroutine object, and a `Thread` invokes a callable.
- A coroutine yields control explicitly with the `await` keyword.
- You don't instantiate `Task` objects yourself, you get them by passing a coroutine to `asyncio.create_task(…)`.
- When `asyncio.create_task(…)` returns a `Task` object, it is already scheduled to run, but a `Thread` instance must be explicitly told to run by calling its `start` method.
- In the threaded `supervisor`, `slow` is a plain function and is directly invoked by the main thread. In the asynchronous `supervisor`, `slow` is a coroutine driven by `await`.
- There's no API to terminate a thread from the outside; instead, you must send a signal—like setting the `done` `Event` object. For tasks, there is the `Task.cancel()` instance method, which raises `CancelledError` at the `await` expression where the coroutine body is currently suspended.
- The `supervisor` coroutine must be started with `asyncio.run` in the `main` function.

This comparison should help you understand how concurrent jobs are orchestrated with `asyncio`, in contrast to how it's done with the `Threading` module which may be more familiar to you.

One final point related to threads versus coroutines: if you've done any nontrivial programming with threads, you know how challenging it is to reason about the program because the scheduler can interrupt a thread at any time. You must remember to hold locks to protect the critical sections of your program, to avoid getting interrupted in the middle of a multistep operation—which could leave data in an invalid state.

With coroutines, your code is protected against interruption by default. You must explicitly `await` to let the rest of the program run. Instead of holding locks to synchronize the operations of multiple threads, coroutines are "synchronized" by definition: only one of them is running at any time. When you want to give up control, you use `await` to yield control back to the scheduler. That's why it is possible to safely cancel a coroutine: by definition, a coroutine can only be cancelled when it's suspended at an `await` expression, so you can perform cleanup by handling the `CancelledError` exception.

The `time.sleep()` call blocks but does nothing. Now we'll experiment with a CPU-intensive call to get a better understanding of the GIL, as well as the effect of CPU-intensive functions in asynchronous code.

The Real Impact of the GIL

In the threading code (Example 20-1), you can replace the `time.sleep(3)` call in the `slow` function with an HTTP client request from your favorite library, and the spinner will keep spinning. That's because a well-designed network library will release the GIL while waiting for the network.

You can also replace the `asyncio.sleep(3)` expression in the `slow` coroutine to `await` for a response from a well-designed asynchronous network library, because such libraries provide coroutines that yield control back to the event loop while waiting for the network. Meanwhile, the spinner will keep spinning.

With CPU intensive code, the story is different. Consider the function `is_prime` in Example 20-10, which returns `True` if the argument is a prime number, `False` if it's not.

Example 20-10. primes.py: an easy to read primality check, from Python's `ProcessPoolExecutor` example.

```
def is_prime(n: int) -> bool:
    if n < 2:
```

```
        return False
    if n == 2:
        return True
    if n % 2 == 0:
        return False

    root = math.isqrt(n)
    for i in range(3, root + 1, 2):
        if n % i == 0:
            return False
    return True
```

The call `is_prime(5_000_111_000_222_021)` takes about 3.3s on the company laptop I am using now.[9]

Quick Quiz

Given what we've seen so far, please take the time to consider the following three-part question. One part of the answer is tricky (at least it was for me).

> *What would happen to the spinner animation if made the following changes, assuming that `n = 5_000_111_000_222_021`—that prime which my machine takes 3.3s to verify:*
>
> 1. *In spinner_proc.py, replace `time.sleep(3)` with a call to `is_prime(n)`?*
> 2. *In spinner_thread.py, replace `time.sleep(3)` with a call to `is_prime(n)`?*
> 3. *In spinner_async.py, replace `await asyncio.sleep(3)` with a call to `is_prime(n)`?*

Before you run the code or read on, I recommend figuring out the answers on your own. Then, you may want to copy and modify the *spinner*.py_ examples as suggested.

Now the answers, from easier to hardest.

1. Answer for `multiprocessing`

The spinner is controlled by a child process, so it continues spinning while the primality test is computed by the parent process.[10]

2. Answer for `threading`

The spinner is controlled by a secondary thread, so it continues spinning while the primality test is computed by the main thread.

I did not get this answer right at first: I was expecting the spinner to freeze because I overestimated the impact of the GIL .

In this particular example the spinner keeps spinning because Python suspends the running thread every 5ms (by default), making the GIL available to other pending threads. Therefore, the main thread running `is_prime` is interrupted every 5ms, allowing the secondary thread to wake up and iterate once through the `for` loop, until it calls the `wait` method of the `done` event, at which time it will release the GIL. The main thread will then grab the GIL, and the `is_prime` computation will proceed for another 5ms.

This does not have a visible impact on the running time of this specific example because the `spin` function quickly iterates once and releases the GIL as it waits for the `done` event, so there is not much contention for the GIL. The main thread running `is_prime` will have the GIL most of the time.

We got away with a compute intensive task using threading in this simple experiment because there are only two threads: one hogging the CPU, and the other waking up only 10 times per second to update the spinner.

But you if you have two ore more threads vying for a lot of CPU time, your program will be slower than sequential code.

3. Answer for `asyncio`

If you call `is_prime(5_000_111_000_222_021)` in the `slow` coroutine of the *spinner_async.py* example, the spinner will never appear. The effect would be the same we had in Example 20-6, when we replaced `await asyncio.sleep(3)` with `time.sleep(3)`: no spinning at all. The flow of control will pass from `supervisor` to `slow`, and then to `is_prime`. When `is_prime` returns, `slow` returns as well, and `supervisor` resumes, cancelling the `spinner` task before it is executed even once. The program appears frozen for about 3s, then shows the answer.

POWER NAPPING WITH SLEEP(0)

One way to keep the spinner alive is to rewrite `is_prime` as a coroutine, and periodically call `asyncio.sleep(0)` in an `await` expression to yield control back to the event loop, like this:

Example 20-11. spinner_async_nap.py: `is_prime` is now a coroutine

```
async def is_prime(n):
    if n < 2:
        return False
    if n == 2:
        return True
    if n % 2 == 0:
        return False

    root = math.isqrt(n)
    for i in range(3, root + 1, 2):
        if n % i == 0:
            return False
        if i % 100_000 == 1:  ❷
            await asyncio.sleep(0) ❶
    return True
```

❶ Micro-optimization: bind `sleep` to `asyncio.sleep` to avoid the attribute lookup inside the loop.

❷ `await sleep(0)` once every 100,000 iterations.

Issue #284 in the `asyncio` repository has an informative discussion about the use of `asyncio.sleep(0)`.

However, be aware this will slow down `is_prime`, and—more importantly—will still slow down the event loop and your whole program with it. When I used `await asyncio.sleep(0)` every 100,000 iterations, the spinner was smooth but the program ran in 4.9s on my machine, almost 50% longer than the original `primes.is_prime` function by itself with the same argument (5_000_111_000_222_021).

Using `await asyncio.sleep(0)` should be considered a stopgap measure before you refactor your asynchronous code to delegate CPU-intensive computations to another process. We'll see one way of doing that with `asyncio.loop.run_in_executor`, covered in Chapter 22. Another option would be a task queue, which we'll briefly discuss in "Distributed task queues".

So far, we've only experimented with a single call to a CPU-intensive function. The next section presents concurrent execution of multiple CPU-intensive calls.

A Homegrown Process Pool

WARNING

I wrote this section to demonstrate the effect of multiple processes for CPU intensive tasks, and the common pattern of using queues to distribute tasks and collect results. Chapter 21 will show a simpler way of distributing tasks to processes: a `ProcessPoolExecutor` from the `concurrent.futures` package, which uses queues internally.

In this section we'll write programs to compute the primality of a sample of 20 integers, from 2 to 9,999,999,999,999,999—i.e. 10^{16}-1, or more than 2^{53}. The sample includes small and large primes, as well as composite numbers with small and large prime factors.

The *sequential.py* program provides the performance baseline. Here is a sample run:

```
$ python3 sequential.py
               2  P  0.000001s
 142702110479723  P  0.568328s
 299593572317531  P  0.796773s
3333333333333301  P  2.648625s
3333333333333333     0.000007s
3333335652092209     2.672323s
```

```
4444444444444423  P  3.052667s
4444444444444444     0.000001s
4444444488888889     3.061083s
5555553133149889     3.451833s
5555555555555503  P  3.556867s
5555555555555555     0.000007s
6666666666666666     0.000001s
6666666666666719  P  3.781064s
6666667141414921     3.778166s
7777777536340681     4.120069s
7777777777777753  P  4.141530s
7777777777777777     0.000007s
9999999999999917  P  4.678164s
9999999999999999     0.000007s
Total time: 40.31
```

The results are shown in three columns:

1. the number to be checked;
2. `P` if it's a prime number, blank if not;
3. elapsed time for checking the primality for that specific number.

In this example, the total time is approximately the sum of the times for each check—but it is computed separately, as you can see in Example 20-12.

Example 20-12. sequential.py: sequential primality check for a small dataset

```
#!/usr/bin/env python3

"""
sequential.py: baseline for comparing sequential, multiprocessing,
and threading code for CPU-intensive work.
"""

from time import perf_counter
from typing import NamedTuple

from primes import is_prime, NUMBERS

class Result(NamedTuple):  ❶
    prime: bool
    elapsed: float
```

```
def check(n: int) -> Result:  ❷
    t0 = perf_counter()
    prime = is_prime(n)
    return Result(prime, perf_counter() - t0)

def main() -> None:
    print(f'Checking {len(NUMBERS)} numbers sequentially:')
    t0 = perf_counter()
    for n in NUMBERS:  ❸
        prime, elapsed = check(n)
        label = 'P' if prime else ' '
        print(f'{n:16}  {label} {elapsed:9.6f}s')

    elapsed = perf_counter() - t0  ❹
    print(f'Total time: {elapsed:.2f}s')

if __name__ == '__main__':
    main()
```

❶ The `check` function (below) returns a `Result` tuple with the boolean value of the `is_prime` call and the elapsed time.

❷ `check(n)` calls `is_prime(n)` and computes the elapsed time to return a `Result`.

❸ For each number in the sample, we call `check` and display the result.

❹ Compute and display the total elapsed time.

Process-based Solution

The next example, *procs.py*, shows the use of multiple processes to distribute the primality checks across multiple CPU cores. These are the times I get with *procs.py*:

```
$ python3 procs.py
Checking 20 numbers with 12 processes:
               2  P  0.000002s
3333333333333333     0.000021s
4444444444444444     0.000002s
5555555555555555     0.000018s
```

```
 6666666666666666     0.000002s
  142702110479723  P  1.350982s
 7777777777777777     0.000009s
  299593572317531  P  1.981411s
 9999999999999999     0.000008s
 3333333333333301  P  6.328173s
 3333335652092209     6.419249s
 4444444488888889     7.051267s
 4444444444444423  P  7.122004s
 5555553133149889     7.412735s
 5555555555555503  P  7.603327s
 6666666666666719  P  7.934670s
 6666667141414921     8.017599s
 7777777536340681     8.339623s
 7777777777777753  P  8.388859s
 9999999999999917  P  8.117313s
 Total time: 9.58s
```

The last line of the output shows that *procs.py* was 4.2 times faster than *sequential.py*.

Understanding the Elapsed Times

Note that the elapsed time in the first column is for checking that specific number. For example, `is_prime(7777777777777753)` took almost 8.4s to return `True`. Meanwhile, other processes were checking other numbers in parallel.

There were 20 numbers to check. I wrote *procs.py* to start a number of worker processes equal to the number of CPU cores, as determined by `multiprocessing.cpu_count()`.

The total time in this case is much less than sum of the elapsed time for the individual checks. There is some overhead in spinning up processes and in inter-process communication, so the end result is that the multiprocess version is only about 4.2 times faster than the sequential. That’s good, but a little disappointing considering the code launches 12 processes to use all cores on this laptop.

> **NOTE**
>
> The `multiprocessing.cpu_count()` function returns `12` on the MacBook Pro I'm using to write this chapter. It's actually a 6-CPU Core-i7, but the OS reports 12 CPUs because of hyper-threading, an Intel technology which executes 2 threads per core. However, hyper-threading works better when one of the threads is not working as hard as the other thread in the same core—perhaps the first is stalled waiting for data after a cache miss, and the other is crunching numbers. Anyway, there's no free lunch: this laptop performs like a 6-CPU machine for compute-intensive work that doesn't use a lot of memory—like that simple primality test. I'm not complaining, just saying.

Code for the Multi-core Prime Checker

When we delegate computing to threads or processes, our code does not call the worker function directly, so we can't simply get a return value. Instead, the worker is driven by the thread or process library, and it eventually produces a result which needs to be stored somewhere. Coordinating workers and collecting results are common uses of queues in concurrent programming (and also in distributed systems, by the way).

Queues are data structures that—usually—enforce FIFO ordering: first in, first out. Queues need to be implemented according to the underlying concurrency model: the `queue` package in Python's standard library provides queue classes to support threads, while the `multiprocessing` and `asyncio` packages implement their own queue classes. The `queue` and `asyncio` packages also include queues that are not FIFO: `LifoQueue` and `PriorityQueue`.

Much of the new code in *procs.py* has to do with setting up and using queues. The top of the file is in Example 20-13.

> **WARNING**
>
> `SimpleQueue` was added to `multiprocessing` in Python 3.9. If you're using an earlier version of Python, you can replace `SimpleQueue` with `Queue` in this example.

Example 20-13. procs.py: multiprocess primality check; imports, types and functions

```
import sys
from time import perf_counter
from typing import NamedTuple
from multiprocessing import Process, SimpleQueue, cpu_count  ❶
from multiprocessing import queues  ❷

from primes import is_prime, NUMBERS

class PrimeResult(NamedTuple):  ❸
    n: int
    prime: bool
    elapsed: float

JobQueue = queues.SimpleQueue[int]  ❹
ResultQueue = queues.SimpleQueue[PrimeResult]  ❺

def check(n: int) -> PrimeResult:  ❻
    t0 = perf_counter()
    res = is_prime(n)
    return PrimeResult(n, res, perf_counter() - t0)

def worker(jobs: JobQueue, results: ResultQueue) -> None:  ❼
    while n := jobs.get():  ❽
        results.put(check(n))  ❾
```

❶ Trying to emulate `threading`, `multiprocessing` provides `multiprocessing.SimpleQueue`, but this is a method bound to a pre-defined instance of a lower-level `BaseContext` class. We must call this `SimpleQueue` to build a queue, but it can't be used in type hints.

❷ `multiprocessing.queues` includes the `SimpleQueue` class we need for type hints.

❸ `PrimeResult` includes the number checked for primality. Keeping `n` together with the other result fields simplifies displaying results later.

❹ We'll use a `SimpleQueue` to send numbers to the processes that will do the work.

❺ A second `SimpleQueue` will collect the results. The values in the queue will be tuples made of the number to be tested for primality, and a `Result` tuple.

❻ This is similar to *sequential.py*.

❼ `worker` gets a queue with the numbers to be checked, and another to put results.

❽ In this code, I use the number `0` as a sentinel: a signal for the worker to finish. If `n` is not `0`, proceed with the loop.[11]

❾ Invoke the primality check and enqueue `PrimeResult`.

WHAT'S A GOOD POISON PILL?

The `worker` function in Example 20-13 follows a common pattern in concurrent programming: looping indefinitely while taking items from a queue and processing each with a function that does the actual work. The loop ends when the queue produces a sentinel. In this pattern, the sentinel that kills the worker is sometimes called a "poison pill".

Besides `None`, calling `object()` is a common way to get a unique value to use as sentinel. However, this does not work across processes, because when you `pickle.dump` and `pickle.load` an instance of `object`, the unpickled instance is distinct from the original and doesn't compare equal. If `None` can occur in the stream, a good alternative is `...`, the `Ellipsis` built-in object, which survives serialization without losing its identity.[12]

Now let's study the `main` function of *procs.py* in Example 20-14.

Example 20-14. procs.py: multiprocess primality check; main function

```
def main() -> None:
    if len(sys.argv) < 2:  ❶
        workers = cpu_count()
    else:
        workers = int(sys.argv[1])

    print(f'Checking {len(NUMBERS)} numbers with {workers}
```

```
processes:')

    jobs: JobQueue = SimpleQueue()  ❷
    results: ResultQueue = SimpleQueue()
    t0 = perf_counter()

    for n in NUMBERS:  ❸
        jobs.put(n)

    for _ in range(workers):
        proc = Process(target=worker, args=(jobs, results))  ❹
        proc.start()  ❺
        jobs.put(0)  ❻

    while True:
        n, prime, elapsed = results.get()  ❼
        label = 'P' if prime else ' '
        print(f'{n:16}  {label} {elapsed:9.6f}s')  ❽
        if jobs.empty():  ❾
            break

    elapsed = perf_counter() - t0
    print(f'Total time: {elapsed:.2f}s')

if __name__ == '__main__':
    main()
```

❶ If no command line argument is given, set the number of workers to the number of CPU cores; otherwise, create as many workers as given in the first argument.

❷ `jobs` and `results` are the queues described in Example 20-13.

❸ Enqueue the numbers to be checked in `jobs`.

❹ Fork a child process for each worker. Each child will run the loop inside its own instance of the `worker` function, until it fetches a `0` from the `jobs` queue.

❺ Start the child process.

❻ Enqueue one `0` for each worker as a sentinel.

❼ Get the checked number `n` and the `Result`. Calling `.get()` on a queue blocks until there is an item in the queue. It's also possible to make this unblocking, or set a timeout. See the `SimpleQueue.get` documentation for details.

❽ The results will not come back in the same order we submitted the jobs, so we needed to put `n` in each `PrimeResult` tuple to make this `print` call. Otherwise, we'd have no way to know which result belonged to each number.

❾ Exit the loop when the `jobs` queue is empty.

In this example, it's safe to exit the last loop when the `jobs` queue is empty because the last item put in that queue is a sentinel. Therefore, when a worker gets that sentinel, all the other workers got their sentinels as well, and no more inter-process communication will happen. If the last item in `jobs` were a big prime, it could happen that `jobs` is empty but a worker is still running.

> **NOTE**
>
> If the main process exits before all workers are done, you may see confusing tracebacks on `FileNotFoundError` exceptions caused by an internal lock in `multiprocessing`. Debugging concurrent code is always hard, and debugging `multiprocessing` is even harder, because of all the complexity behind the thread-like façade. Fortunately, the `ProcessPoolExecutor` we'll meet in Chapter 21 is simpler and more robust than this example.

Experimenting with More or Less Workers

You may want try running *procs.py* passing arguments to set the number of worker processes. For example, this command…

```
$ python3 procs.py 2
```

…will launch two worker processes, producing results almost twice as fast as *sequential.py*—if your machine has at least two cores and is not too busy running other programs.

I ran *procs.py* 12 times with 1 to 20 processes, totalling 240 runs. Then I computed the median time for all runs with the same number of processes, and plotted Figure 20-2.

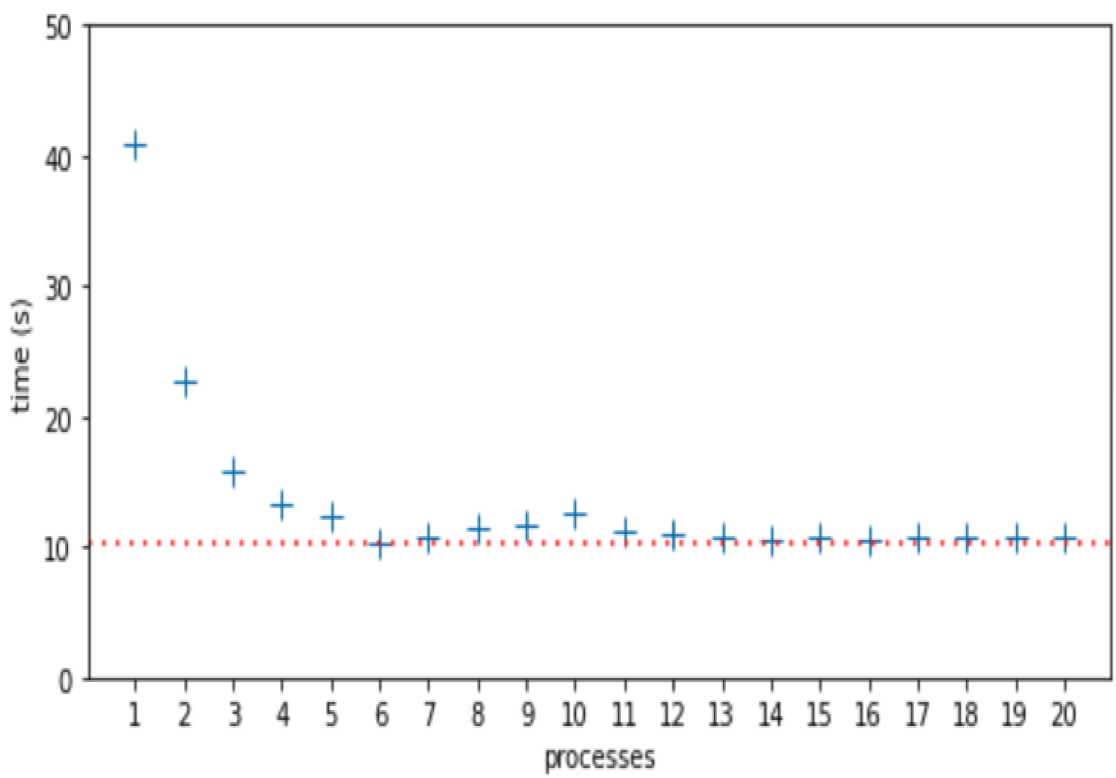


Figure 20-2. Median run times for each number of processes from 1 to 20. Highest median time was 40.81s, with 1 process. Lowest median was 10.39, with 6 processes, indicated by the dotted line.

In this 6-core laptop, the lowest median time was with 6 processes: 10.39s—marked by the dotted line in Figure 20-2. I expected the run time to increase after 6 processes due to CPU contention, and it reaches a local maximum of 12.51s at 10 processes. I did not expect and I can't explain why the performance improves at 11 processes and stays almost flat from 13 to 20 processes, with median times only slightly higher than the lowest median time at 6 processes.

Thread-based Non-solution

I also wrote *threads.py*, a version of *procs.py* using `threading` instead of `multiprocessing`. The code is very similar—as is usually the case when converting simple examples between these two APIs.[13]. Due to the GIL and the compute-intensive nature of `is_prime`, the threaded version is slower than the sequential code, and it gets slower as the number of threads increase, because of CPU contention and the cost of context switching: to switch to a new thread, the OS needs to save CPU registers and update the program counter and stack pointer—triggering expensive side-effects like invalidating caches and swapping memory pages.[14]

The next two chapters will cover more about concurrent programming in Python, using the high-level `concurrent.futures` library to manage threads and processes (Chapter 21) and the `asyncio` library for asynchronous programming (Chapter 22).

The remaining sections in this chapter aim to answer the question:

> *Given the limitations discussed so far, how is Python thriving in a multi-core world?*

The Big Picture

Consider this citation from the widely quoted article *The Free Lunch Is Over* by Herb Sutter:

> *The major processor manufacturers and architectures, from Intel and AMD to Sparc and PowerPC, have run out of room with most of their traditional approaches to boosting CPU performance. Instead of driving clock speeds and straight-line instruction throughput ever higher, they are instead turning en masse to hyperthreading and multicore architectures.*[15]

What Sutter calls the “free lunch” was the trend of software getting faster with no additional developer effort because CPUs were executing sequential code faster, year after year. Since 2004, that is no longer true:

clock speeds and execution optimizations reached a plateau, and now any significant increase in performance must come from leveraging multiple cores or hyper-threading, advances that only benefit code that is written for concurrent execution.

Python's story started in the early 1990's, when CPUs were still getting exponentially faster at sequential code execution. No talk about multi-core CPUs except in supercomputers back then. At the time, the decision to have a GIL was a no-brainer. The GIL makes the interpreter faster when running on a single core, and its implementation simpler.[16] The GIL also makes it easier to write simple extensions through the Python/C API.

> **NOTE**
>
> I just wrote "simple extensions" because an extension does not need to deal with the GIL at all. A function written in C or Fortran may be hundreds of times faster than the same in Python.[17] Therefore the added complexity of releasing the GIL to leverage multi-core CPUs may not be needed in many cases. So we can thank the GIL for many extensions available for Python—and that is certainly one of the key reasons why the language is so popular today.

Despite the GIL, Python is thriving in applications that require concurrent or parallel execution, thanks to libraries and software architectures that work around the limitations of CPython.

Now let's discuss how Python is used in system administration, data science, and server-side application development in the multi-core, distributed computing world of 2021.

System Administration

Python is widely used to manage large fleets of servers, routers, load balancers, network-attached storage (NAS). It's also a leading option in software-defined networking (SDN) and ethical hacking. Major cloud service providers support Python through libraries and tutorials authored by the providers themselves or by their large communities of Python users.

In this domain, Python scripts automate configuration tasks by issuing commands to be carried out by the remote machines, so rarely there are CPU-bound operations to be done. Threads or coroutines are well suited for such jobs. In particular, the `concurrent.futures` package we'll see in Chapter 21 can be used to perform the same operations on many remote machines at the same time without a lot of complexity.

There is also a growing number of libraries for system administration supporting coroutines and `asyncio`. In 2016, Facebook's Production Engineering team reported: "We are increasingly relying on AsyncIO, which was introduced in Python 3.4, and seeing huge performance gains as we move codebases away from Python 2."

Data Science

Data Science—including Artificial Intelligence—and scientific computing are very well served by Python. Applications in these fields are compute-intensive, but Python users benefit from a vast ecosystem of numeric computing libraries written in C, C++, Fortran, Cython, etc.—many of which are able to leverage multi-core machines, GPUs, and/or distributed parallel computing in heterogeneous clusters.

As of 2021, Python's data science ecosystem includes impressive tools such as:

Project Jupyter

> Two browser based interfaces—Jupyter Notebook and JupyterLab—that allow users to run and document analytics code potentially running across the network on remote machines. Both are hybrid Python/JavaScript applications, supporting computing kernels written in different languages, all integrated via ZeroMQ—an asynchronous messaging library for distributed applications. The name *Jupyter* actually comes from Julia, Python, and R, the first three languages supported by the Notebook. The rich ecosystem built on top of the Jupyter tools include Bokeh, a powerful interactive visualization library that lets users navigate and interact with large datasets or continuously

updated streaming data, thanks to the performance of modern JavaScript engines and browsers.

TensorFlow and PyTorch

These are the top two deep learning frameworks, according to O'Reilly Media's January 2021 report on usage of their learning resources during 2020. Both projects are written in C++, and are able to leverage multiple cores, GPUs, and clusters. They support other languages as well, but Python is their main focus and is used by the majority of their users. TensorFlow was created and is used internally by Google; PyTorch by Facebook.

Dask

A parallel computing library that can farm out work to local processes or clusters of machines, "tested on some of the largest supercomputers in the world"—as their home page states. Dask offers APIs that closely emulate NumPy, Pandas, and Scikit-Learn—the most popular libraries in data science and machine learning today. Dask can be used from JupyterLab or Jupyter Notebook, and leverages Bokeh not only for data visualization but also for an interactive dashboard showing the flow of data and computations across the processes/machines in near real-time. Dask is so impressive that I recommend watching a video such as this 15-minute demo in which Matthew Rocklin—a maintainer of the project—shows Dask crunching data on 64 cores distributed in 8 EC2 machines on AWS.

These are only some examples to illustrate how the data science community is creating solutions that leverage the best of Python and overcome the limitations of the CPython runtime.

Server-side Web/Mobile Development

Python is widely used in Web applications and for the back-end APIs supporting mobile applications. How is it that Google, YouTube, Dropbox, Instagram, Quora, and Reddit—among others—managed to build Python server-side applications serving hundreds of millions of users 24x7? Again, the answer goes way beyond what Python provides "out of the box."

Before we discuss tools to support Python at scale, I must quote an admonition from the Thoughtworks Technology Radar:

> ***High performance envy/web scale envy***
>
> *We see many teams run into trouble because they have chosen complex tools, frameworks or architectures because they "might need to scale". Companies such as Twitter and Netflix need to support extreme loads and so need these architectures, but they also have extremely skilled development teams able to handle the complexity. Most situations do not require these kinds of engineering feats; teams should keep their* ***web scale envy*** *in check in favor of simpler solutions that still get the job done.*[18]

At *Web scale*, the key is an architecture that allows horizontal scaling. At that point, all systems are distributed systems, and no single programming language is likely to be the right choice for every part of solution.

Distributed systems is a field of academic research, but fortunately some practitioners have written accessible books anchored on solid research and practical experience. One of them is Martin Kleppmann, the author of *Designing Data-Intensive Applications* (O'Reilly, 2017).

Consider Figure 20-3, the first of many architecture diagrams in Kleppmann's book. Here are some components I've seen in Python engagements that I worked on or have firsthand knowledge:

- application caches[19]: *memcached*, *Varnish*, *Redis*;
- relational databases: *PostgreSQL*, *MySQL*;
- document databases: *Apache CouchDB*, *MongoDB*;
- full-text indexes: *Elasticsearch*, *Apache Solr*;
- message queues: *RabbitMQ*, *Redis*.

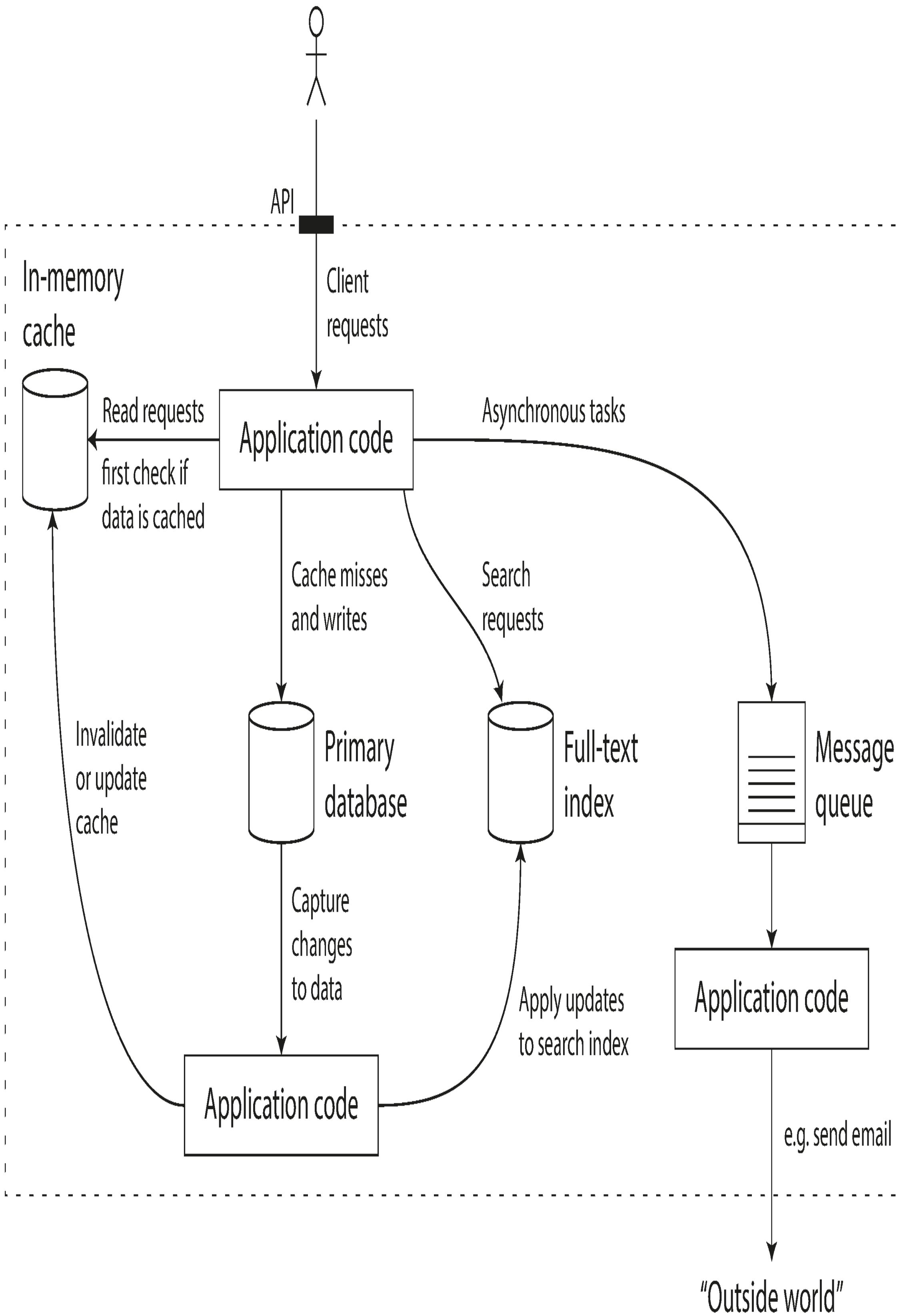

API
In-memory cache
Client requests
Read requests first check if data is cached
Application code
Asynchronous tasks
Cache misses and writes
Search requests
Invalidate or update cache
Primary database
Full-text index
Message queue
Capture changes to data
Apply updates to search index
Application code
Application code
e.g. send email
“Outside world”

Figure 20-3. One possible architecture for a data system that combines several components.[20]

There are other industrial-strength Open Source products in each of those categories. Major cloud providers also offer their own proprietary alternatives.

Kleppmann's diagram is general and language-independent—as is his book. For Python server-side applications, two specific components are often deployed:

- An application server to distribute the load among several instances of the Python application. The application server would appear near the top in Figure 20-3, handling client requests before they reached the application code.
- A task queue built around the message queue on the right-hand side of Figure 20-3, providing a higher level, easier to use API to distribute tasks to workers running on other machines.

The next two sections explore these components that are recommended best practices in Python server-side deployments.

WSGI Application servers

WSGI—the Web Server Gateway Interface—is a standard API for a Python framework or application to receive requests from a HTTP server and send responses to it.[21] The WSGI API is implemented by application servers manage one or more Python processes running your application, maximizing the use of the available CPUs. Figure 20-4 illustrates a typical deployment.

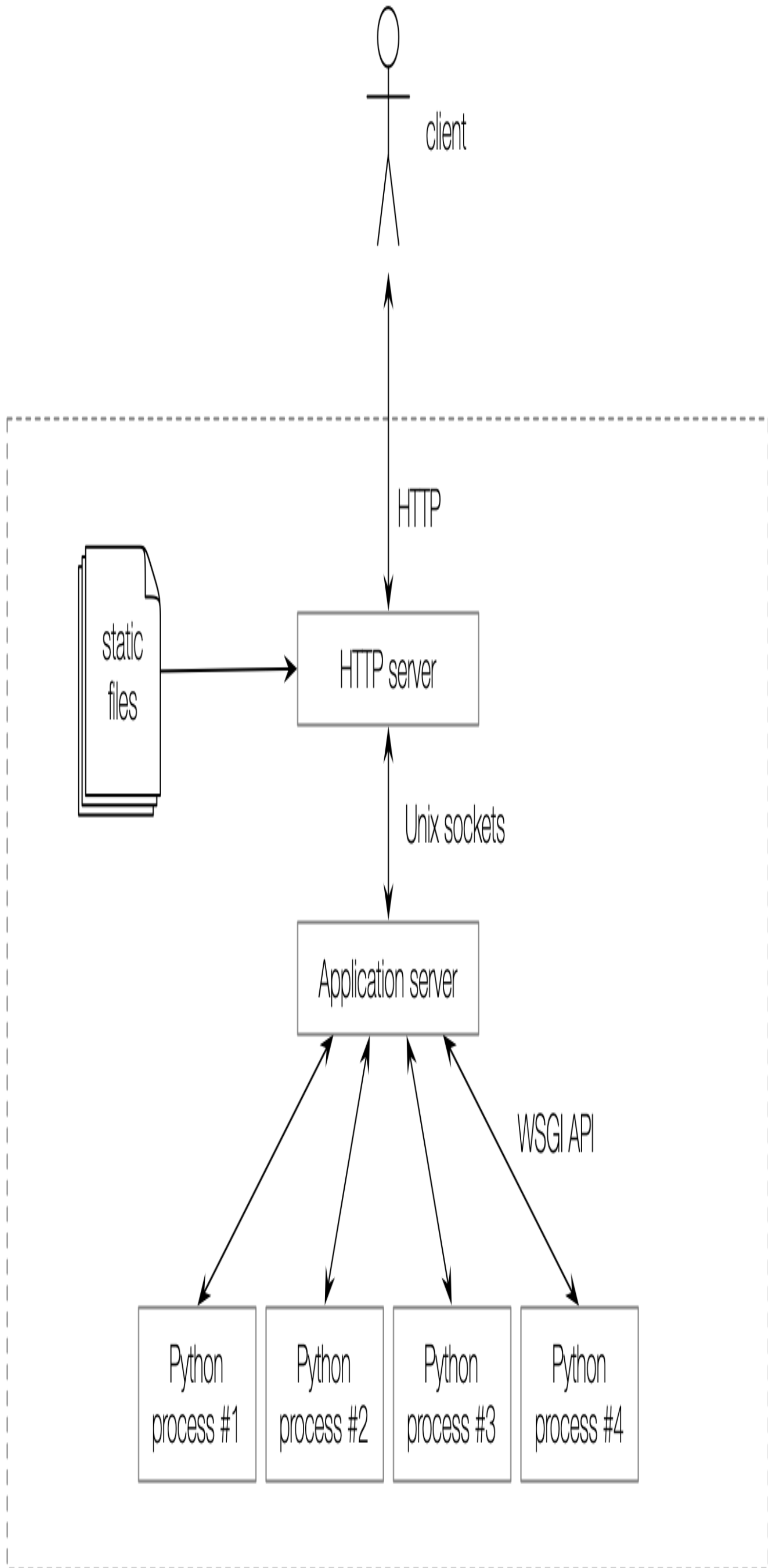

client
HTTP
static
files
HTTP server
Unix sockets
Application server
WSGI API
Python
process #1
Python
process #2
Python
process #3
Python
process #4

Figure 20-4. Clients connect to a HTTP server that delivers static files and routes other requests to the application server, which forks several Python processes to run the application code, maximizing the use of the CPU cores.

The best known application servers in Python Web projects are:

- *mod_wsgi*;
- *uWSGI*;[22]
- *gunicorn*;
- *NGINX Unit*.

For users Apache HTTP, *mod_wsgi* is the best option. It’s as old as WSGI itself, but is actively maintained, and now provides a command-line launcher called `mod_wsgi-express` that makes it easier to configure and more suitable for use in Docker containers.

uWSGI and *gunicorn* are the top choices in recent projects I know about. Both are often used with the *NGINX* HTTP server. *uWSGI* offers a lot of extra functionality, including an application cache, a task queue, cron-like periodic tasks, and many other features. On the flip side, *uWSGI* is much harder to configure properly than *gunicorn*.[23]

Released in 2018, *NGINX Unit* is a new product from the makers of the well known *NGINX* HTTP server and reverse proxy.

mod_wsgi and *gunicorn* support Python Web apps only, while *uWSGI* and *NGINX Unit* work with other languages as well. Please browse their docs to learn more.

The main point: all of these application servers leverage all CPU cores on the server by forking multiple Python processes to run traditional Web apps written in good old sequential code in *Django*, *Flask*, *Pyramid* etc. This explains why it’s been possible to earn a living as a Python Web developer without ever studying the `threading`, `multiprocessing`, or `asyncio` modules: the application server handles concurrency transparently.

ASGI—ASYNCHRONOUS SERVER GATEWAY INTERFACE

WSGI is a synchronous API. It doesn't support coroutines with `async/await`—the most efficient way to implement WebSockets or HTTP long polling in Python. The ASGI specification is a successor to WSGI designed for asynchronous Python Web frameworks such as *aiohttp*, *Sanic*, *FastAPI* etc. as well as *Django* and *Flask*, which are gradually adding asynchronous functionality.

Now let's turn to another way of bypassing the GIL to achieve higher performance with server-side Python applications.

Distributed task queues

When the application server delivers a request to one of the Python processes running your code, your app needs to respond quickly: you want the process to be available to handle the next request as soon as possible. However, some requests demand actions that may take longer—for example, sending e-mail or generating a PDF. That's the problem that distributed task queues are designed to solve.

Celery and RQ are the best known Open Source task queues with Python APIs. Cloud providers also offer their own proprietary task queues.

These products wrap a message queue and offer a high-level API for delegating tasks to workers, possibly running on different machines.

NOTE

In the context of task queues, the words *producer* and *consumer* are used instead of traditional client/server terminology. For example, a *Django* view handler *produces* job requests which are put in the queue to be *consumed* by one or more PDF rendering processes.

Quoting directly from *Celery*'s FAQ, here are some typical use cases:

- *Running something in the background. For example, to finish the web request as soon as possible, then update the users page incrementally. This gives the user the impression of good performance and "snappiness", even though the real work might actually take some time.*
- *Running something after the web request has finished.*
- *Making sure something is done, by executing it asynchronously and using retries.*
- *Scheduling periodic work.*

Besides solving these immediate problems, task queues support horizontal scalability. Producers and consumers are decoupled: a producer doesn't call a consumer, it puts a request in a queue. Consumers don't need to know anything about the producers (but the request may include information about the producer, if an acknowledgement is required). Crucially, you can easily add more workers to consume tasks as demand grows. That's why *Celery* and *RQ* are called distributed task queues.

Recall that our simple *procs.py* (Example 20-13) used two queues: one for job requests, the other for collecting results. The distributed architecture of *Celery* and *RQ* uses a similar pattern. Both support using the *Redis* NoSQL database as a message queue and result storage. *Celery* also supports other message queues like *RabbitMQ* or *Amazon SQS*, as well other databases for result storage.

This wraps up our introduction to concurrency in Python. The next two chapters will continue this theme, focusing on the `concurrent.futures` and `asyncio` packages of the standard library.

Chapter Summary

After a bit of theory, this chapter presented the spinner scripts implemented in each of Python's three native concurrency programming models:

- Threads, with the `threading` package;
- Processes, with `multiprocessing`;
- Asynchronous coroutines with `asyncio`.

We then explored the real impact of the GIL with an experiment: changing the spinner examples to compute the primality of a large integer and observe the resulting behavior. This demonstrated graphically that CPU-intensive functions must be avoided in `asyncio`, as they block the event loop. The threaded version of the experiment worked—despite the GIL—because Python periodically interrupts threads, and the example used only two threads: one doing compute-intensive work, and the other driving the animation only 10 times per second. The `multiprocessing` variant worked around the GIL, starting a new process just for the animation while the main process did the primality check.

The next example, computing several primes, highlighted the difference between `multiprocessing` and `threading`, proving that only processes allow Python to benefit from multicore CPUs. Python's GIL makes threads worse than sequential code for heavy computations.

The GIL dominates discussions about concurrent and parallel computing in Python, but we should not overestimate its impact. That was the point of "The Big Picture". For example, the GIL doesn't affect many use cases of Python in systems administration. On the other hand, the data science and server-side development communities have worked around the GIL with industrial-strength solutions tailored to their specific needs. The last two sections mentioned two common elements to support Python server-side applications at scale: WSGI application servers and distributed task queues.

Further Reading

This chapter has an extensive reading list, so I split it in subsections.

Concurrency with threads and processes

The `concurrent.futures` library covered in Chapter 21 uses threads, processes, locks, and queues under the hood, but you won't see individual instances of them; they're bundled and managed by the higher-level abstractions of a `ThreadPoolExecutor` and a `ProcessPoolExecutor`. If you want to learn more about the practice of concurrent programming with those low-level objects, An Intro to Threading in Python by Jim Anderson is a good first read. Doug Hellmann has a chapter titled *Concurrency with Processes, Threads, and Coroutines* in his site and book: Python 3 Standard Library by Example (Addison-Wesley, 2017).

Brett Slatkin's *Effective Python, Second Edition* (Addison-Wesley, 2019), David Beazley's *Python Essential Reference, 4th Edition* (Addison-Wesley Professional, 2009), and Martelli, Ravenscroft & Holden's *Python in a Nutshell*, 3E (O'Reilly) are other general Python references with significant coverage of `threading` and `multiprocessing`. The vast `multiprocessing` official documentation includes useful advice in its Programming guidelines section.

Jesse Noller and Richard Oudkerk contributed the `multiprocessing` package, introduced in PEP 371 — Addition of the multiprocessing package to the standard library. The official documentation for the package is a 93 KB *.rst* file—that's about 63 pages—making it one of the longest chapters in the Python standard library.

In *High Performance Python, 2nd Edition* (O'Reilly, 2020), authors Micha Gorelick and Ian Ozsvald includes a chapter about `multiprocessing` with an example about checking for primes with a different strategy than our *procs.py* example: for each number, they split the range of possible factors—from 2 to `sqrt(n)`—into sub-ranges, and make each worker iterate over one of the sub-ranges. Their divide-and-conquer approach is typical of scientific computing applications where the data sets are huge, and workstations (or clusters) have more CPU cores than users. On a server-side system handling requests from many users, it is simpler and more efficient to let each process work on one computation from start to finish—reducing the overhead of communication and coordination among processes. Besides `multiprocessing`, Gorelick & Ozsvald present many other ways of developing and deploying high performance data science applications leveraging multiple cores, GPUs, clusters, profilers, and compilers like Cython and Numba. Their last chapter, *Lessons from the Field*, is a valuable collection of short case studies contributed by other practitioners of high-performance computing in Python.

In *Advanced Python Development* (Apress, 2020), author Matthew Wilkes is a rare book that includes short examples to explain concepts, while also showing how to build a realistic application ready for production: a data aggregator, similar to DevOps monitoring systems or IoT data collectors for distributed sensors. Two chapters in *Advanced Python Development* cover concurrent programming with `threading` and `asyncio`.

Jan Palach's *Parallel Programming with Python* (Packt, 2014), explains the core concepts behind concurrency and parallelism, covering Python's standard library as well as *Celery*.

The Truth About Threads is the title of chapter 2 in *Using Asyncio in Python* by Caleb Hattingh (O'Reilly, 2020).[24] The chapter covers the benefits and drawbacks of threading—with compelling quotes from several authoritative sources—making it clear that the fundamental challenges of threads have nothing to do with Python or the GIL. Quoting verbatim from page 14 of *Using Asyncio in Python*:

> *These themes repeat throughout:*
>
> - *Threading makes code hard to reason about.*
> - *Threading is an inefficient model for large-scale concurrency (thousands of concurrent tasks).*

If you want to learn the hard way how difficult it is to reason about threads and locks—without risking your job—try the exercises in Alen Downey's workbook *The Little Book of Semaphores*. The exercises in Downey's book range from easy to very hard to unsolvable, but even the easy ones are eye opening.

The GIL

If you are intrigued about the GIL, start with the *Python Library and Extension FAQ* ("Can't we get rid of the Global Interpreter Lock?"). Also worth reading are posts by Guido van Rossum and Jesse Noller (contributor of the `multiprocessing` package): "It isn't Easy to Remove the GIL" and "Python Threads and the Global Interpreter Lock."

CPython Internals by Anthony Shaw explains the implementation of the CPython 3 interpreter at the C programming level. Shaw's longest chapter is *Parallelism and Concurrency*: a deep dive into Python's native support for threads and processes, including managing the GIL from extensions using the C/Python API.

Finally, David Beazley has a detailed exploration on the inner workings of the GIL: "Understanding the Python GIL."[25] In slide #54 of the presentation, Beazley reports some alarming results, including a 20× increase in processing time for a particular benchmark with the new GIL algorithm introduced in Python 3.2. However, Beazley apparently used an empty `while True: pass` to simulate CPU-bound work, and that is not realistic. The issue is not significant with real workloads, according to a comment by Antoine Pitrou—who implemented the new GIL algorithm—in the bug report submitted by Beazley.

Concurrency beyond the standard library

I've already mentioned two books that cover concurrency using Python's standard library, which also include significant coverage of third-party libraries and tools: *High Performance Python, 2nd Edition* and *Parallel Programming with Python*.

Francesco Pierfederici's Distributed Computing with Python (Packt, 2016), which also addresses using cloud providers and HPC (High-Performance Computing) clusters.

Python, Performance, and GPUs by Matthew Rocklin is "a status update for using GPU accelerators from Python", posted in June 2019.

"Instagram currently features the world's largest deployment of the *Django* web framework, which is written entirely in Python." That's the opening sentence of the blog post Web Service Efficiency at Instagram with Python written by Min Ni—a software engineer at Instagram. The post describes metrics and tools Instagram uses to optimize the efficiency of their Python codebase, as well as detect and diagnose performance regressions as they deploy their back end "30-50 times a day."

Architecture Patterns with Python: Enabling Test-Driven Development, Domain-Driven Design, and Event-Driven Microservices by Harry Percival & Bob Gregory (O'Reilly, 2020) presents architectural patterns for Python server-side applications. The authors also made the book freely available online at cosmicpython.com.

Two elegant and easy to use libraries for parallelizing tasks over processes are *lelo* by João S. O. Bueno and *python-parallelize* by Nat Pryce. The *lelo* package defines a `@parallel` decorator that you can apply to any function to magically make it unblocking: when you call the decorated function, its execution is started in another process. Nat Pryce's *python-parallelize* package provides a `parallelize` generator that distributes the execution of a `for` loop over multiple CPUs. Both packages are built on the `multiprocessing` library.

Python core developer Eric Snow maintains a Multi-core Python wiki, with notes about his and other people's efforts to improve Python's support for parallel execution. Snow is the author of PEP 554—Multiple Interpreters in the Stdlib. If approved and implemented, PEP 554 lays the groundwork for future enhancements that may eventually allow Python to use multiple cores without the overheads of `multiprocessing`. One of the biggest blockers is the complex interaction between multiple active subinterpreters and extensions that assume a single interpreter.

Mark Shannon—also a Python maintainer—created a useful table comparing concurrent models in Python *https://gist.github.com/markshannon/79cace3656b40e21b7021504daee950c* referenced in a discussion about subinterpreters between him, Eric Snow, and other developers on the *python-dev* mailing list. In Shannon's table, the "Ideal CSP" column refers to the theoretical Communicating sequential processes model proposed by Tony Hoare in 1978. Go also allows shared objects, violating an essential constraint of CSP: execution units should communicate through message passing through channels.

The actor model of concurrent programming underlies the highly scalable Erlang and Elixir languages, as well as the Akka framework for Scala and Java. If you want to try out the actor model in Python, check out the Thespian and Pykka libraries.

My remaining recommendations have few or zero mentions of Python, but are nevertheless relevant to readers interested in the theme of this chapter.

Concurrency and scalability beyond Python

RabbitMQ in Action by Alvaro Videla and Jason J. W. Williams (Manning, 2012) is a very well written introduction to *RabbitMQ* and the Advanced Message Queuing Protocol (AMQP) standard, with examples in Python, PHP, and Ruby. Regardless of the rest of your tech stack, and even if you plan to use *Celery* with *RabbitMQ* under the hood, I recommend this book for its coverage of concepts, motivation, and patterns for distributed message queues, as well as operating and tuning *RabbitMQ* at scale.

I learned a lot reading *Seven Concurrency Models in Seven Weeks*, by Paul Butcher (Pragmatic Bookshelf, 2014)—with the eloquent subtitle *When Threads Unravel*. Chapter 1 of the book presents the core concepts and challenges of programming with threads and locks in Java.[26] The remaining six chapters the book are devoted to what the author considers better alternatives for concurrent and parallel programming, as supported by different languages, tools and libraries. The examples use Java, Clojure, Elixir, and C (for the chapter about parallel programming with the OpenCL framework). The CSP model is exemplified with Clojure code, although the Go language deserves credit for popularizing that approach. Elixir is the language of the examples illustrating the actor model. A freely available, alternative bonus chapter about actors uses Scala and the Akka framework. Unless you already know Scala, Elixir is a more accessible language to learn and experiment with the actor model and the Erlang/OTP distributed systems platform.

Unmesh Joshi of Thoughtworks has contributed several pages documenting *Patterns of Distributed Systems* to Martin Fowler's blog. The opening page is a great introduction the topic, with links to individual patterns. Joshi is adding patterns incrementally, but what's already there distills years of hard-earned experience in mission-critical systems.

Martin Kleppmann's *Designing Data-Intensive Applications* (O'Reilly, 2017) is a rare book written by a practitioner with deep industry experience and advanced academic background. The author worked with large-scale data infrastructure at LinkedIn and two startups, before becoming a researcher of distributed systems at the University of Cambridge. Each chapter in Kleppmann's book ends with an extensive list of references including recent research results. The book also includes numerous illuminating diagrams and beautiful concept maps.

I was fortunate to be in the audience for Francesco Cesarini's outstanding workshop on the architecture of reliable distributed systems at OSCON 2016: *Designing and architecting for scalability with Erlang/OTP* (video at the O'Reilly Learning Platform). Despite the title, 9:35 into the video Cesarini explains:

> *Very little of what I am going to say will be Erlang-specific […]. The fact remains that Erlang will remove a lot of accidental difficulties to making systems which are resilient and which never fail, and are scalable. So it will be much easier if you do use Erlang, or a language running on the Erlang virtual machine.*

That workshop was based on the last four chapters of *Designing for Scalability with Erlang/OTP* by Francesco Cesarini and Steve Vinoski (O'Reilly, 2016).

Programming distributed systems is challenging and exciting, but beware of *Web-scale envy*. The KISS principle remains solid engineering advice.

Check out the paper *Scalability! But at what COST?* by Frank McSherry, Michael Isard & Derek G. Murray. The authors identified parallel graph-processing systems presented in academic symposia that require hundreds of cores to outperform a "competent single-threaded implementation." They also found systems that "underperform one thread for all of their reported configurations."

Those findings remind me of a classic hacker quip:

> *My Perl script is faster than your Hadoop cluster.*

SOAPBOX

Concurrency in the competition

MRI—the reference implementation of Ruby—also has a GIL, so its threads are under the same limitations as Python's. Meanwhile, JavaScript interpreters don't support user-level threads at all; asynchronous programming is their only path to concurrency. I mention this because Ruby and JavaScript are the closest direct competitors to Python as general-purpose, dynamic programming languages.

Looking at languages born in the 21st century, Go and Elixir are probably the ones best positioned to eat Python's lunch when concurrency matters. Both were designed from day 0 to allow highly efficient and reliable concurrent programming. Elixir, Go, and Python are my favorite languages today—in alphabetical order.

To manage complexity, we need constraints

I learned to program on a TI-58 calculator. Its "language" was similar to assembly. At that level, all "variables" are globals, and you don't have the luxury of structured flow control statements. You have conditional jumps: instructions that take the execution directly to an arbitrary location—ahead or behind the current spot—depending on the value of a CPU register or flag.

Basically you can do anything in assembly, and that's the challenge: there are very few constraints to keep you from making mistakes, and to help maintainers understand the code when changes are needed.

The second language I learned the was the unstructured BASIC that came with 8-bit computers—nothing like VisualBasic, which appeared much later. There were `FOR`, `GOSUB` and `RETURN` statements, but still no concept of local variables. `GOSUB` did not support parameter passing: it was just a fancy `GOTO` that put a return line number in a stack so that `RETURN` had a target to jump to. Subroutines could help themselves to the global data, and put results there too. We had to improvise other forms of flow control with combinations of `IF` and `GOTO`—which, again, allowed you to jump to any line of the program.

After a few years of programming with jumps and global variables, I remember the struggle to rewire my brain for "structured programming" when I learned Pascal. Now I had to use flow control statements around blocks of code that have a single entry point. I couldn't jump to any instruction I liked. Global variables were unavoidable in BASIC, but now they were taboo. I needed to rethink the flow of data and explicitly pass arguments to functions.

The next challenge for me was learning Object Oriented Programming. At core, OOP is structured programming with more constraints and polymorphism. Information hiding forces yet another rethink of where data lives. I remember being frustrated more than once because I had to refactor my code so that a method I was writing could get information that was encapsulated in an object that my method could not reach.

Functional programming languages add other constraints, but immutability is the hardest to swallow after decades of imperative programming and OOP.

After we get used to these constraints, we see them as blessings. They make reasoning about the code much easier.

Lack of constraints is the main problem with the threads-and-locks model of concurrent programming.

When summarizing chapter 1 of *Seven Concurrency Models in Seven Weeks*, Paul Butcher wrote:

> *The greatest weakness of the approach, however, is that threads-and-locks programming is hard. It may be easy for a language designer to add them to a language, but they provide us, the poor programmers, with very little help.*

Some examples of unconstrained behavior in that model:

- Threads can share access to arbitrary mutable data structures.

- The scheduler can interrupt a thread at almost any point, including in the middle of a simple operation like `a += 1`. Very few operations are atomic at the level of source code expressions.
- Locks are usually *advisory*. That's a technical term meaning that you must remember to explicitly hold a lock before updating a shared data structure. If you forget to get the lock, nothing prevents your code from messing up the data while another thread dutifully holds the lock and is updating the same data.

In contrast, consider some constraints enforced by the actor model, where the unit of execution is called "actor" instead of thread.[27]

- An actor can have internal state, but cannot share state with other actors.
- Actors can only communicate by sending and receiving messages.
- Messages only hold copies of data, not references to mutable data.
- An actor only handles one message at a time. There is no concurrent execution inside a single actor.

Of course, you can adopt an *actor style* of coding in any language, by following these rules. You can also use OOP idioms in C, and even structured programming patterns in assembly. But doing any of that requires a lot of agreement and discipline among everyone who touches the code.

Managing locks is unnecessary in the actor model, as implemented by Erlang and Elixir, where all data types are immutable.

Threads-and-locks are not going away. I just don't think dealing with such low-level entities is a good use of my time as I write applications

—as opposed to kernel modules or databases.

I reserve the right to change my mind, always. But right now, I am convinced that the actor model is the most sensible, general purpose concurrent programming model available. CSP (Communicating Sequential Process) is also sensible, but its implementation in Go leaves out some constraints.

Old habits die hard

Like the actor model, CSP also advocates a form of message passing. The best practice is that goroutines—the unit of execution in Go—communicate through channels which are essentially queues with blocking puts and gets. Rob Pike—co-creator of Go—is known for his "proverbs", one of which says:

> *Don't communicate by sharing memory, share memory by communicating.*

In the name of performance, I've seen Go developers advocate sharing memory as standard practice, instead of an optimization technique to be considered in extreme cases, mostly in libraries, and rarely in application code. Go's standard library provides locks, enabling a coroutine-and-locks style that contradicts the essence of CSP.

In the name of performance, why don't we go back to assembly?

We need constraints to keep our thinking straight and our systems running.

---

1 Slide 5 of the talk "Concurrency Is Not Parallelism (It's Better)".

2 I studied and worked with Prof. Imre Simon who liked to say there are two major sins in science: using different words to mean the same thing and using one word to mean different things. Imre Simon (1943–2009) was a pioneer of computer science in Brazil who made seminal contributions to Automata Theory and started the field of Tropical Mathematics. He was also an advocate of free software and free culture.

3 You can see the configured interval by calling `sys.getswitchinterval()` and change it via `sys.setswitchinterval(s)`.

4 A syscall is a call from user code to a function of the operating system kernel. I/O, timers, and locks are some of the kernel services available through syscalls. To learn more, read the Wikipedia System call article.

5 The `zlib` and `bz2` modules are specifically mentioned in a python-dev message by Antoine Pitrou, who contributed the time-slicing GIL logic to Python 3.2.

6 Source: slide 106 of “Generators: The Final Frontier”.

7 Source: last paragraph of the Thread objects section

8 Unicode has lots of characters useful for simple animations, like the Braille patterns for example. I used the ASCII `"\|/-"` to keep the examples simple.

9 It’s a 15″ MacBook Pro 2018 with a 6-core, 2.2 GHz Intel Core i7 CPU.

10 This is true today because you are probably using a modern OS with *preemptive multitasking*. Windows before the NT era and MacOS before the OSX era were not “preemptive”, therefore any process could take over 100% of the CPU and freeze the whole system. We are not completely free of this kind of problem today but trust this gray beard: this troubled every user in the 1990s, and a hard reset was the only cure.

11 In this example, `0` is a convenient sentinel. `None` is also commonly used for that. Using `0` keeps the type hints for `PrimeResult` and `PrimeResult`—and the code for `worker`—as simple as possible.

12 Surviving serialization without losing our identity is a pretty good life goal.

13 Look for *primes/threads.py* the *Fluent Python 2e* code repository if you are curious.

14 To learn more, see Context switch in the English Wikipedia.

15 *The Free Lunch Is Over: A Fundamental Turn Toward Concurrency in Software—Dr. Dobb’s Journal*, March 2005. Available online.

16 These are probably the same reasons that prompted the creator of the Ruby language, Yukihiro Matsumoto, to use a GIL in his interpreter as well.

17 As an exercise in college, I had to implemented the LZW compression algorithm in C. But first I wrote it in Python, to check my understanding of the spec. The C version was about 900× faster.

18 Source: Thoughtworks Technology Advisory Board, Technology Radar—November 2015.

19 Contrast application caches—used directly by your application code—with HTTP caches, which would be placed on the top edge of Figure 20-3 to serve static assets like images, CSS, and JS files. Content Delivery Networks (CDN) offer another type of HTTP cache, deployed in data centers closer to the end users of your application.

20 Diagram and caption from Figure 1-1 *Designing Data-Intensive Applications* (O’Reilly, 2017)

21 Some speakers spell out the WSGI acronym, while others pronounce it as one word rhyming with “whisky”.

22 *uWSGI* is spelled with a lowercase "u", but that is pronounced as the Greek letter "µ", so the whole name sounds like "micro-whisky" with a "g" instead of the "k".

23 Bloomberg engineers Peter Sperl and Ben Green wrote Configuring uWSGI for Production Deployment, explaining how many of the default settings in *uWSGI* are not suitable for many common deployment scenarios. Sperl presented a summary of their recommendations at EuroPython 2019. Highly recommended for users of *uWSGI*.

24 Caleb is one of the tech reviewers of *Fluent Python, Second Edition*

25 Thanks to Lucas Brunialti for sending me a link to this talk.

26 Python's `threading` and `concurrent.futures` APIs are heavily influenced by the Java standard library.

27 The Erlang community uses the term "process" for actors. In Erlang, each process is a function in its own loop, so they are very lightweight and it's feasible to have millions of them active at once in a single machine—no relation to the heavyweight OS processes we've been talking about elsewhere in this chapter. So here we have examples of the two sins described by Prof. Simon: using different words to mean the same thing, and using one word to mean different things.

Chapter 21. Concurrency with Futures

> ### A NOTE FOR EARLY RELEASE READERS
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 21st chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *The people bashing threads are typically system programmers which have in mind use cases that the typical application programmer will never encounter in her life. […] In 99% of the use cases an application programmer is likely to run into, the simple pattern of spawning a bunch of independent threads and collecting the results in a queue is everything one needs to know.*[1]
>
> —Michele Simionato, Python deep thinker

This chapter focuses on the `concurrent.futures` library that encapsulates the pattern of "spawning a bunch of independent threads and collecting the results in a queue" described by Michele Simionato, making it almost trivial to use. The package also supports processes, useful for compute-intensive tasks.

Here I also introduce the concept of "futures"—objects representing the asynchronous execution of an operation, similar to JavaScript promises.

This primitive idea is the foundation not only of `concurrent.futures` but also of the `asyncio` package, the subject of Chapter 22.

What's new in this chapter

This chapter had few important changes from the first edition, because the `concurrent.futures` API is stable, with minor changes since its introduction in Python 3.2.

Example 21-3 (*flags_threadpool.py*) is a bit simpler after I removed some code to set up the number of workers, now that the `ThreadPoolExecutor` in Python 3.8 got smarter: it doesn't start unnecessary threads, and its logic for automatically setting the number of workers was updated. I added a few paragraphs explaining the new logic at the end of "Downloading with concurrent.futures".

I was able to greatly simplify the setup for the experiments in "Downloads with Progress Display and Error Handling" thanks to the multi-threaded server added to the `http.server` package in Python 3.7. Previously, that package offered only the single-threaded `BaseHttpServer` which was no good for experimenting with concurrent clients, so I had to resort to external tools in the *First Edition*.

In "Launching Processes with concurrent.futures", I replaced the previous examples using `ProcessPoolExecutor` with a new version of the primality checker, showing how that class simplifies the code we saw in "Code for the Multi-core Prime Checker".

Finally, I moved some conceptual content to the new Chapter 20–*Concurrency Models in Python*.

Concurrent Web Downloads

Concurrency is essential to efficient network I/O: instead of wasting CPU cycles waiting for remote machines, the application should do something else until a response comes back over the wire.

To make this last point with code, I wrote three simple programs to download images of 20 country flags from the Web. The first one, *flags.py*, runs sequentially: it only requests the next image when the previous one is downloaded and saved locally. The other two scripts make concurrent downloads: they request several images practically at the same time, and save them as they arrive. The *flags_threadpool.py* script uses the `concurrent.futures` package, while *flags_asyncio.py* uses `asyncio`.

Example 21-1 shows the result of running the three scripts, three times each. I also posted a 73s video on YouTube so you can watch them running while a MacOS Finder window displays the flags as they are saved. The scripts are downloading images from *fluentpython.com*, which is behind a CDN, so you may see slower results in the first runs. The results in Example 21-1 were obtained after several runs, so the CDN cache was warm.

Example 21-1. Three typical runs of the scripts flags.py, flags_threadpool.py, and flags_asyncio.py

```
$ python3 flags.py
BD BR CD CN DE EG ET FR ID IN IR JP MX NG PH PK RU TR US VN  ❶
20 flags downloaded in 7.26s  ❷
$ python3 flags.py
BD BR CD CN DE EG ET FR ID IN IR JP MX NG PH PK RU TR US VN
20 flags downloaded in 7.20s
$ python3 flags.py
BD BR CD CN DE EG ET FR ID IN IR JP MX NG PH PK RU TR US VN
20 flags downloaded in 7.09s
$ python3 flags_threadpool.py
DE BD CN JP ID EG NG BR RU CD IR MX US PH FR PK VN IN ET TR
20 flags downloaded in 1.37s  ❸
$ python3 flags_threadpool.py
EG BR FR IN BD JP DE RU PK PH CD MX ID US NG TR CN VN ET IR
20 flags downloaded in 1.60s
$ python3 flags_threadpool.py
BD DE EG CN ID RU IN VN ET MX FR CD NG US JP TR PK BR IR PH
20 flags downloaded in 1.22s
$ python3 flags_asyncio.py  ❹
BD BR IN ID TR DE CN US IR PK PH FR RU NG VN ET MX EG JP CD
20 flags downloaded in 1.36s
$ python3 flags_asyncio.py
```

```
RU CN BR IN FR BD TR EG VN IR PH CD ET ID NG DE JP PK MX US
20 flags downloaded in 1.27s
$ python3 flags_asyncio.py
RU IN ID DE BR VN PK MX US IR ET EG NG BD FR CN JP PH CD TR  ❺
20 flags downloaded in 1.42s
```

❶ The output for each run starts with the country codes of the flags as they are downloaded, and ends with a message stating the elapsed time.

❷ It took *flags.py* an average 7.18s to download 20 images.

❸ The average for *flags_threadpool.py* was 1.40s.

❹ For *flags_asyncio.py*, 1.35 was the average time.

❺ Note the order of the country codes: the downloads happened in a different order every time with the concurrent scripts.

The difference in performance between the concurrent scripts is not significant, but they are both more than five times faster than the sequential script—and this is just for the small task of downloading 20 files of a few kilobytes each. If you scale the task to hundreds of downloads, the concurrent scripts can outpace the sequential code by a factor or 20 or more.

> **WARNING**
>
> While testing concurrent HTTP clients against public Web servers you may inadvertently launch a denial-of-service (DoS) attack, or be suspected of doing so. In the case of Example 21-1, it's OK to do it because those scripts are hardcoded to make only 20 requests. We'll use Python's `http.server` package to run tests later in this chapter.

Now let's study the implementations of two of the scripts tested in Example 21-1: *flags.py* and *flags_threadpool.py*. I will leave the third script, *flags_asyncio.py*, for Chapter 22, but I wanted to demonstrate all three together to make two points:

1. Regardless of the concurrency constructs you use—threads or coroutines—you'll see vastly improved throughput over sequential code in network I/O operations, if you code it properly.
2. For HTTP clients that can control how many requests they make, there is no significant difference in performance between threads and coroutines.[2]

On to the code.

A Sequential Download Script

Example 21-2 is not very interesting, but we'll reuse most of its code and settings to implement the concurrent scripts, so it deserves some attention.

> **NOTE**
>
> For clarity, there is no error handling in Example 21-2. We will deal with exceptions later, but here we want to focus on the basic structure of the code, to make it easier to contrast this script with the concurrent ones.

Example 21-2. flags.py: sequential download script; some functions will be reused by the other scripts

```
import time
from pathlib import Path
from typing import Callable

import requests  ❶

POP20_CC = ('CN IN US ID BR PK NG BD RU JP '
            'MX PH VN ET EG DE IR TR CD FR').split()  ❷

BASE_URL = 'http://fluentpython.com/data/flags'       ❸
DEST_DIR = Path('downloaded')                         ❹

def save_flag(img: bytes, filename: str) -> None:     ❺
```

```python
    (DEST_DIR / filename).write_bytes(img)

def get_flag(cc: str) -> bytes:  ❻
    url = f'{BASE_URL}/{cc}/{cc}.gif'.lower()
    resp = requests.get(url)
    return resp.content

def download_many(cc_list: list[str]) -> int:  ❼
    for cc in sorted(cc_list):                 ❽
        image = get_flag(cc)
        save_flag(image, f'{cc}.gif')
        print(cc, end=' ', flush=True)         ❾
    return len(cc_list)

def main(downloader: Callable[[list[str]], int]) -> None:  ❿
    t0 = time.perf_counter()                               ⓫
    count = downloader(POP20_CC)
    elapsed = time.perf_counter() - t0
    print(f'\n{count} downloads in {elapsed:.2f}s')

if __name__ == '__main__':
    main(download_many)     ⓬
```

❶ Import the `requests` library; it's not part of the standard library, so by convention we import it after the standard library modules `os`, `time`, and `sys`, and insert a blank line to separate them.

❷ List of the ISO 3166 country codes for the 20 most populous countries in order of decreasing population.

❸ The directory with the flag images.[3]

❹ Local directory where the images are saved.

❺ Save the `img` bytes to `filename` in the `DEST_DIR`.

❻ Given a country code, build the URL and download the image using `requests`, returning the binary contents of the response.

❼ `download_many` is the key function to compare with the concurrent implementations.

8. Loop over the list of country codes in alphabetical order, to make it easy to see that the ordering is preserved in the output; return the number of country codes downloaded.

9. Display a country code and flush `sys.stdout` so we can see progress as each download happens; flushing is needed because, otherwise, Python waits for a line break to output the `stdout` buffer.

10. `main` must be called with the function that will make the downloads; that way, we can use `main` as library function with other implementations of `download_many` in the `threadpool` and `ascyncio` examples.

11. `main` records and reports the elapsed time after running the `downloader` function.

12. Call `main` with the `download_many` function.

> **TIP**
>
> The *requests* library is more powerful and easier to use than the `urllib.request` module from the Python 3 standard library. In fact, `requests` is considered a model Pythonic API.

There's really nothing new to *flags.py*. It serves as a baseline for comparing the other scripts and I used it as a library to avoid redundant code when implementing them. Now let's see a reimplementation using `concurrent.futures`.

Downloading with concurrent.futures

The main features of the `concurrent.futures` package are the `ThreadPoolExecutor` and `ProcessPoolExecutor` classes, which implement an API for to submitting callables for execution in different threads or processes, respectively. The classes transparently manage a pool of worker threads or processes, and queues to distribute jobs and collect results. But the interface is very high level, and we don't need to know about any of those details for a simple use case like our flag downloads.

Example 21-3 shows the easiest way to implement the downloads concurrently, using the `ThreadPoolExecutor.map` method.

Example 21-3. flags_threadpool.py: threaded download script using futures.ThreadPoolExecutor

```
from concurrent import futures

from flags import save_flag, get_flag, main  ❶

def download_one(cc: str):  ❷
    image = get_flag(cc)
    save_flag(image, f'{cc}.gif')
    print(cc, end=' ', flush=True)
    return cc

def download_many(cc_list: list[str]) -> int:
    with futures.ThreadPoolExecutor() as executor:         ❸
        res = executor.map(download_one, sorted(cc_list))  ❹

    return len(list(res))                                  ❺

if __name__ == '__main__':
    main(download_many)  ❻
```

❶ Reuse some functions from the `flags` module (Example 21-2).

❷ Function to download a single image; this is what each worker will execute.

❸ Instantiate the `ThreadPoolExecutor` as a context manager; the `executor.__exit__` method will call `executor.shutdown(wait=True)`, which will block until all threads are done.

❹

The `map` method is similar to the `map` built-in, except that the `download_one` function will be called concurrently from multiple threads; it returns a generator that you can iterate to retrieve the value returned by each function call—in this case, each call to `download_one` will return a country code.

5. Return the number of results obtained; if any of the threaded calls raises an exception, that exception is raised here when the implicit `next()` call inside the `list` constructor tries to retrieve the corresponding return value from the iterator.

6. Call the `main` function from the `flags` module, passing the concurrent version of `download_many`.

Note that the `download_one` function from Example 21-3 is essentially the body of the `for` loop in the `download_many` function from Example 21-2. This is a common refactoring when writing concurrent code: turning the body of a sequential `for` loop into a function to be called concurrently.

> **TIP**
>
> Example 21-3 is very short because I was able to reuse most functions from the sequential _`flags.py`_ script. One of the best features of `concurrent.futures` is to make it simple to add concurrent execution on top of legacy sequential code.

The `ThreadPoolExecutor` constructor takes several arguments not shown, but the first and most important one is `max_workers`, setting the maximum number of worker threads to be executed. Until Python 3.4, `max_workers` was required. In 3.5, `max_workers` became optional, with a default of `None`. When `max_workers` is None, the `ThreadPoolExecutor` decides its value using the following expression —since Python 3.8:

```
max_workers = min(32, os.cpu_count() + 4)
```

The rationale is well explained in the `ThreadPoolExecutor` documentation:

> *This default value preserves at least 5 workers for I/O bound tasks. It utilizes at most 32 CPU cores for CPU bound tasks which release the GIL. And it avoids using very large resources implicitly on many-core machines.*
>
> *`ThreadPoolExecutor` now reuses idle worker threads before starting `max_workers` worker threads too.*

To conclude: the computed default for `max_workers` is sensible, and `ThreadPoolExecutor` avoids starting new workers unnecessarily. Understanding the logic behind `max_workers` may help you decide when and how to set it yourself.

The library is called `concurrency.futures` yet there are no futures to be seen in Example 21-3, so you may be wondering where they are. The next section explains.

Where Are the Futures?

Futures are essential components in the internals of `concurrent.futures` and of `asyncio`, but as users of these libraries we sometimes don't see them. Example 21-3 leverages futures behind the scenes, but the code I wrote does not touch them directly. This section is an overview of futures, with an example that shows them in action.

Since Python 3.4, there are two classes named `Future` in the standard library: `concurrent.futures.Future` and `asyncio.Future`. They serve the same purpose: an instance of either `Future` class represents a deferred computation that may or may not have completed. This is similar to the `Deferred` class in Twisted, the `Future` class in Tornado, and `Promise` in modern JavaScript.

Futures encapsulate pending operations so that they can be put in queues, their state of completion can be queried, and their results (or exceptions) can be retrieved when available.

An important thing to know about futures is that you and I should not create them: they are meant to be instantiated exclusively by the concurrency framework, be it `concurrent.futures` or `asyncio`. Here is why: a `Future` represents something that will eventually run, and the only way to be sure that something will run is to schedule its execution. In particular, `concurrent.futures.Future` instances are created only as the result of scheduling a callable for execution with a `concurrent.futures.Executor` subclass. For example, the `Executor.submit()` method takes a callable, schedules it to run, and returns a `Future`.

Client code is not supposed to change the state of a future: the concurrency framework changes the state of a future when the computation it represents is done, and we can't control when that happens.

Both types of `Future` have a `.done()` method that is nonblocking and returns a Boolean that tells you whether the callable wrapped that future has executed or not. However, instead of repeatedly asking whether a future is done, client code usually asks to be notified. That's why both `Future` classes have an `.add_done_callback()` method: you give it a callable, and the callable will be invoked with the future as the single argument when the future is done.

There is also a `.result()` method, which works the same in both classes when the future is done: it returns the result of the callable, or re-raises whatever exception might have been thrown when the callable was executed. However, when the future is not done, the behavior of the `result` method is very different between the two flavors of `Future`. In a `concurrency.futures.Future` instance, invoking `f.result()` will block the caller's thread until the result is ready. An optional `timeout` argument can be passed, and if the future is not done in the specified time, the `result` method raises `TimeoutError`. In [Link to Come], we'll see that the `asyncio.Future.result` method does not support timeout, and the preferred way to get the result of futures in that library is to use `await`—which doesn't work with `concurrency.futures.Future` instances.

Several functions in both libraries return futures; others use them in their implementation in a way that is transparent to the user. An example of the latter is the `Executor.map` we saw in Example 21-3: it returns an iterator in which `__next__` calls the `result` method of each future, so we get the results of the futures, and not the futures themselves.

To get a practical look at futures, we can rewrite Example 21-3 to use the `concurrent.futures.as_completed` function, which takes an iterable of futures and returns an iterator that yields futures as they are done.

Using `futures.as_completed` requires changes to the `download_many` function only. The higher-level `executor.map` call is replaced by two `for` loops: one to create and schedule the futures, the other to retrieve their results. While we are at it, we'll add a few `print` calls to display each future before and after it's done Example 21-4 shows the code for a new `download_many` function. The code for `download_many` grew from 5 to 17 lines, but now we get to inspect the mysterious futures. The remaining functions are the same as in Example 21-3.

Example 21-4. flags_threadpool_futures.py: replacing executor.map with executor.submit and futures.as_completed in the download_many function

```
def download_many(cc_list: list[str]) -> int:
    cc_list = cc_list[:5]  ❶
    with futures.ThreadPoolExecutor(max_workers=3) as executor:  ❷
        to_do: list[futures.Future] = []
        for cc in sorted(cc_list):  ❸
            future = executor.submit(download_one, cc)  ❹
            to_do.append(future)  ❺
            print(f'Scheduled for {cc}: {future}')  ❻

        for count, future in enumerate(futures.as_completed(to_do),
1):  ❼
            res: str = future.result()  ❽
            print(f'{future} result: {res!r}')  ❾
```

```
    return count
```

❶ For this demonstration, use only the top five most populous countries.

❷ Set `max_workers` to `3` so we can see pending futures in the output.

❸ Iterate over country codes alphabetically, to make it clear that results will arrive out of order.

❹ `executor.submit` schedules the callable to be executed, and returns a `future` representing this pending operation.

❺ Store each `future` so we can later retrieve them with `as_completed`.

❻ Display a message with the country code and the respective `future`.

❼ `as_completed` yields futures as they are completed.

❽ Get the result of this `future`.

❾ Display the `future` and its result.

Note that the `future.result()` call will never block in this example because the `future` is coming out of `as_completed`. Example 21-5 shows the output of one run of Example 21-4.

Example 21-5. Output of flags_threadpool_futures.py

```
$ python3 flags_threadpool_futures.py
Scheduled for BR: <Future at 0x100791518 state=running>  ❶
Scheduled for CN: <Future at 0x100791710 state=running>
Scheduled for ID: <Future at 0x100791a90 state=running>
Scheduled for IN: <Future at 0x101807080 state=pending>  ❷
Scheduled for US: <Future at 0x101807128 state=pending>
CN <Future at 0x100791710 state=finished returned str> result: 'CN'
❸
BR ID <Future at 0x100791518 state=finished returned str> result:
'BR'  ❹
```

```
<Future at 0x100791a90 state=finished returned str> result: 'ID'
IN <Future at 0x101807080 state=finished returned str> result: 'IN'
US <Future at 0x101807128 state=finished returned str> result: 'US'

5 downloads in 0.70s
```

❶ The futures are scheduled in alphabetical order; the `repr()` of a future shows its state: the first three are `running`, because there are three worker threads.

❷ The last two futures are `pending`, waiting for worker threads.

❸ The first `CN` here is the output of `download_one` in a worker thread; the rest of the line is the output of `download_many`.

❹ Here two threads output codes before `download_many` in the main thread can display the result of the first thread.

> **TIP**
>
> I recommend experimenting with *flags_threadpool_futures.py*. If you run it several times, you'll see the order of the results varying. Increasing `max_workers` to `5` will increase the variation in the order of the results. Decreasing it to `1` will make this script run sequentially, and the order of the results will always be the order of the `submit` calls.

We saw two variants of the download script using `concurrent.futures`: Example 21-3 with `ThreadPoolExecutor.map` and Example 21-4 with `futures.as_completed`. If you are curious about the code for *flags_asyncio.py*, you may peek at Example 22-3 in Chapter 22, where it is explained.

Now let's take a brief look at a simple way to work around the GIL for CPU-bound jobs using `concurrent.futures`.

Launching Processes with concurrent.futures

The `concurrent.futures` documentation page is subtitled “Launching parallel tasks”. The package enables parallel computation on multi-core machines because it supports distributing work among multiple Python processes using the `ProcessPoolExecutor` class.

Both `ProcessPoolExecutor` and `ThreadPoolExecutor` implement the `Executor` interface, so it’s easy to switch from a thread-based to a process-based solution using `concurrent.futures`.

There is no advantage in using a `ProcessPoolExecutor` for the flags download example or any I/O-bound job. It’s easy to verify this; just change these lines in Example 21-3:

```
def download_many(cc_list: list[str]) -> int:
    with futures.ThreadPoolExecutor() as executor:
```

To this:

```
def download_many(cc_list: list[str]) -> int:
    with futures.ProcessPoolExecutor() as executor:
```

The constructor for `ProcessPoolExecutor` also has a `max_workers` parameter which defaults to `None`. In that case, the executor limits the number of workers to the number returned by `os.cpu_count()`.

Processes use more memory and take longer to start than threads, so the real value of `ProcessPoolExecutor` is in CPU-intensive jobs. Let’s go back to the primality test example of “A Homegrown Process Pool”, rewriting it with `concurrent.futures`.

Multi-core Prime Checker Redux

In “Code for the Multi-core Prime Checker” we studied *procs.py*, a script that checked the primality of some large numbers using `multiprocessing`. In Example 21-6 we solve the same problem in the *proc_pool.py* program using a `ProcessPoolExecutor`. From the first import to the `main()` call at the end, *procs.py* has 43 non-blank lines of code, and *proc_pool.py* has 31—28% shorter.

Example 21-6. proc_pool.py: procs.py rewritten with `ProcessPoolExecutor`

```
import sys
from concurrent import futures  ❶
from time import perf_counter
from typing import NamedTuple

from primes import is_prime, NUMBERS

class PrimeResult(NamedTuple):  ❷
    n: int
    flag: bool
    elapsed: float

def check(n: int) -> PrimeResult:
    t0 = perf_counter()
    res = is_prime(n)
    return PrimeResult(n, res, perf_counter() - t0)

def main() -> None:
    if len(sys.argv) < 2:
        workers = None      ❸
    else:
        workers = int(sys.argv[1])

    executor = futures.ProcessPoolExecutor(workers)  ❹
    actual_workers = executor._max_workers  # type: ignore  ❺

    print(f'Checking {len(NUMBERS)} numbers with {actual_workers}
processes:')

    t0 = perf_counter()

    numbers = sorted(NUMBERS, reverse=True)  ❻
    with executor:  ❼
        for n, prime, elapsed in executor.map(check, numbers):  ❽
            label = 'P' if prime else ' '
            print(f'{n:16}  {label} {elapsed:9.6f}s')

    time = perf_counter() - t0
```

```
    print(f'Total time: {time:.2f}s')

if __name__ == '__main__':
    main()
```

❶ No need to import `multiprocessing`, `SimpleQueue` etc.; `concurrent.futures` hides all that.

❷ The `PrimeResult` tuple and the `check` function are the same we saw in *procs.py*, but we don't need the queues and the `worker` function anymore.

❸ Instead of deciding ourselves how many workers to use if no command-line argument was given, we set `workers` to `None` and let the `ProcessPoolExecutor` decide.

❹ Here I build the `ProcessPoolExecutor` before the `with` block in ❼ so that I can display the actual number of workers in the next line.

❺ `_max_workers` is an undocumented instance attribute of a `ProcessPoolExecutor`. I decided to use it to show the number of workers when the `workers` variable is `None`; *mypy* correctly complains when I access it, so I put the `type: ignore` comment to silence it.

❻ Sort the numbers to be checked in descending order. This will expose a difference in the behavior of *proc_pool.py* when compared with *procs.py*. See below.

❼ Use the `executor` as a context manager, as usual.

❽ The `executor.map` call will return the `PrimeResult` instances returned by `check` in the same order as the `numbers` arguments.

If you run Example 21-6, you'll see the results appearing in strict descending order, as shown in Example 21-7. In contrast, the ordering of the output of *procs.py* (shown in “Process-based Solution”) is heavily influenced by the difficulty in checking whether each number is a prime. For example, *procs.py* shows the result for 7777777777777777 near the top, because it has a low divisor, 7, so `is_prime` quickly determines it’s not a prime. In contrast, 7777777536340681 is 88191709^2 so `is_prime` will take much longer to determine that it’s a composite number, end even longer to find out that 7777777777777753 is prime—therefore both of these numbers appear near the end of the output of *procs.py*.

Running *proc_pool.py* you’ll observe not only the descending order of the results, but also that the program will appear to be stuck after showing the result for 9999999999999999.

Example 21-7. Output of proc_pool.py

```
$ ./proc_pool.py
Checking 20 numbers with 12 processes:
9999999999999999     0.000024s  ❶
9999999999999917  P  9.500677s  ❷
7777777777777777     0.000022s  ❸
7777777777777753  P  8.976933s
7777777536340681     8.896149s
6666667141414921     8.537621s
6666666666666719  P  8.548641s
6666666666666666     0.000002s
5555555555555555     0.000017s
5555555555555503  P  8.214086s
5555553133149889     8.067247s
4444444488888889     7.546234s
4444444444444444     0.000002s
4444444444444423  P  7.622370s
3333335652092209     6.724649s
3333333333333333     0.000018s
3333333333333301  P  6.655039s
 299593572317531  P  2.072723s
 142702110479723  P  1.461840s
               2  P  0.000001s
Total time: 9.65s
```

❶ This line appears very quickly.

❷ This line takes more than 9.5s to show up.

❸ All the remaining lines appear almost immediately.

Here is why *proc_pool.py* behaves in that way:

- As mentioned before, `executor.map(check, numbers)` returns the result in the same order as the `numbers` are given.
- By default, *proc_pool.py* uses as many workers as there are CPUs—it's what `ProcessPoolExecutor` does when `max_workers` is `None`. That's 12 processes in this laptop.
- Because we are submitting `numbers` in descending order, the first is 9999999999999999, with 9 as a divisor it returns quickly.
- The second number is 9999999999999917, the largest prime in the sample. This will take longer than all the others to check.
- Meanwhile, the remaining 11 processes will be checking other numbers which are either primes or composites with large factors, or composites with very small factors.
- When the worker in charge of 9999999999999917 finally determines that's a prime, all the other processes have completed their last jobs, so the results appear immediately after.

> **NOTE**
>
> Although the progress of *proc_pool.py* is not as visible as that of *procs.py*, the overall execution time is practically the same as depicted in Figure 20-2, for the same number of workers and CPU cores.

Understanding how concurrent programs behave is not straightforward, so here's is a second experiment that may help you visualize the operation of `Executor.map`.

Experimenting with Executor.map

Let’s investigate Executor.map`, now using a `ThreadPoolExecutor` with three workers running five callables that output timestamped messages. The code is in Example 21-8, the out put in Example 21-9.

Example 21-8. demo_executor_map.py: Simple demonstration of the map method of ThreadPoolExecutor

```
from time import sleep, strftime
from concurrent import futures

def display(*args):  ❶
    print(strftime('[%H:%M:%S]'), end=' ')
    print(*args)

def loiter(n):  ❷
    msg = '{}loiter({}): doing nothing for {}s...'
    display(msg.format('\t'*n, n, n))
    sleep(n)
    msg = '{}loiter({}): done.'
    display(msg.format('\t'*n, n))
    return n * 10  ❸

def main():
    display('Script starting.')
    executor = futures.ThreadPoolExecutor(max_workers=3)  ❹
    results = executor.map(loiter, range(5))  ❺
    display('results:', results)  ❻
    display('Waiting for individual results:')
    for i, result in enumerate(results):  ❼
        display(f'result {i}: {result}')

if __name__ == '__main__':
    main()
```

❶ This function simply prints whatever arguments it gets, preceded by a timestamp in the format `[HH:MM:SS]`.

❷ `loiter` does nothing except display a message when it starts, sleep for *n* seconds, then display a message when it ends; tabs are used to indent the messages according to the value of *n*.

❸ `loiter` returns `n * 10` so we can see how to collect results.

❹ Create a `ThreadPoolExecutor` with three threads.

❺ Submit five tasks to the `executor`. Since there are only three threads, only three of those tasks will start immediately: the calls `loiter(0)`, `loiter(1)`, and `loiter(2)`); this is a nonblocking call.

❻ Immediately display the `results` of invoking `executor.map`: it's a generator, as the output in Example 21-9 shows.

❼ The `enumerate` call in the `for` loop will implicitly invoke `next(results)`, which in turn will invoke `_f.result()` on the (internal) `_f` future representing the first call, `loiter(0)`. The `result` method will block until the future is done, therefore each iteration in this loop will have to wait for the next result to be ready.

I encourage you to run Example 21-8 and see the display being updated incrementally. While you're at it, play with the `max_workers` argument for the `ThreadPoolExecutor` and with the `range` function that produces the arguments for the `executor.map` call—or replace it with lists of handpicked values to create different delays.

Example 21-9 shows a sample run of Example 21-8.

Example 21-9. Sample run of demo_executor_map.py from Example 21-8

```
$ python3 demo_executor_map.py
[15:56:50] Script starting.  ❶
[15:56:50] loiter(0): doing nothing for 0s...  ❷
[15:56:50] loiter(0): done.
[15:56:50]      loiter(1): doing nothing for 1s...  ❸
[15:56:50]              loiter(2): doing nothing for 2s...
[15:56:50] results: <generator object result_iterator at
0x106517168>  ❹
[15:56:50]                      loiter(3): doing nothing for 3s...
❺
[15:56:50] Waiting for individual results:
[15:56:50] result 0: 0  ❻
```

```
[15:56:51]      loiter(1): done. ❼
[15:56:51]                              loiter(4): doing nothing
for 4s...
[15:56:51] result 1: 10  ❽
[15:56:52]              loiter(2): done.  ❾
[15:56:52] result 2: 20
[15:56:53]                     loiter(3): done.
[15:56:53] result 3: 30
[15:56:55]                              loiter(4): done.  ❿
[15:56:55] result 4: 40
```

❶ This run started at 15:56:50.

❷ The first thread executes `loiter(0)`, so it will sleep for 0s and return even before the second thread has a chance to start, but YMMV.[4]

❸ `loiter(1)` and `loiter(2)` start immediately (because the thread pool has three workers, it can run three functions concurrently).

❹ This shows that the `results` returned by `executor.map` is a generator; nothing so far would block, regardless of the number of tasks and the `max_workers` setting.

❺ Because `loiter(0)` is done, the first worker is now available to start the fourth thread for `loiter(3)`.

❻ This is where execution may block, depending on the parameters given to the `loiter` calls: the `__next__` method of the `results` generator must wait until the first future is complete. In this case, it won't block because the call to `loiter(0)` finished before this loop started. Note that everything up to this point happened within the same second: 15:56:50.

❼ `loiter(1)` is done one second later, at 15:56:51. The thread is freed to start `loiter(4)`.

❽ The result of `loiter(1)` is shown: 10. Now the `for` loop will block waiting for the result of `loiter(2)`.

- ❾ The pattern repeats: `loiter(2)` is done, its result is shown; same with `loiter(3)`.
- ❿ There is a 2s delay until `loiter(4)` is done, because it started at 15:56:51 and did nothing for 4s.

The `Executor.map` function is easy to use, but often it's preferable to get the results as they are ready, regardless of the order they were submitted. To do that, we need a combination of the `Executor.submit` method and the `futures.as_completed` function, as we saw in Example 21-4. We'll come back to this technique in "Using futures.as_completed".

> **TIP**
>
> The combination of `executor.submit` and `futures.as_completed` is more flexible than `executor.map` because you can `submit` different callables and arguments, while `executor.map` is designed to run the same callable on the different arguments. In addition, the set of futures you pass to `futures.as_completed` may come from more than one executor—perhaps some were created by a `ThreadPoolExecutor` instance while others are from a `ProcessPoolExecutor`.

In the next section, we will resume the flag download examples with new requirements that will force us to iterate over the results of `futures.as_completed` instead of using `executor.map`.

Downloads with Progress Display and Error Handling

As mentioned, the scripts in "Concurrent Web Downloads" have no error handling to make them easier to read and to contrast the structure of the three approaches: sequential, threaded, and asynchronous.

In order to test the handling of a variety of error conditions, I created the `flags2` examples:

flags2_common.py

> This module contains common functions and settings used by all `flags2` examples, including a `main` function, which takes care of command-line parsing, timing, and reporting results. This is really support code, not directly relevant to the subject of this chapter, so I will not list the source code here, but you can find it the *Fluent Python 2e* code repository.

flags2_sequential.py

> A sequential HTTP client with proper error handling and progress bar display. Its `download_one` function is also used by `flags2_threadpool.py`.

flags2_threadpool.py

> Concurrent HTTP client based on `futures.ThreadPoolExecutor` to demonstrate error handling and integration of the progress bar.

flags2_asyncio.py

> Same functionality as previous example but implemented with `asyncio` and `aiohttp`. This will be covered in "Enhancing the asyncio downloader", in Chapter 22.

> ### BE CAREFUL WHEN TESTING CONCURRENT CLIENTS
>
> When testing concurrent HTTP clients on public Web servers, you may generate many requests per second, and that's how denial-of-service (DoS) attacks are made. Carefully throttle your clients when hitting public servers. For high-concurrency experiments, set up a local HTTP server for testing. The `ThreadingHTTPServer` that comes with Python is OK for testing[5], and it can serve files in the current directory if you run it with:
>
> ```
> python -m http.server
> ```
>
> Append the `-h` option to the command above for more options.

The most visible feature of the `flags2` examples is that they have an animated, text-mode progress bar implemented with the TQDM package. I posted a 108s video on YouTube to show the progress bar and contrast the speed of the three `flags2` scripts. In the video, I start with the sequential download, but I interrupt it after 32s because it was going to take more than 5 minutes to hit on 676 URLs and get 194 flags; I then run the threaded and `asyncio` scripts three times each, and every time they complete the job in 6s or less (i.e., more than 60 times faster). Figure 21-1 shows two screenshots: during and after running *flags2_threadpool.py*.

Figure 21-1. Top-left: flags2_threadpool.py running with live progress bar generated by tqdm; bottom-right: same terminal window after the script is finished.

TQDM is very easy to use, the simplest example appears in an animated *.gif* in the project's *README.md*. If you type the following code in the Python console after installing the `tqdm` package, you'll see an animated progress bar were the comment is:

```
>>> import time
>>> from tqdm import tqdm
>>> for i in tqdm(range(1000)):
...     time.sleep(.01)
...
>>> # -> progress bar will appear here <-
```

Besides the neat effect, the `tqdm` function is also interesting conceptually: it consumes any iterable and produces an iterator which, while it's consumed, displays the progress bar and estimates the remaining time to complete all iterations. To compute that estimate, `tqdm` needs to get an iterable that has a `len`, or receive as a second argument the expected number of items. Integrating TQDM with our `flags2` examples provides an opportunity to look deeper into how the concurrent scripts actually work, by forcing us to use the `futures.as_completed` and the `asyncio.as_completed` functions so that `tqdm` can display progress as each future is completed.

The other feature of the `flags2` example is a command-line interface. All three scripts accept the same options, and you can see them by running any of the scripts with the `-h` option. Example 21-10 shows the help text.

Example 21-10. Help screen for the scripts in the flags2 series

```
$ python3 flags2_threadpool.py -h
usage: flags2_threadpool.py [-h] [-a] [-e] [-l N] [-m CONCURRENT]
[-s LABEL]
                            [-v]
                            [CC [CC ...]]

Download flags for country codes. Default: top 20 countries by
population.

positional arguments:
  CC                      country code or 1st letter (eg. B for
BA...BZ)

optional arguments:
  -h, --help              show this help message and exit
  -a, --all               get all available flags (AD to ZW)
  -e, --every             get flags for every possible code (AA...ZZ)
  -l N, --limit N         limit to N first codes
  -m CONCURRENT, --max_req CONCURRENT
                          maximum concurrent requests (default=30)
  -s LABEL, --server LABEL
                          Server to hit; one of DELAY, ERROR, LOCAL,
REMOTE
                          (default=LOCAL)
  -v, --verbose           output detailed progress info
```

All arguments are optional. The most important arguments are discussed next.

One option you can't ignore is `-s/--server`: it lets you choose which HTTP server and base URL will be used in the test. You can pass one of four strings to determine where the script will look for the flags (the strings are case insensitive):

`LOCAL`

Use `http://localhost:8000/flags`; this is the default. You should configure a local HTTP server to answer at port 8000. See "Setting up test servers" for instructions.

`REMOTE`

Use `http://fluentpython.com/data/flags`; that is a public website owned by me, hosted on a shared server. Please do not pound it with too many concurrent requests. The `fluentpython.com` domain is handled by the Cloudflare CDN (Content Delivery Network) so you may notice that the first downloads are slower, but they get faster when the CDN cache warms up.[6]

`DELAY`

Use `http://localhost:8001/flags`; a server delaying HTTP responses should be listening to port 8001. I wrote *slow_server.py* to make it easier to experiment. You'll find it in the *21-futures/getflags/* directory of the *Fluent Python 2e* code repository. See "Setting up test servers" for instructions.

`ERROR`

Use `http://localhost:8002/flags`; a server introducing HTTP errors and delaying responses should be installed at port 8002. Running *slow_server.py* is an easy way to do it. See "Setting up test servers".

SETTING UP TEST SERVERS

If you don't already have a local HTTP server for testing, here are the steps for an easy way to do it:

1. Clone or download the *Fluent Python 2e* code repository.
2. Open your shell and go to the *21-futures/getflags/* directory of your local copy of the repository.
3. Unzip the *flags.zip* file, creating a *flags* directory at *21-futures/getflags/flags/*.
4. Open a second shell, go to the *21-futures/getflags/* directory and run `python3 -m http.server`. This will start a `ThreadingHTTPServer` listening to port 8000, serving the local files. If you open the URL *http://localhost:8000/flags/* with your browser, you'll see a long list of directories named with two-letter country codes from `ad/` to `zw/`.
5. Now you can go back to the first shell and run the *flags2*.py* examples with the default `--server LOCAL` option.
6. To test with the `--server DELAY` option, go to *21-futures/getflags/* and run `python3 slow_server.py 8001`. This will add a .5s delay before each response.
7. To test with the `--server ERROR` option, go to *21-futures/getflags/* and run `python3 slow_server.py 8002 --error-rate .25`. Each request will have a 25% probability of getting a 418 I'm a teapot response, and all responses will be delayed .5s.

I wrote *slow_server.py* reusing code from Python's `http.server` standard library module, which "is not recommended for production"—according to the documentation. To set up a more reliable testing environment, I recommend configuring Nginx and toxiproxy with equivalent parameters.

By default, each *flags2*.py* script will fetch the flags of the 20 most populous countries from the `LOCAL` server (`http://localhost:8000/flags`) using a default number of concurrent connections, which varies from script to script. Example 21-11 shows a sample run of the *flags2_sequential.py* script using all defaults.

Example 21-11. Running flags2_sequential.py with all defaults: LOCAL site, top-20 flags, 1 concurrent connection

```
$ python3 flags2_sequential.py
LOCAL site: http://localhost:8000/flags
Searching for 20 flags: from BD to VN
1 concurrent connection will be used.
--------------------
20 flags downloaded.
Elapsed time: 0.10s
```

You can select which flags will be downloaded in several ways. Example 21-12 shows how to download all flags with country codes starting with the letters A, B, or C.

Example 21-12. Run flags2_threadpool.py to fetch all flags with country codes prefixes A, B, or C from DELAY server

```
$ python3 flags2_threadpool.py -s DELAY a b c
DELAY site: http://localhost:8001/flags
Searching for 78 flags: from AA to CZ
30 concurrent connections will be used.
--------------------
43 flags downloaded.
35 not found.
Elapsed time: 1.72s
```

Regardless of how the country codes are selected, the number of flags to fetch can be limited with the `-l/--limit` option. Example 21-13 demonstrates how to run exactly 100 requests, combining the `-a` option to get all flags with `-l 100`.

Example 21-13. Run flags2_asyncio.py to get 100 flags (-al 100) from the ERROR server, using 100 concurrent requests (-m 100)

```
$ python3 flags2_asyncio.py -s ERROR -al 100 -m 100
ERROR site: http://localhost:8002/flags
Searching for 100 flags: from AD to LK
100 concurrent connections will be used.
--------------------
73 flags downloaded.
27 errors.
Elapsed time: 0.64s
```

That's the user interface of the `flags2` examples. Let's see how they are implemented.

Error Handling in the flags2 Examples

The common strategy in all three examples to deal with HTTP errors is that 404 errors (not found) are handled by the function in charge of downloading a single file (`download_one`). Any other exception propagates to be handled by the `download_many` function or the `supervisor` coroutine —in the `asyncio` example.

Once more, we'll start by studying the sequential code, which is easier to follow—and mostly reused by the thread pool script. Example 21-14 shows the functions that perform the actual downloads in the *flags2_sequential.py* and *flags2_threadpool.py* scripts.

Example 21-14. flags2_sequential.py: basic functions in charge of downloading; both are reused in flags2_threadpool.py

```
def get_flag(base_url: str, cc: str) -> bytes:
    url = f'{base_url}/{cc}/{cc}.gif'.lower()
    resp = requests.get(url)
    if resp.status_code != 200:  ❶
        resp.raise_for_status()
    return resp.content

def download_one(cc: str, base_url: str, verbose: bool = False):
    try:
        image = get_flag(base_url, cc)
    except requests.exceptions.HTTPError as exc:  ❷
        res = exc.response
```

```
        if res.status_code == 404:
            status = HTTPStatus.not_found  ❸
            msg = 'not found'
        else:  ❹
            raise
    else:
        save_flag(image, f'{cc}.gif')
        status = HTTPStatus.ok
        msg = 'OK'

    if verbose:  ❺
        print(cc, msg)

    return Result(status, cc)  ❻
```

❶ `get_flag` uses `requests.Response.raise_for_status` to raise an exception for any HTTP code other than 200.

❷ `download_one` catches `requests.exceptions.HTTPError` to handle HTTP code 404 specifically…

❸ …by setting its local `status` to `HTTPStatus.not_found`; `HTTPStatus` is an `Enum` imported from *flags2_common.py*.

❹ Any other `HTTPError` exception is re-raised; other exceptions will just propagate to the caller.

❺ If the `-v/--verbose` command-line option is set, the country code and status message will be displayed; this how you'll see progress in the verbose mode.

❻ The `Result` tuple returned by `download_one` will have a `status` field with a value of `HTTPStatus.not_found` or `HTTPStatus.ok`.

Example 21-15 lists the sequential version of the `download_many` function. This code is straightforward, but its worth studying to contrast with the concurrent versions coming up. Focus on how it reports progress, handles errors, and tallies downloads.

Example 21-15. flags2_sequential.py: the sequential implementation of download_many

```
def download_many(cc_list: list[str],
                  base_url: str,
                  verbose: bool,
                  _unused_concur_req: int) -> Counter[int]:
    counter: Counter[int] = Counter()  ❶
    cc_iter = sorted(cc_list)  ❷
    if not verbose:
        cc_iter = tqdm.tqdm(cc_iter)  ❸
    for cc in cc_iter:  ❹
        try:
            res = download_one(cc, base_url, verbose)  ❺
        except requests.exceptions.HTTPError as exc:  ❻
            error_msg = 'HTTP error {res.status_code} -
{res.reason}'
            error_msg = error_msg.format(res=exc.response)
        except requests.exceptions.ConnectionError:  ❼
            error_msg = 'Connection error'
        else:  ❽
            error_msg = ''
            status = res.status

        if error_msg:
            status = HTTPStatus.error  ❾
        counter[status] += 1           ❿
        if verbose and error_msg:      ⓫
            print(f'*** Error for {cc}: {error_msg}')

    return counter  ⓬
```

❶ This `Counter` will tally the different download outcomes: `HTTPStatus.ok`, `HTTPStatus.not_found`, or `HTTPStatus.error`.

❷ `cc_iter` holds the list of the country codes received as arguments, ordered alphabetically.

❸ If not running in verbose mode, `cc_iter` is passed to the `tqdm` function, which will return an iterator that yields the items in `cc_iter` while also displaying the animated progress bar.

❹ This `for` loop iterates over `cc_iter` and…

❺ …performs the download by successive calls to `download_one`.

❻ HTTP-related exceptions raised by `get_flag` and not handled by `download_one` are handled here.

❼ Other network-related exceptions are handled here. Any other exception will abort the script, because the `flags2_common.main` function that calls `download_many` has no `try/except`.

❽ If no exception escaped `download_one`, then the `status` is retrieved from the `HTTPStatus` `namedtuple` returned by `download_one`.

❾ If there was an error, set the local `status` accordingly.

❿ Increment the counter by using the value of the `HTTPStatus` `Enum` as key.

⓫ If running in verbose mode, display the error message for the current country code, if any.

⓬ Return the `counter` so that the `main` function can display the numbers in its final report.

We'll now study the refactored thread pool example, *flags2_threadpool.py*.

Using futures.as_completed

In order to integrate the TQDM progress bar and handle errors on each request, the *flags2_threadpool.py* script uses `futures.ThreadPoolExecutor` with the `futures.as_completed` function we've already seen. Example 21-16 is the full listing of *flags2_threadpool.py*. Only the `download_many` function is implemented; the other functions are reused from *flags2_common.py* and *flags2_sequential.py*.

Example 21-16. flags2_threadpool.py: full listing

```
from collections import Counter
from concurrent import futures

import requests
import tqdm  # type: ignore  ❶

from flags2_common import main, HTTPStatus  ❷
from flags2_sequential import download_one  ❸

DEFAULT_CONCUR_REQ = 30  ❹
MAX_CONCUR_REQ = 1000  ❺


def download_many(cc_list: list[str],
                  base_url: str,
                  verbose: bool,
                  concur_req: int) -> Counter[int]:
    counter: Counter[int] = Counter()
    with futures.ThreadPoolExecutor(max_workers=concur_req) as
executor:  ❻
        to_do_map = {}  ❼
        for cc in sorted(cc_list):  ❽
            future = executor.submit(download_one, cc,
                                     base_url, verbose)  ❾
            to_do_map[future] = cc  ❿
        done_iter = futures.as_completed(to_do_map)  ⓫
        if not verbose:
            done_iter = tqdm.tqdm(done_iter, total=len(cc_list))  ⓬
        for future in done_iter:  ⓭
            try:
                res = future.result()  ⓮
            except requests.exceptions.HTTPError as exc:  ⓯
                error_fmt = 'HTTP {res.status_code} - {res.reason}'
                error_msg = error_fmt.format(res=exc.response)
            except requests.exceptions.ConnectionError:
                error_msg = 'Connection error'
            else:
                error_msg = ''
                status = res.status
```

```
            if error_msg:
                status = HTTPStatus.error
            counter[status] += 1
            if verbose and error_msg:
                cc = to_do_map[future]  ⓰
                print(f'*** Error for {cc}: {error_msg}')

    return counter


if __name__ == '__main__':
    main(download_many, DEFAULT_CONCUR_REQ, MAX_CONCUR_REQ)
```

❶ Import the progress-bar display library, and tell *mypy* to skip checking it.

❷ Import one function and one `Enum` from the `flags2_common` module.

❸ Reuse the `download_one` from `flags2_sequential` (Example 21-14).

❹ If the `-m/--max_req` command-line option is not given, this will be the maximum number of concurrent requests, implemented as the size of the thread pool; the actual number may be smaller, if the number of flags to download is smaller.

❺ `MAX_CONCUR_REQ` caps the maximum number of concurrent requests regardless of the number of flags to download or the `-m/--max_req` command-line option; it's a safety precaution.

❻ Create the `executor` with `max_workers` set to `concur_req`, computed by the `main` function as the smaller of: `MAX_CONCUR_REQ`, the length of `cc_list`, and the value of the `-m/--max_req` command-line option. This avoids creating more threads than necessary.

❼ This `dict` will map each `Future` instance—representing one download—with the respective country code for error reporting.

❽ Iterate over the list of country codes in alphabetical order. The order of the results will depend on the timing of the HTTP responses more than anything, but if the size of the thread pool (given by `concur_req`) is much smaller than `len(cc_list)`, you may notice the downloads batched alphabetically.

❾ Each call to `executor.submit` schedules the execution of one callable and returns a `Future` instance. The first argument is the callable, the rest are the arguments it will receive.

❿ Store the `future` and the country code in the `dict`.

⓫ `futures.as_completed` returns an iterator that yields futures as they are done.

⓬ If not in verbose mode, wrap the result of `as_completed` with the `tqdm` function to display the progress bar; because `done_iter` has no `len`, we must tell `tqdm` what is the expected number of items as the `total=` argument, so `tqdm` can estimate the work remaining.

⓭ Iterate over the futures as they are completed.

⓮ Calling the `result` method on a future either returns the value returned by the callable, or raises whatever exception was caught when the callable was executed. This method may block waiting for a resolution, but not in this example because `as_completed` only returns futures that are done.

⓯ Handle the potential exceptions; the rest of this function is identical to the sequential version of `download_many` (Example 21-15), except for the next callout.

⓰ To provide context for the error message, retrieve the country code from the `to_do_map` using the current `future` as key. This was not necessary in the sequential version because we were iterating over the list of country codes, so we had the current `cc`; here we are iterating over the futures.

> **TIP**
>
> Example 21-16 uses an idiom that's very useful with `futures.as_completed`: building a `dict` to map each future to other data that may be useful when the future is completed. Here the `to_do_map` maps each future to the country code assigned to it. This makes it easy to do follow-up processing with the result of the futures, despite the fact that they are produced out of order.

Python threads are well suited for I/O-intensive applications, and the `concurrent.futures` package makes them trivially simple to use for certain use cases. With `ProcessPoolExecutor`, you can also solve CPU-intensive problems on multiple cores—if the computations are "embarrassingly parallel". This concludes our basic introduction to `concurrent.futures`.

Chapter Summary

We started the chapter by comparing two concurrent HTTP clients with a sequential one, demonstrating significant performance gains over the sequential script.

After studying the first example based on `concurrent.futures`, we took a closer look at future objects, either instances of `concurrent.futures.Future`, or `asyncio.Future`, emphasizing what these classes have in common (their differences will be emphasized in Chapter 22). We saw how to create futures by calling `Executor.submit`, and iterate over completed futures with `concurrent.futures.as_completed`.

We then discussed the use of multiple processes with the `concurrent.futures.ProcessPoolExecutor` class, to go around the GIL and use multiple CPU cores to simplify the multicore prime checker we first saw in Chapter 20.

In the following section, we took a close look at how the `concurrent.futures.ThreadPoolExecutor` works, with a didactic example launching tasks that did nothing for a few seconds, except displaying their status with a timestamp.

Next we went back to the flag downloading examples. Enhancing them with a progress bar and proper error handling prompted further exploration of the `future.as_completed` generator function showing a common pattern: storing futures in a `dict` to link further information to them when submitting, so that we can use that information when the future comes out of the `as_completed` iterator.

Further Reading

The `concurrent.futures` package was contributed by Brian Quinlan, who presented it in a great talk titled "The Future Is Soon!" at PyCon Australia 2010. Quinlan's talk has no slides; he shows what the library does by typing code directly in the Python console. As a motivating example, the presentation features a short video with XKCD cartoonist/programmer Randall Munroe making an unintended DOS attack on Google Maps to build a colored map of driving times around his city. The formal introduction to the library is PEP 3148 - `futures` - execute computations asynchronously. In the PEP, Quinlan wrote that the `concurrent.futures` library was "heavily influenced by the Java `java.util.concurrent` package."

For additional resources covering `concurrent.futures`, please see "Further Reading" (Chapter 20). All the references that cover Python's `threading` and `multiprocessing` in "Concurrency with threads and processes" also cover `concurrent.futures`.

SOAPBOX

Thread avoidance

> *Concurrency: one of the most difficult topics in computer science (usually best avoided).*[7]
>
> —David Beazley, Python coach and mad scientist

I agree with the apparently contradictory quotes by David Beazley, above, and Michele Simionato at the start of this chapter.

I attended a course about concurrency at the university. All we did was POSIX threads programming. What I learned: I don't want to manage threads and locks myself, for the same reason that I don't want to manage memory allocation and deallocation. Those jobs are best carried out by the systems programmers who have the know-how, the inclination, and the time to get them right—hopefully. I am paid to develop applications, not operating systems. I don't need all the fine grained control of threads, locks, `malloc`, and `free`—see C dynamic memory allocation.

That's why I think the `concurrent.futures` package is interesting: it treats threads, processes, and queues as infrastructure at your service, not something you have to deal with directly. Of course, it's designed with simple jobs in mind, the so-called embarrassingly parallel problems. But that's a large slice of the concurrency problems we face when writing applications—as opposed to operating systems or database servers, as Simionato points out in that quote.

For "nonembarrassing" concurrency problems, threads and locks are not the answer either. Threads will never disappear at the OS level, but every programming language I've found exciting in the last several years provides higher-level, concurrency abstractions that are easier to use correctly, as the *Seven Concurrency Models in Seven Weeks* book demonstrates. Go, Elixir, and Clojure are among them. Erlang—the implementation language of Elixir—is a prime example of a language designed from the ground up with concurrency in mind. It doesn't excite me for a simple reason: I find its syntax ugly. Python spoiled me that way.

José Valim, previously a Ruby on Rails core contributor, designed Elixir with a pleasant, modern syntax. Like Lisp and Clojure, Elixir implements syntactic macros. That's a double-edged sword. Syntactic macros enable powerful DSLs, but the proliferation of sublanguages can lead to incompatible codebases and community fragmentation. Lisp drowned in a flood of macros, with each Lisp shop using its own arcane dialect. Standardizing around Common Lisp resulted in a bloated language. I hope José Valim can inspire the Elixir community to avoid a similar outcome. So far, it's looking good. The Ecto database wrapper and query generator is a joy to use: a great example of using macros to create a flexible yet user-friendly DSL—Domain Specific Language—for interacting with relational and non-relational databases.

Like Elixir, Go is a modern language with fresh ideas. But, in some regards, it's a conservative language, compared to Elixir. Go doesn't have macros, and its syntax is simpler than Python's. Go doesn't support inheritance or operator overloading, and it offers fewer opportunities for metaprogramming than Python. These limitations are considered features. They lead to more predictable behavior and performance. That's a big plus in the highly concurrent, mission-critical settings where Go aims to replace C++, Java, and Python.

While Elixir and Go are direct competitors in the high-concurrency space, their design philosophies appeal to different crowds. Both are likely to thrive. But in the history of programming languages, the conservative ones tend to attract more coders. After I finish writing this book, I will devote more time to become fluent in Go, Elixir, and the Erlang/OTP platform.

---

1 From Michele Simionato's post Threads, processes and concurrency in Python: some thoughts, subtitled "Removing the hype around the multicore (non) revolution and some (hopefully) sensible comment about threads and other forms of concurrency."

2 For servers which may be hit by many clients, there is a difference: coroutines scale better because they use much less memory than threads, and also reduce the cost of context switching, which I mentioned in “Thread-based Non-solution”.

3 The images are originally from the CIA World Factbook, a public-domain, U.S. government publication. I copied them to my site to avoid the risk of launching a DOS attack on CIA.gov.

4 Your mileage may vary: with threads, you never know the exact sequencing of events that should happen practically at the same time; it’s possible that, in another machine, you see `loiter(1)` starting before `loiter(0)` finishes, particularly because `sleep` always releases the GIL so Python may switch to another thread even if you sleep for 0s.

5 In my testing, about 1% of the requests I make to `ThreadingHTTPServer` fail. The docs warn that it’s not intended for production, and for testing purposes it’s good that not all requests work.

6 Before configuring Cloudflare, I got HTTP 503 errors—Service Temporarily Unavailable—when testing the scripts with a few dozen concurrent requests on my inexpensive shared host account. Now those errors are gone.

7 Slide #9 from “A Curious Course on Coroutines and Concurrency,” tutorial presented at PyCon 2009.

Chapter 22. Asynchronous Programming

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 22nd chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *The problem with normal approaches to asynchronous programming as that they're all-or-nothing propositions. You rewrite all your code so none of it blocks or you're just wasting your time.*[1]
>
> —Alvaro Videla & Jason J. W. Williams, RabbitMQ in Action

This chapter addresses three major topics that are closely related:

- Python's `async def`, `await`, `async with`, and `async for` constructs;
- Objects supporting those constructs: native coroutines and asynchronous variants of context managers, iterables, generators, and comprehensions;
- `asyncio` and other asynchronous libraries.

That’s a lot, so we’ll only scratch the surface `asyncio` and the other libraries. The other topics build on ideas we’ve seen before: iterables and generators (Chapter 17), context managers (Chapter 18), and coroutines (Chapter 19).

Also covered here:

- How to avoid blocking the event loop by delegating slow operations to a thread or process pool;
- Simple network programs using `asyncio`, `aiohttp`, *FastAPI*, and *Curio*;
- Advantages and pitfalls of asynchronous programming.

> **TIP**
>
> The `asyncio` documentation is much better after Yuri Selivanov[2] reorganized it, separating the few functions useful to application developers from the low-level API for creators of packages like Web frameworks and database drivers.
>
> For book-length coverage of `asyncio`, I recommend *Using Asyncio in Python* by Caleb Hattingh (O’Reilly, 2020). Full disclosure: he is one of the tech reviewers of this book.

What’s New in this Chapter

When I wrote *Fluent Python, First Edition*, the `asyncio` library was provisional and the `async/await` keywords did not exist. Therefore, I had to update all examples in this chapter. I also created new examples: domain probing scripts, a *FastAPI* Web service, and experiments with Python’s new asynchronous console mode.

New sections cover language features that did not exist at the time, such as native coroutines, `async with`, `async for` and the objects that support those constructs.

The ideas in "How Async Works and How It Doesn't" reflect hard earned lessons that I consider essential reading for anyone using asynchronous programming. They may save you a lot of trouble—whether you're using Python or *Node.js*.

Finally, I removed several paragraphs about `asyncio.Futures`, which is now considered part of the low-level `asyncio` APIs.

A few definitions

At the start of Chapter 19, we saw that Python 3.5 and later offer three kinds of coroutines:

native coroutines

A coroutine defined with `async def`. You can delegate from a native coroutine to another native coroutine using the `await` keyword, similar to how classic coroutines use `yield from`. The `async def` statement always defines a native coroutine, even if the `await` keyword is not used in its body. The `await` keyword cannot be used outside of a native coroutine.[3]

classic coroutines

A generator function that consumes data sent to it via `my_coro.send(data)` calls, and reads that data by using `yield` in an expression. Classic coroutines can delegate to other classic coroutines using `yield from`. Classic coroutines cannot be driven by `await`, and are no longer supported by `asyncio`.

generator-based coroutines

A generator function decorated with `@types.coroutine`—introduced in Python 3.5. That decorator makes the generator compatible with the new `await` keyword.

In this chapter, we focus on native coroutines.

@ASYNCIO.COROUTINE HAS NO FUTURE[4]

The `@asyncio.coroutine` decorator for classic coroutines and generator-based coroutines was deprecated in Python 3.8 and is scheduled for removal in Python 3.11, according to issue43216. In contrast, `@types.coroutine` should remain, per issue36921. It is no longer supported by `asyncio`, but is used in low-level code in the *Curio* and *Trio* asynchronous frameworks.

Example: Probing Domains

Imagine you are about to start a new blog on Python, and you plan to register a domain using a Python keyword and the .DEV suffix—for example: AWAIT.DEV. Example 22-1 is a script using `asyncio` to check several domains concurrently. This is the output it produces:

```
$ python3 blogdom.py
  with.dev
+ elif.dev
+ def.dev
  from.dev
  else.dev
  or.dev
  if.dev
  del.dev
+ as.dev
  none.dev
  pass.dev
  true.dev
+ in.dev
+ for.dev
+ is.dev
+ and.dev
+ try.dev
+ not.dev
```

Note that the domains appear unordered. If you run the script, you'll see them displayed one after the other, with varying delays. The `+` sign indicates your machine was able to resolve the domain via DNS. Otherwise, the domain did not resolve and may be available.[5]

In *blogdom.py*, the DNS probing is done via native coroutine objects. Because the asynchronous operations are interleaved, the time needed to check the 18 domains is much less than checking them sequentially. In fact, the total time is practically the same as the time for the single slowest DNS response, instead of the sum of the times of all responses.

Here is the code for *blogdom.py*:

Example 22-1. blogdom.py: search for domains for a Python blog

```
#!/usr/bin/env python3
import asyncio
import socket
from keyword import kwlist

MAX_KEYWORD_LEN = 4  ❶


async def probe(domain: str) -> tuple[str, bool]:  ❷
    loop = asyncio.get_running_loop()  ❸
    try:
        await loop.getaddrinfo(domain, None)  ❹
    except socket.gaierror:
        return (domain, False)
    return (domain, True)


async def main() -> None:  ❺
    names = (kw for kw in kwlist if len(kw) <= MAX_KEYWORD_LEN)  ❻
    domains = (f'{name}.dev'.lower() for name in names)  ❼
    coros = [probe(domain) for domain in domains]  ❽
    for coro in asyncio.as_completed(coros):  ❾
        domain, found = await coro  ❿
        mark = '+' if found else ' '
        print(f'{mark} {domain}')


if __name__ == '__main__':
    asyncio.run(main())  ⓫
```

❶ Set maximum length of keyword for domains, because shorter is better.

❷ `probe` returns a tuple with the domain name and a boolean; `True` means the domain resolved. Returning the domain name will make it easier to display the results.

❸ Get a reference to the `asyncio` event loop, so we can use it next.

❹ The `loop.getaddrinfo(…)` coroutine-method returns a five-part tuple of parameters to connect to the given address using a socket. In this example, we don't need the result. If we got it, the domain resolves; otherwise, it doesn't.

❺ `main` must be a coroutine, so that we can use `await` in it.

❻ Generator to yield Python keywords with length up to `MAX_KEYWORD_LEN`.

❼ Generator to yield domain names with the `.dev` suffix.

❽ Build a list of coroutine objects by invoking the `probe` coroutine with each `domain` argument.

❾ `asyncio.as_completed` is a generator that yields the coroutines in the order they are completed—not the order they were submitted. It's similar to `futures.as_completed`, which we saw in Chapter 21, Example 21-4.

❿ At this point, we know the coroutine is done because that's how `as_completed` works. Therefore, the `await` expression will not block but we need it to get the result from `coro`. If `coro` raised an unhandled exception, it would be re-raised here.

⓫ This is a common pattern for scripts that use `asyncio`: implement `main` as a coroutine, and drive it here with `asyncio.run`.

> **TIP**
>
> The `asyncio.get_running_loop` function was added in Python 3.7 for use inside coroutines as shown in `probe`. Its implementation is simpler and faster than `asyncio.get_event_loop` (which may start an event loop if necessary). If there's no running loop, `asyncio.get_running_loop` raises `RuntimeError`.

Guido's trick to read asynchronous code

There are a lot of new concepts to grasp in `asyncio` but the overall logic of Example 22-1 is easy to follow if you employ a trick suggested by Guido van Rossum himself: squint and pretend the `async` and `await` keywords are not there. If you do that, you'll realize that coroutines read like plain old sequential functions.

For example, imagine that the body of this coroutine…

```
async def probe(domain: str) -> tuple[str, bool]:
    loop = asyncio.get_running_loop()
    try:
        await loop.getaddrinfo(domain, None)
    except socket.gaierror:
        return (domain, False)
    return (domain, True)
```

…works like the following function, except that it magically never blocks:

```
def probe(domain: str) -> tuple[str, bool]:  # no async
    loop = asyncio.get_running_loop()
    try:
        loop.getaddrinfo(domain, None)  # no await
    except socket.gaierror:
        return (domain, False)
    return (domain, True)
```

Using the syntax `await loop.getaddrinfo(...)` avoids blocking because `await` suspends the current coroutine object—for example, `probe('if.dev')`. A new coroutine object is created, `getaddrinfo('if.dev', None)`, it starts the low-level `addrinfo` query and yields control back to the event loop, which can drive other pending coroutine objects, such as `probe('or.dev')`. When the event loop gets a response for the `getaddrinfo('if.dev', None)` query, that specific coroutine object resumes and returns control back to the `probe('if.dev')`—which was suspended at `await`—and can now handle a possible exception and return the result tuple.

So far, we've only seen `asyncio.as_completed` and `await` applied to coroutines. But they handle any *awaitable* object. That concept is explained next.

New concept: awaitable

The `for` keyword works with *iterables*. The `await` keyword works with *awaitables*.

As an end user of `asyncio`, these are the awaitables you will see on a daily basis:

- A *native coroutine object*, which you get by calling a *native coroutine function*.
- An `asyncio.Task`, which usually you get by passing a coroutine object to `asyncio.create_task()`.

However, end-user code does not always need to `await` on a `Task`. We use `asyncio.create_task(one_coro())` to schedule `one_coro` for concurrent execution, without waiting for its return. That's what we did with the `spinner` coroutine in *spinner_async.py* (Example 20-4). If you don't expect to cancel the task or wait for it, there is no need to keep the `Task` object returned from `create_task`. Creating the task is enough to schedule the coroutine to run.

In contrast, we use `await other_coro()` to run `other_coro` right now and wait for its completion because we need its result before we can proceed. In *spinner_async.py*, the `supervisor` coroutine did `res = await slow()` to execute `slow` and get its result.

When implementing asynchronous libraries or contributing to `asyncio` itself, you may also deal with these lower-level awaitables:

- An object with an `__await__` method that returns an iterator; for example, an `asyncio.Future` instance (`asyncio.Task` is a subclass of `asyncio.Future`).
- Objects written in other languages using the Python/C API with a `tp_as_async.am_await` function, returning an iterator (similar to `__await__` method).

Existing codebases may also have one additional kind of awaitable: *generator-based coroutine objects*—which are in the process of being deprecated.

> **NOTE**
>
> PEP 492 states that the `await` expression "uses the `yield from` implementation with an extra step of validating its argument" and "`await` only accepts an awaitable." The PEP does not explain that implementation in detail, but refers to PEP 380, which introduced `yield from`. In this book there is a detailed explanation in "The Meaning of yield from".

Now let's study the `asyncio` version of a script that downloads a fixed set of flag images.

Downloading with asyncio and aiohttp

The *flags_asyncio.py* script downloads a fixed set of 20 flags from *fluentpython.com*. We first mentioned it "Concurrent Web Downloads", but now we'll study it in detail, applying the concepts we just saw.

As of Python 3.9, `asyncio` only supports TCP and UDP directly, and there are no asynchronous HTTP client or server packages in the standard library. I am using *aiohttp* 3.7.4 in the HTTP client examples.

We'll explore *flags_asyncio.py* from the bottom up—that is, looking first at the functions that set up the action in Example 22-2.

> **WARNING**
>
> To make the code easier to read, *flags_asyncio.py* has no error handling. As we introduce `async/await`, it's useful to focus on the "happy path" initially, to understand how regular functions and coroutines are arranged in a program.
>
> Starting with "Enhancing the asyncio downloader", the examples include error handling and more features.

Example 22-2. flags_asyncio.py: startup functions

```
def download_many(cc_list: list[str]) -> int:      ❶
    return asyncio.run(supervisor(cc_list))         ❷

async def supervisor(cc_list: list[str]) -> int:
    async with ClientSession() as session:          ❸
        to_do = [download_one(session, cc)          ❹
                 for cc in sorted(cc_list)]
        res = await asyncio.gather(*to_do)          ❺

    return len(res)                                 ❻

if __name__ == '__main__':
    main(download_many)
```

❶ This needs to be a plain function—not a coroutine—so it can be passed to and called by the `main` function from the *flags.py* module (Example 21-2).

❷ Execute the event loop driving the `supervisor(cc_list)` coroutine object until it returns. This will block while the event loop runs. The result of this line is whatever `supervisor` returns.

❸ HTTP client operations in `aiohttp` are methods of `ClientSession`, which is also an asynchronous context manager: a context manager with asynchronous set-up and tear-down methods (more about this in "Asynchronous Context Managers"). All HTTP requests in `aiohttp` must execute in the context of an active `ClientSession`.

❹ Build a list of coroutine objects by calling the `download_one` coroutine once for each flag to be retrieved.

❺ Wait for the `asynctio.gather` coroutine, which accepts one or more awaitable arguments and waits for all of them to complete, returning a list of results for the given awaitables in the order they were submitted.

❻ `supervisor` returns the length the list returned by `asyncio.gather`.

Now let's review the top of *flags_asyncio.py*. I reorganized the coroutines so we can read them in the order they are started by the event loop.

Example 22-3. flags_asyncio.py: imports and download functions

```
import asyncio

from aiohttp import ClientSession  ❶

from flags import BASE_URL, save_flag, main  ❷

async def download_one(session: ClientSession, cc: str):  ❸
    image = await get_flag(session, cc)
    save_flag(image, f'{cc}.gif')
    print(cc, end=' ', flush=True)
    return cc

async def get_flag(session: ClientSession, cc: str) -> bytes:  ❹
    url = f'{BASE_URL}/{cc}/{cc}.gif'.lower()
    async with session.get(url) as resp:  ❺
        return await resp.read()          ❻
```

❶ `aiohttp` must be installed—it’s not in the standard library.

❷ Reuse code from *flags.py* (Example 21-2).

❸ `download_one` must be a native coroutine, so it can `await` on `get_flag`—which does the HTTP request. Then it displays the code of the downloaded flag, and saves the image.

❹ `get_flag` needs to receive the `ClientSession` to make the request.

❺ The `get` method of an `aiohttp.ClientSession` instance returns a `ClientResponse` object which is also an asynchronous context manager.

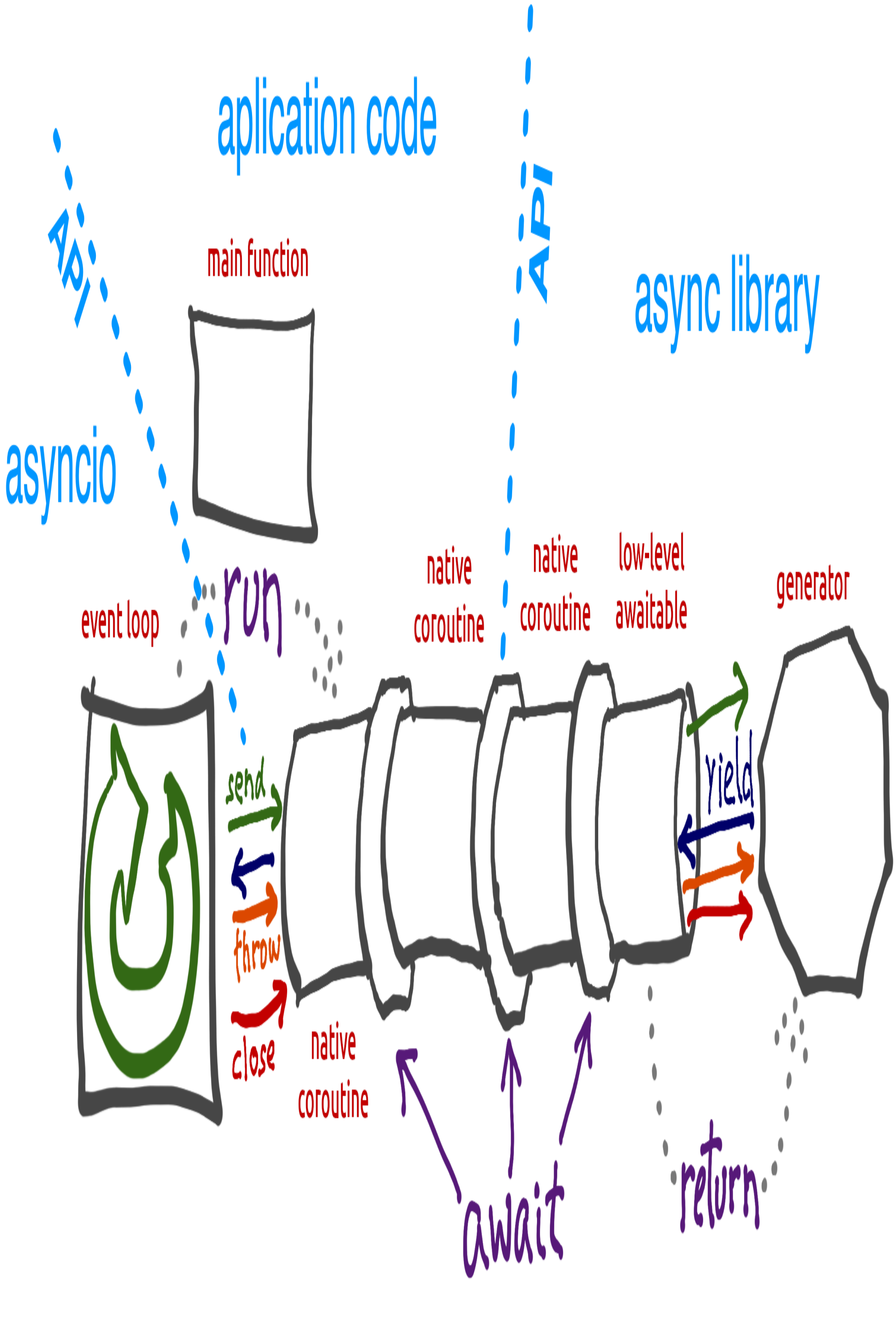
❻ Network I/O operations are implemented as coroutine-methods, so they are driven asynchronously by the `asyncio` event loop.

> **NOTE**
>
> For better performance, the `save_flag` call inside `get_flag` should be asynchronous, but `asyncio` does not provide an asynchronous filesystem API at this time—as *Node.js* does. If profiling reveals that is a bottleneck in your application, you can use the `loop.run_in_executor` function to run `save_flag` in a thread pool. Example 22-8 will show how.

Your code delegates to the `aiohttp` coroutines explicitly through `await` or implicitly through the special methods of the asynchronous context managers, such as `ClientSession` and `ClientResponse`—as we’ll see in “Asynchronous Context Managers”.

The Secret of Native Coroutines: Humble Generators

A key difference between the classic coroutine examples we saw in Chapter 19 and *flags_asyncio.py* is that there are no visible `.send()` calls or `yield` expressions in the latter. Your code sits between the `asyncio` library and the asynchronous libraries you are using, such as `aiohttp`. This is illustrated in Figure 22-1.



aplication code
API
API
main function
async library
asyncio
run
event loop
native
coroutine
native
coroutine
low-level
awaitable
generator
send
throw
close
yield
native
coroutine
await
return

Figure 22-1. In an asynchronous program, a user's function starts the event loop, scheduling an initial coroutine with `asyncio.run`. Each user's coroutine drives the next with an `await` expression, forming a channel that enables communication between a library such as `aiohttp` and the event loop. Compare this with Figure 19-2.

Under the hood, the `asyncio` event loop makes the `.send` calls that drive your coroutines, and your coroutines `await` on other coroutines, including library coroutines. As mentioned, `await` borrows most of its implementation from `yield from`, which also makes `.send` calls to drive coroutines.

The `await` chain eventually reaches a low-level awaitable, which returns a plain generator that the event loop can drive in response to events such as timers or network I/O. The low-level awaitables and generators at the end of these `await` chains are implemented deep into the libraries, are not part of their APIs, and may be written in C.

Using functions like `asyncio.gather` and `asyncio.create_task`, you can start multiple concurrent `await` channels, enabling concurrent execution of multiple I/O operations driven by a single event loop, in a single thread.

The all-or-nothing problem

Note that in Example 22-3 I could not reuse the `get_flag` function from *flags.py* (Example 21-2) because it uses the `requests` library, which performs blocking I/O: it would block the event loop. To leverage `asyncio`, we must replace every function that hits the network with an asynchronous version that is activated with `await` or `asyncio.create_task, so that control is given back to the event loop. Using `await` in `get_flag` means that it must be driven as a coroutine.

If you can't rewrite a blocking function as a native coroutine, you should run it in a separate thread or process, as we'll see in "Using an Executor to Avoid Blocking the Event Loop".

This is why I chose the epigraph for this chapter, which says: “You rewrite all your code so none of it blocks or you’re just wasting your time.”

For the same reason, I could not reuse the `download_one` function from *flags_threadpool.py* (Example 21-3) either. The code in Example 22-3 drives `get_flag` with `await`, so `download_one` must also be a coroutine. For each request, a `download_one` coroutine object is created in `supervisor`, and they are all driven by the `asyncio.gather` coroutine.

Now let’s study the `async with` statement that appeared in `supervisor` (Example 22-2) and `get_flag` (Example 22-3).

Asynchronous Context Managers

In “Context Managers and with Blocks” we saw how an object can be used to run code before and after the body of a `with` block, if its class provides the `__enter__` and `__exit__` methods.

Now, consider this Example 22-4, from the *asyncpg* asyncio-compatible PostgreSQL driver documentation on transactions:

Example 22-4. Sample code from the documentation of the asyncpg PostgreSQL driver.

```
tr = connection.transaction()
await tr.start()
try:
    await connection.execute("INSERT INTO mytable VALUES (1, 2,
3)")
except:
    await tr.rollback()
    raise
else:
    await tr.commit()
```

A database transaction is a natural fit for the context manager protocol: the transaction has to be started, data is changed with `connection.execute`, and then a rollback or commit must happen, depending on the outcome of the changes.

In an asynchronous driver like *asyncpg*, the set up and wrap up need to be coroutines—so that other operations can happen concurrently. However, the implementation of the classic `with` statement doesn't support coroutines doing the work of `__enter__` or `__exit__`.

That's why PEP 492—Coroutines with async and await syntax introduced the `async with` statement, which works with asynchronous context managers: objects implementing the `__aenter__` and `__aexit__` methods as coroutines.

With `async with`, Example 22-4 can be written like this other snippet from the *asyncpg* documentation:

```
async with connection.transaction():
    await connection.execute("INSERT INTO mytable VALUES (1, 2,
3)")
```

In the *asyncpg* `Transaction` class, the `__aenter__` coroutine method does `await self.start()` and the `__aexit__` coroutine awaits on private `__rollback` or `__commit` coroutine methods, depending on whether an exception occurred or not. The use of coroutines to implement `Transaction` as an asynchronous context manager allows *asyncpg* to handle many transactions concurrently.

Back to *flags_asyncio.py*, the `ClientSession` and `ClientResponse` classes of `aiohttp` are both asynchronous context managers to be able to use awaitables their `__aenter__` and `__aexit__` special coroutine methods. The *aiohttp* documentation has a high-level explanation about these asynchronous context managers titled Why is aiohttp client API that way?

> **NOTE**
>
> "Asynchronous Generators as Context Managers" shows how to use Python's `contextlib` to create an asynchronous context manager without having to write a class. That explanation comes later in this chapter because of a pre-requisite topic: "Asynchronous Generator Functions".

We'll now enhance the `asyncio` flag download example with a progress bar, which will lead us to explore a bit more of the `asyncio` API.

Enhancing the asyncio downloader

Recall from "Downloads with Progress Display and Error Handling" that the *flags2* set of examples share the same command-line interface, and they display a progress bar while the downloads are happening. They also include error handling.

> **TIP**
>
> I encourage you to play with the *flags2* examples to develop an intuition of how concurrent HTTP clients perform. Use the `-h` option to see the help screen in Example 21-10. Use the `-a`, `-e`, and `-l` command-line options to control the number of downloads, and the `-m` option to set the number of concurrent downloads. Run tests against the `LOCAL`, `REMOTE`, `DELAY`, and `ERROR` servers. Discover the optimum number of concurrent downloads to maximize throughput against each server. Tweak the options for the test servers as described in "Setting up test servers".

For instance, Example 22-5 shows how to get 100 flags (`-al 100`) from the `ERROR` server, using 100 concurrent requests (`-m 100`).

Example 22-5. Running flags2_asyncio.py

```
$ python3 flags2_asyncio.py -s ERROR -al 100 -m 100
ERROR site: http://localhost:8002/flags
Searching for 100 flags: from AD to LK
100 concurrent connections will be used.
--------------------
73 flags downloaded.
```

```
27 errors.
Elapsed time: 0.64s
```

> **ACT RESPONSIBLY WHEN TESTING CONCURRENT CLIENTS**
>
> Even if the overall download time is not much different between the threaded and `asyncio` HTTP clients, `asyncio` can send requests faster, so it's more likely that the server will suspect a DOS attack. To really exercise these concurrent clients at full throttle, please set up local HTTP servers for testing as explained in "Setting up test servers".

Now let's see how *flags2_asyncio.py* is implemented.

Using asyncio.as_completed and a semaphore

In Example 22-3, we passed several coroutines to `asyncio.gather`, which returns a list with results of the coroutines in the order they were submitted. This means that `asyncio.gather` can only return when all the awaitables are done. However, to update a progress bar we need to get results as they are done.

Fortunately, there is an `asyncio` equivalent of the `as_completed` generator function we used in the thread pool example with the progress bar (Example 21-16).

Example 22-6 shows the top of the *flags2_asyncio.py* script where the `get_flag` and `download_one` coroutines are defined. Example 22-7 lists the rest of the source, with `supervisor` and `download_many`. This script is longer than *flags_asyncio.py* because of error handling.

Example 22-6. flags2_asyncio.py: Top portion of the script; remaining code is in Example 22-7

```
import asyncio
from collections import Counter

import aiohttp
import tqdm  # type: ignore
```

```
from flags2_common import main, HTTPStatus, Result, save_flag

# default set low to avoid errors from remote site, such as
# 503 - Service Temporarily Unavailable
DEFAULT_CONCUR_REQ = 5
MAX_CONCUR_REQ = 1000


class FetchError(Exception):  ❶
    def __init__(self, country_code: str):
        self.country_code = country_code


async def get_flag(session: aiohttp.ClientSession,  ❷
                   base_url: str,
                   cc: str) -> bytes:
    url = f'{base_url}/{cc}/{cc}.gif'.lower()
    async with session.get(url) as resp:
        if resp.status == 200:
            return await resp.read()
        else:
            resp.raise_for_status()  ❸
            return bytes()

async def download_one(session: aiohttp.ClientSession,  ❹
                       cc: str,
                       base_url: str,
                       semaphore: asyncio.Semaphore,
                       verbose: bool) -> Result:
    try:
        async with semaphore:  ❺
            image = await get_flag(session, base_url, cc)
    except aiohttp.ClientResponseError as exc:
        if exc.status == 404:            ❻
            status = HTTPStatus.not_found
            msg = 'not found'
        else:
            raise FetchError(cc) from exc  ❼
    else:
        save_flag(image, f'{cc}.gif')
        status = HTTPStatus.ok
        msg = 'OK'
    if verbose and msg:
        print(cc, msg)
    return Result(status, cc)
```

❶

We’ll use this custom exception to wrap other HTTP or network exceptions and carry the `country_code` for error reporting.

❷ `get_flag` will either return the bytes of the image downloaded, raise `web.HTTPNotFound` if the HTTP response status is 404, or raise an `aiohttp.HttpProcessingError` for other HTTP status codes.

❸ This raises an exception for codes >= 400. If that’s not the case, return 0 bytes in the next line.

❹ The `semaphore` argument is an instance of `asyncio.Semaphore`, a synchronization device that limits the number of concurrent requests.

❺ The `semaphore` is used as an asynchronous context manager so that the system as whole is not blocked: only this coroutine is suspended when the semaphore counter is zero. More about this in “About Semaphores”.

❻ If the HTTP status was 404—not found—save it to add to the `Result` to be returned, and set an appropriate message for verbose mode reporting.

❼ Wrap any other `aiohttp.ClientResponseError` as a `FetchError` with the country code and the original exception chained using the `raise X from Y` syntax introduced in PEP 3134 — Exception Chaining and Embedded Tracebacks.

Network client code of the sort we are studying should always use some throttling mechanism to avoid pounding the server with too many concurrent requests. In *flags2_threadpool.py* (Example 21-16), the throttling was done by instantiating the `ThreadPoolExecutor` with the required `max_workers` argument set to `concur_req` in the `download_many` function. In *flags2_asyncio.py* I used an `asyncio.Semaphore` created by the `supervisor` function (shown next, in Example 22-7) and passed as the `semaphore` argument to `download_one` in Example 22-6.

ABOUT SEMAPHORES

The semaphore is a simple but flexible synchronization primitive invented by computer scientist Edsger W. Dijkstra in the early 1960's. Other synchronization objects—such as locks and barriers—can be built on top of semaphores.

There are three `Semaphore` classes in Python's standard library: one in `threading`, another in `multiprocessing`, and a third one in `asyncio`. Here we'll discuss the latter.

An `asyncio.Semaphore` has an internal counter that is decremented whenever we drive the `.acquire()` coroutine method, and incremented when we call the `.release()` method—which is not a coroutine because it never blocks.

The initial value of the counter is set when the `Semaphore` is instantiated, as in this line of `supervisor`:

```
    semaphore = asyncio.Semaphore(concur_req)
```

Calling `.acquire()` does not block when the counter is greater than zero, but if the counter is zero, `.acquire()` will suspend the calling coroutine until some other coroutine calls `.release()` on the same `Semaphore`, thus incrementing the counter. In Example 22-6, I don't use `.acquire()` or `.release()` directly, but use the `semaphore` as an asynchronous context manager in this block of code inside `download_one`:

```
        async with semaphore:
            image = await get_flag(session, base_url, cc)
```

The `Semaphore.__aenter__` coroutine method awaits for `.acquire()`, and its `__aexit__` coroutine method calls `.release()`.

That snippet guarantees that no more than `concur_req` instances of `get_flags` coroutines will be active at any time.

Each of the `Semaphore` classes in the standard library has a `BoundedSemaphore` subclass that enforces an additional constraint: the internal counter can never become larger than the initial value when there are more `.release()` than `.acquire()` operations.[6]

Now let's take a look at the rest of the script in Example 22-7.

Example 22-7. flags2_asyncio.py: Script continued from Example 22-6

```
async def supervisor(cc_list: list[str],
                     base_url: str,
                     verbose: bool,
                     concur_req: int) -> Counter[HTTPStatus]:  ❶
    counter: Counter[HTTPStatus] = Counter()
    semaphore = asyncio.Semaphore(concur_req)  ❷
    async with aiohttp.ClientSession() as session:
        to_do = [download_one(session, cc, base_url, semaphore,
verbose)
                 for cc in sorted(cc_list)]  ❸
        to_do_iter = asyncio.as_completed(to_do)  ❹
        if not verbose:
            to_do_iter = tqdm.tqdm(to_do_iter, total=len(cc_list))
❺
        for coro in to_do_iter:  ❻
            try:
                res = await coro  ❼
            except FetchError as exc:  ❽
                country_code = exc.country_code  ❾
                try:
                    error_msg = exc.__cause__.message  # type:
ignore  ❿
                except AttributeError:
                    error_msg = 'Unknown cause'  ⓫
                if verbose and error_msg:
                    print(f'*** Error for {country_code}:
{error_msg}')
                status = HTTPStatus.error
            else:
                status = res.status
            counter[status] += 1  ⓬
    return counter  ⓭
```

```
def download_many(cc_list: list[str],
                  base_url: str,
                  verbose: bool,
                  concur_req: int) -> Counter[HTTPStatus]:
    coro = supervisor(cc_list, base_url, verbose, concur_req)
    counts = asyncio.run(coro)  ⓮

    return counts

if __name__ == '__main__':
    main(download_many, DEFAULT_CONCUR_REQ, MAX_CONCUR_REQ)
```

❶ `supervisor` takes the same arguments as the `download_many` function, but it cannot be invoked directly from `main` precisely because it's a coroutine and not a plain function like `download_many`.

❷ Create an `asyncio.Semaphore` that will allow at most `concur_req` active coroutines among those using this semaphore. The value of `concur_req` is computed by the `main` function from *flags2_common.py*, based on command-line options and constants set in each example.

❸ Create a list of coroutine objects, one per call to the `download_one` coroutine.

❹ Get an iterator that will return coroutine objects as they are done. I did not place this call to `as_completed` directly in the `for` loop below because I may need to wrap it with the `tqdm` iterator for the progress bar, depending on the user's choice for verbosity.

❺ Wrap the `as_completed` iterator with the `tqdm` generator function to display progress.

❻ Iterate over the completed coroutine objects; this loop is similar to the one in `download_many` in Example 21-16; most changes have to do with exception handling because of differences in the HTTP libraries (`requests` versus `aiohttp`).

7. `await` on the coroutine to get its result. This will not block because `as_completed` only produces coroutines that are done.

8. Every exception in `download_one` is wrapped in a `FetchError` with the original exception chained.

9. Get the country code where the error occurred from the `FetchError` exception.

10. Try to retrieve the error message from the original exception. Despite being protected by `try/except AttributeError`, Mypy reports two missing attribute errors in this line. Fortunately, we can silence it. Thank Guido for optional typing.

11. If the error message cannot be found in the original exception, use the name of the chained exception class as the error message.

12. Tally outcomes.

13. Return the counter, as in the other scripts.

14. `download_many` instantiates the `supervisor` coroutine object and passes it to the event loop with `asyncio.run`.

In Example 22-7, we could not use the mapping of futures to country codes we saw in Example 21-16 because the awaitables returned by `asyncio.as_completed` are not necessarily the same awaitables we pass into the `as_completed` call. Internally, the `asyncio` machinery may replace the awaitables we provide with others that will, in the end, produce the same results.[7]

Because I could not use the awaitables as keys to retrieve the country code from a `dict` in case of failure, I implemented the custom `FetchError` exception (shown in Example 22-6). `FetchError` wraps a network exception and holds the country code associated with it, so the country code can be reported with the error in verbose mode. If there is no error, the country code is available as the result of the `await coro` expression at the top of the `for` loop.

This wraps up the discussion of an `asyncio` example functionally equivalent to the *flags2_threadpool.py* we saw earlier.

While discussing Example 22-3, I noted that `save_flag` performs file I/O and should be executed asynchronously for better performance. The following section shows how.

Using an Executor to Avoid Blocking the Event Loop

In the Python community, we tend to overlook the fact that local filesystem access is blocking, rationalizing that it doesn't suffer from the higher latency of network access—which is also dangerously unpredictable. In contrast, *Node.js* programmers are constantly reminded that all filesystem functions are blocking because their signatures require a callback. Each time event loop is blocked because of any I/O, you are wasting millions of CPU cycles. This may have a significant impact on the overall performance of the application.

In Example 22-6, the blocking function is `save_flag`. In the threaded version of the script (Example 21-16), `save_flag` blocks the thread that's running the `download_one` function, but that's only one of several worker threads. Behind the scenes, the blocking I/O call releases the GIL, so another thread can proceed. But in *flags2_asyncio.py*, `save_flag` blocks the single thread our code shares with the `asyncio` event loop, therefore the whole application freezes while the file is being saved. The solution to this problem is the `run_in_executor` method of the event loop object.

The `asyncio` event loop provides a thread pool executor, and you can send callables to be executed by it with `loop.run_in_executor`. This allows potentially blocking code to run in other threads, without blocking the event loop in the main thread or our program. Of course, the main thread and the thread pool will still share the same GIL, but that should not be a problem if the thread pool is used for I/O.

To use this feature in our example, we only need to change a few lines in the `download_one` coroutine, as shown in Example 22-8.

Example 22-8. flags2_asyncio_executor.py: Using the default thread pool executor to run save_flag

```
async def download_one(session: aiohttp.ClientSession,
                       cc: str,
                       base_url: str,
                       semaphore: asyncio.Semaphore,
                       verbose: bool) -> Result:
    try:
        async with semaphore:
            image = await get_flag(session, base_url, cc)
    except aiohttp.ClientResponseError as exc:
        if exc.status == 404:
            status = HTTPStatus.not_found
            msg = 'not found'
        else:
            raise FetchError(cc) from exc
    else:
        loop = asyncio.get_running_loop()   ❶
        loop.run_in_executor(None,          ❷
            save_flag, image, f'{cc}.gif')  ❸
        status = HTTPStatus.ok
        msg = 'OK'
    if verbose and msg:
        print(cc, msg)
    return Result(status, cc)
```

❶ Get a reference to the event loop object.

❷ The first argument to `run_in_executor` is an `concurrent.futures.Executor` instance; if `None`, the default thread pool executor provided by the event loop is used.

❸ The remaining arguments are the callable and its positional arguments.

When I tested Example 22-8, there was no noticeable change in performance for using `run_in_executor` to save the flag images because they are small (13 KB each, on average). But you'll see an effect if you edit the `save_flag` function in *flags2_common.py* to save 10 times as many bytes on each file—just by coding `fp.write(img * 10)` instead of `fp.write(img)`. With an average download size of 130 KB, the advantage of using `run_in_executor` becomes clear. If you're downloading megapixel images, the speedup will be significant.

The implementation of `asyncio` itself uses `run_in_executor` under the hood in a few places. For example the, `loop.getaddrinfo(…)` coroutine we saw in Example 22-1 is implemented by calling the `getaddrinfo` function from the `socket` module—which is a blocking function that may take seconds to return, as it depends on DNS resolution.

> **TIP**
>
> A common pattern in asynchronous APIs is to wrap blocking calls that are implementation details in coroutines using `run_in_executor` internally. That way, you provide a consistent interface of coroutines to be driven with `await`, and hide the threads you need to use for pragmatic reasons. The Motor asynchronous driver for *MongoDB* has an API compatible with `async/await` that is really a façade around a threaded core which talks to the database server. A. Jesse Jiryu Davis, the lead developer of *Motor*, explains his reasoning in *Response to "Asynchronous Python and Databases"*.

The main reason to pass an explict `Executor` to `loop.run_in_executor` is to employ a `ProcessPoolExecutor` if the function to execute is CPU intensive, so that it runs in a different Python process, avoiding contention for the GIL. Because of the high start-up cost, it would be better to start the `ProcessPoolExecutor` in the `supervisor`, and pass it to the coroutines that need to use it.

The next example demonstrates the simple pattern of executing one asynchronous task after the other using coroutines. This deserves our attention because anyone with previous experience with JavaScript knows that running one asynchronous function after the other was the reason for the nested coding pattern known as pyramids of doom. The `await` keyword makes that curse go away. That’s why we now have it in Python and JavaScript.

Making Multiple Requests for Each Download

Suppose you want to save each country flag with the name of the country and the country code, instead of just the country code. Now you need to make two HTTP requests per flag: one to get the flag image itself, the other to get the *metadata.json* file in the same directory as the image: that’s where the name of the country is recorded.

Articulating multiple requests in the same task is easy in the threaded script: just make one request then the other, blocking the thread twice, and keeping both pieces of data (country code and name) in local variables, ready to use when saving the files. If you needed to do the same in an asynchronous script with callbacks, you needed nested functions so that the country code and name were available in their closures until you could save the file because each callback runs in a different local scope. The `await` keyword provides relief from that, allowing you to drive the asynchronous requests one after the other from the local scope of a coroutine.

The third variation of the `asyncio` flag downloading script has a couple of changes:

`get_country`

: This new coroutine fetches the *metadata.json* file for the country code, and gets the name of the country from it.

`download_one`

: This coroutine now uses `await` to delegate to `get_flag` and the new `get_country` coroutine, using the result of the latter to build the name of the file to save.

Let’s start with the code for `get_country`. Note that it is very similar to `get_flag` from Example 22-6.

Example 22-9. flags3_asyncio.py: get_country coroutine

```
async def get_country(session: aiohttp.ClientSession,  ❶
                      base_url: str,
                      cc: str) -> str:
    url = f'{base_url}/{cc}/metadata.json'
    async with session.get(url) as resp:
        if resp.status == 200:
            metadata = await resp.json()  ❷
            return metadata.get('country', 'no name')  ❸
        else:
            resp.raise_for_status()
            return ''
```

❶ This coroutine returns a string with the country name—if all goes well.

❷ `metadata` will get a Python `dict` built from the JSON contents of the response.

❸ Get the country name or `'no name'` if it is missing.

Now the modified `download_one`, which has only a few lines changed from the same coroutine in Example 22-6

Example 22-10. flags3_asyncio.py: download_one coroutine

```
async def download_one(session: aiohttp.ClientSession,
                       cc: str,
                       base_url: str,
                       semaphore: asyncio.Semaphore,
                       verbose: bool) -> Result:
    try:
        async with semaphore:
            image = await get_flag(session, base_url, cc)  ❶
        async with semaphore:
            country = await get_country(session, base_url, cc)  ❷
    except aiohttp.ClientResponseError as exc:
        if exc.status == 404:
            status = HTTPStatus.not_found
            msg = 'not found'
        else:
            raise FetchError(cc) from exc
    else:
        filename = country.replace(' ', '_')  ❸
        filename = f'{filename}.gif'
```

```
        loop = asyncio.get_running_loop()
        loop.run_in_executor(None,
                             save_flag, image, filename)
        status = HTTPStatus.ok
        msg = 'OK'
    if verbose and msg:
        print(cc, msg)
    return Result(status, cc)
```

❶ Get the flag image…

❷ …then the country name.

❸ Use the country name to create a filename. As a command-line user, I don't like to see spaces in filenames.

Much better than nested callbacks!

I could schedule both `get_flag` and `get_country` in parallel using `asyncio.gather`, but if `get_flag` raises an exception there is no image to save, so it's pointless to run `get_country`. But there are cases where it makes sense to use `asyncio.gather` to hit several APIs at the same time instead of waiting for one response before making the next request.

I put the calls to `get_flag` and `get_country` in separate `with` blocks controlled by the `semaphore` because it's good practice to hold semaphores and locks for the shortest possible time.

In *flags3_asyncio.py*, the `await` syntax appears six times, and `async with` five times. Hopefully, you should be getting the hang of asynchronous programming in Python. One challenge is to know when you have to use `await` and when you can't use it. The answer in principle is easy, you `await` coroutines and other awaitables, such as `asyncio.Task` instances. But some APIs are tricky, mixing coroutines and plain functions in seemingly arbitrary ways, like the `StreamWriter` class we'll use in Example 22-14.

Example 22-10 wraps up the *flags* set of examples. We'll now go from client scripts to writing servers with `asyncio`.

Writing asyncio Servers

The classic toy example of a TCP server is an echo server. We'll build slightly more interesting toys: server-side Unicode character search utilities, first using HTTP with *FastAPI*, then using plain TCP with `asyncio` only.

These servers let users query for Unicode characters based on words in their standard names from the `unicodedata` module we discussed in "The Unicode Database". Figure 22-2 shows a session with the *web_mojifinder.py* server.

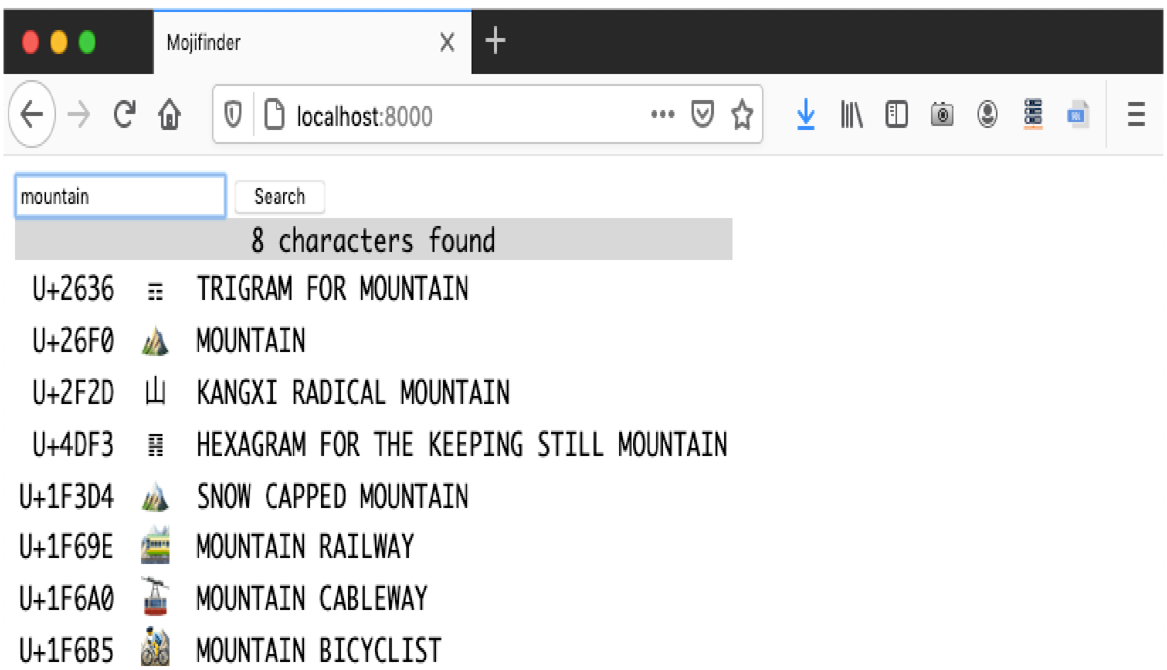


Figure 22-2. Browser window displaying search results for "mountain" from the web_mojifinder.py service.

The Unicode search logic in these examples is in the `InvertedIndex` class in the *charindex.py* module in the *Fluent Python 2e* code repository. There's nothing concurrent in that small module, so I'll only give a brief overview in the optional box below. You can skip to the HTTP server implementation in “A FastAPI Web Service”.

WHAT IS AN INVERTED INDEX

An inverted index usually maps words to documents in which they occur. In the *mojifinder* examples, the "documents" are characters. The `charindex.InvertedIndex` class indexes each word that appears in each character name in the Unicode database, and creates an inverted index stored in a `defaultdict`. For example, to index character U+0037—DIGIT SEVEN—the `InvertedIndex` initializer appends the character `'7'` to the entries under the keys `'DIGIT'` and `'SEVEN'`. After indexing the Unicode 13.0.0 data bundled with Python 3.9.1, `'DIGIT'` maps to 868 characters, and `'SEVEN'` maps to 143, including U+1F556—CLOCK FACE SEVEN OCLOCK and U+2790—DINGBAT NEGATIVE CIRCLED SANS-SERIF DIGIT SEVEN (which appears in many code listings in this book).

See Figure 22-3 for a demonstration using the entries for `'CAT'` and `'FACE'`.

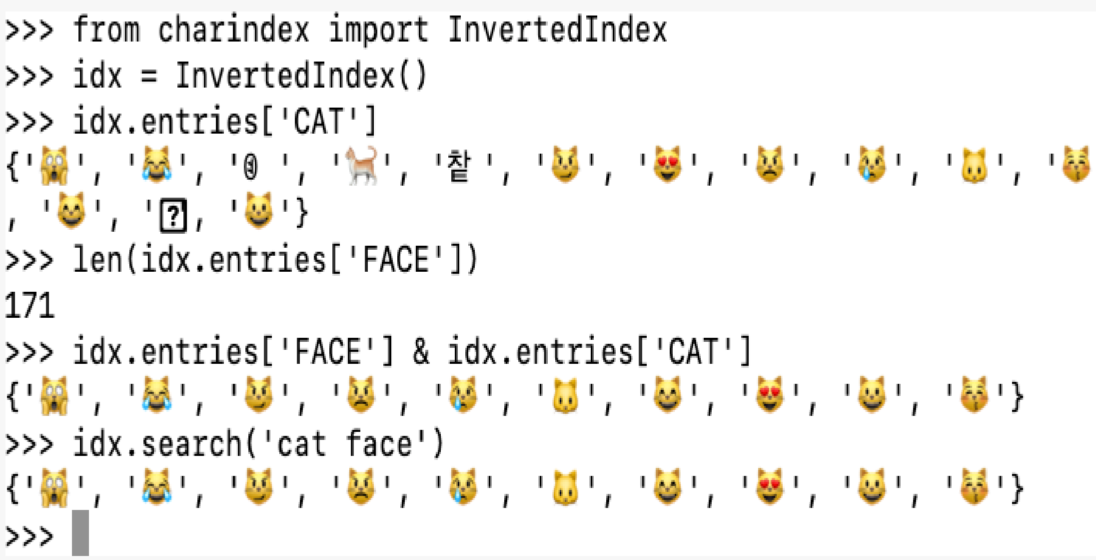


Figure 22-3. Python console exploring `InvertedIndex` attribute `entries` and `search` method.

The `InvertedIndex.search` method breaks the query into words, and returns the intersection of the entries for each word. That's why searching for “face” finds 171 results, “cat” finds 14, but “cat face” only 10.

That’s the beautiful idea behind an inverted index: a fundamental building block in information retrieval—the theory behind search engines. See the English Wikipedia article Inverted Index to learn more.

A FastAPI Web Service

I wrote the next example—*web_mojifinder.py*—using *FastAPI*: one of the Python ASGI Web frameworks mentioned in “ASGI—Asynchronous Server Gateway Interface”. Figure 22-2 is a screenshot of the front-end. It’s a super simple SPA (Single Page Application): after the initial HTML download, the UI is updated by client-side JavaScript communicating with the server.

FastAPI is designed to implement back-ends for SPA and mobile apps, which mostly consist of Web API end points returning JSON responses instead of server-rendered HTML. *FastAPI* leverages decorators, type hints, and code introspection to eliminate a lot of the boilerplate code for Web APIs, and also automatically publishes interactive OpenAPI—a.k.a. Swagger—documentation for the APIs we create. Figure 22-4 shows the auto-generated `/docs` page for *web_mojifinder.py*.

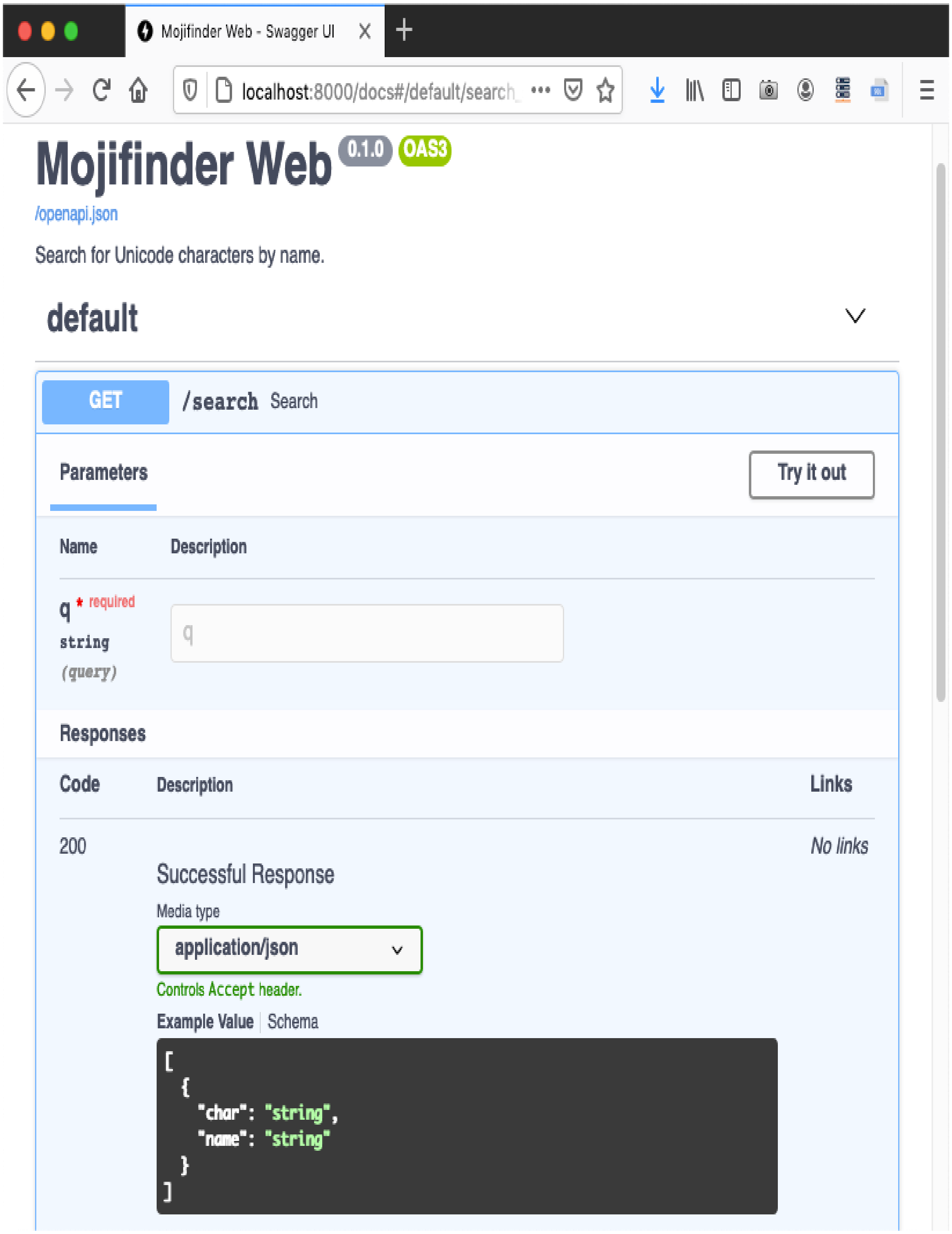


Figure 22-4. Auto-generated OpenAPI schema for the `/search` endpoint.

Example 22-11 is the code for *web_mojifinder.py*, but that's just the back-end code. When you hit the root URL `/`, the server sends the *form.html* file which has 81 lines of code, including 54 lines of JavaScript to communicate with the server and fill a table with the results. If you're interested in reading plain framework-less JavaScript, please find *22-async/mojifinder/static/form.html* in the *Fluent Python 2e* code repository

To run *web_mojifinder.py*, you need to install two packages and their dependencies: *FastAPI* and *uvicorn*.[8].

This is the command to run Example 22-11 with *uvicorn* in development mode:

```
$ uvicorn web_mojifinder:app --reload
```

The parameters are:

`web_mojifinder:app`

The package name, a colon, and the name of the ASGI application defined in it—`app` is the conventional name.

`--reload`

Make *uvicorn* monitor changes to application source files and automatically reload them. Useful only during development.

Now let's study the source code for *web_mojifinder.py*.

Example 22-11. web_mojifinder.py: complete source

```
from pathlib import Path
from unicodedata import name

from fastapi import FastAPI
from fastapi.responses import HTMLResponse
from pydantic import BaseModel

from charindex import InvertedIndex

app = FastAPI(  ❶
    title='Mojifinder Web',
    description='Search for Unicode characters by name.',
)
```

```
class CharName(BaseModel):  ❷
    char: str
    name: str

def init(app):  ❸
    app.state.index = InvertedIndex()
    static = Path(__file__).parent.absolute() / 'static'  ❹
    app.state.form = (static / 'form.html').read_text()

init(app)  ❺

@app.get('/search', response_model=list[CharName])  ❻
async def search(q: str):  ❼
    chars = app.state.index.search(q)
    return ({'char': c, 'name': name(c)} for c in chars)  ❽

@app.get('/', response_class=HTMLResponse, include_in_schema=False)
def form():  ❾
    return app.state.form

# no main funcion  ❿
```

❶ This line defines the ASGI app. It could be as simple as `app = FastAPI()`. The parameters shown are metadata for the auto-generated documentation.

❷ A *pydantic* schema for a JSON response with `char` and `name` fields.[9]

❸ Build the `index` and load the static HTML form, attaching both to the `app.state` for later use.

❹ Unrelated to the theme of this chapter, but worth noting: the elegant use of the overloaded `/` operator by `pathlib`.[10]

❺ Run `init` when this module is loaded by the ASGI server.

❻ Route for the `/search` endpoint; `response_model` uses that `CharName` *pydantic* model to describe the response format.

❼ *FastAPI* assumes that any arguments that appear in the function or coroutine signature that are not in the route path will be passed in the

HTTP query string, e.g. `/search?q=cat`. Since `q` has no default, *FastAPI* will return a 422 (Unprocessable Entity) status if `q` is missing from the query string.

❽ Returning an iterable of `dicts` compatible with the `response_model` schema allows *FastAPI* to build the JSON response according to the `response_model` in the `@app.get` decorator.

❾ Regular functions can also be used to produce responses.

❿ This module has no main function. It is loaded and driven by the ASGI server—*uvicorn* in this example.

Example 22-11 has no direct calls to `asyncio`. *FastAPI* is built on the *Starlette* ASGI toolkit, which in turn uses `asyncio`.

Also note that the body of `search` doesn't use `await`, `async with` or `async for`, therefore it could be a plain function. I defined `search` as a coroutine just to show that *FastAPI* knows how to handle it. In a real app, most endpoints will query databases or hit other remote servers, so it is a critical advantage of *FastAPI*—and ASGI frameworks in general—to support coroutines that can take advantage of asynchronous libraries for network I/O.

> **TIP**
>
> The `init` and `form` functions I wrote to load and serve the static HTML form are a hack to make the example short and easy to run. The recommended best practice is to have a proxy/load-balancer in front of the ASGI server to handle all static assets, and also use a CDN (Content Delivery Network) when possible. One such proxy/load-balancer is *Traefik*, a self-described "edge router" that "receives requests on behalf of your system and finds out which components are responsible for handling them." *FastAPI* has project generation scripts that prepare your code to do that.

The typing enthusiast may have noticed that there are no return type hints in `search` and `form`. Instead, *FastAPI* relies on the `response_model=` keyword argument in the route decorators. The Response Model page in the *FastAPI* documentation explains:

> *The response model is declared in this parameter instead of as a function return type annotation, because the path function may not actually return that response model but rather return a dict, database object or some other model, and then use the `response_model` to perform the field limiting and serialization.*

For example, in `search` I returned a generator of `dict` items, not a list of `CharName` objects, but that's good enough for *FastAPI* and *pydantic* to validate my data and build the appropriate JSON response compatible with `response_model=list[CharName]`.

We'll now focus on the *tcp_mojifinder.py* script that is answering the queries in Figure 22-5.

An asyncio TCP Server

The *tcp_mojifinder.py* program uses plain TCP to communicate with a client like Telnet or Netcat, so I could write it using `asyncio` without external dependencies—and without reinventing HTTP. Figure 22-5 shows text-based UI.

```
luciano — telnet localhost 2323 — 83×30
TW-LR-MBP:~ luciano$ telnet localhost 2323
Trying 127.0.0.1...
Connected to localhost.
Escape character is '^]'.
?> fire
U+2632 ☲      TRIGRAM FOR FIRE
U+2EA3 ⺣      CJK RADICAL FIRE
U+2F55 ⽕      KANGXI RADICAL FIRE
U+322B ㈫      PARENTHESIZED IDEOGRAPH FIRE
U+328B ㊋      CIRCLED IDEOGRAPH FIRE
U+4DDD ䷝      HEXAGRAM FOR THE CLINGING FIRE
U+1F525 🔥     FIRE
U+1F692 🚒     FIRE ENGINE
U+1F6F1 ?     ONCOMING FIRE ENGINE
U+1F702 🜂     ALCHEMICAL SYMBOL FOR FIRE
U+1F9EF 🧯     FIRE EXTINGUISHER
──────────────────────────────────────────────── 11 found
```

Figure 22-5. Telnet session with the tcp_mojifinder.py server: querying for "cat face" then "fire".

This program is twice as long as *web_mojifinder.py*, so I split the presentation into three parts: Example 22-12, Example 22-14, and Example 22-15. The top of *tcp_mojifinder.py*—including the `import` statements—is in Example 22-14, but I will start describing the `supervisor` coroutine and the `main` function that drives the program.

Example 22-12. tcp_mojifinder.py: a simple TCP server; continues in Example 22-14.

```
async def supervisor(index: InvertedIndex, host: str, port: int):
    server = await asyncio.start_server(    ❶
        functools.partial(finder, index),    ❷
        host, port)                          ❸

    socket_list = cast(tuple[TransportSocket, ...], server.sockets)
❹
    addr = socket_list[0].getsockname()
    print(f'Serving on {addr}. Hit CTRL-C to stop.')  ❺
    await server.serve_forever()  ❻

def main(host: str = '127.0.0.1', port_arg: str = '2323'):
    port = int(port_arg)
    print('Building index.')
    index = InvertedIndex()                            ❼
    try:
        asyncio.run(supervisor(index, host, port))     ❽
    except KeyboardInterrupt:                          ❾
        print('\nServer shut down.')

if __name__ == '__main__':
    main(*sys.argv[1:])
```

❶ This `await` quickly gets an instance of `asyncio.Server`, a TCP socket server. By default, `start_server` creates and starts the server, so it’s ready to receive connections.

❷ The first argument to `start_server` is `client_connected_cb`, a callback to run when a new client connection starts. The callback can be a function or a coroutine, but it must accept exactly two arguments: an `asyncio.StreamReader` and an `asyncio.StreamWriter`. However, my `finder` coroutine also needs to get an `index`, so I used `functools.partial` to bind that parameter and obtain a callable which takes the reader and writer. Adapting user functions to callback APIs is the most common use case for `functools.partial`.

❸ `host` and `port` are the second and third arguments to `start_server`. See the full signature in the [`asyncio` documentation](#).

❹ This `cast` is needed because *typeshed* has an outdated type hint for the `sockets` property of the `Server` class—as of May 2021. See issue #5535 on *typeshed*.

❺ Display address and port of the first socket of the server.

❻ Although `start_server` already started the server as a concurrent task, I need to `await` on the `server_forever` method so that my `supervisor` is suspended here. Without this line, `supervisor` would return immediately, ending the loop started with `asyncio.run(supervisor(…))`, and exiting the program. The documentation for `Server.serve_forever` says: "This method can be called if the server is already accepting connections."

❼ Build the inverted index.[11]

❽ Start the event loop running `supervisor`.

❾ Catch the `KeyboardInterrupt` to avoid a distracting traceback when I stop the server with `CTRL-C` on the terminal running it.

You may find it easier to understand how control flows in *tcp_mojifinder.py* if you study the output it generates on the server console, listed in Example 22-13.

Example 22-13. tcp_mojifinder.py: this is the server side of the session depicted in Figure 22-5

```
$ python3 tcp_mojifinder.py
Building index.  ❶
```

```
Serving on ('127.0.0.1', 2323). Hit CTRL-C to stop.  ❷
 From ('127.0.0.1', 58192): 'cat face'   ❸
   To ('127.0.0.1', 58192): 10 results.
 From ('127.0.0.1', 58192): 'fire'       ❹
   To ('127.0.0.1', 58192): 11 results.
 From ('127.0.0.1', 58192): '\x00'       ❺
Close ('127.0.0.1', 58192).              ❻
^C  ❼
Server shut down.  ❽
$
```

❶ Output by `main`. Before the next line appears, I see a 0.6s delay on my machine while the index is built.

❷ Output by `supervisor`.

❸ First iteration of a `while` loop in `finder`. The TCP/IP stack assigned port 58192 to my Telnet client. If you connect several clients to the server, you'll see their various ports in the output.

❹ Second iteration of the `while` loop in `finder`.

❺ I hit `CTRL-C` on the client terminal; the `while` loop in `finder` exits.

❻ The `finder` coroutine displays this message then exits. Meanwhile the server is still running, ready to service another client.

❼ I hit `CTRL-C` on the server terminal; `server.serve_forever` is cancelled, ending `supervisor` and the event loop.

❽ Output by `main`.

After `main` builds the index and starts the event loop, `supervisor` quickly displays the `Serving on`… message and is suspended at the `await server.serve_forever()` line. At that point, control flows into the event loop and stays there, occasionally coming back to the `finder` coroutine, which yields control back to the event loop whenever it needs to wait for the network to send or receive data.

While the event loop is alive, a new instance of the `finder` coroutine will be started for each client that connects to the server. In this way, many clients can be handled concurrently by this simple server. This continues until a `KeyboardInterrupt` occurs on the server or its process is killed by the OS.

Now let's see the top of *tcp_mojifinder.py*, with the `finder` coroutine.

Example 22-14. tcp_mojifinder.py: continued from Example 22-12.

```
import asyncio
import functools
import sys
from asyncio.trsock import TransportSocket
from typing import cast

from charindex import InvertedIndex, format_results  ❶

CRLF = b'\r\n'
PROMPT = b'?> '

async def finder(index: InvertedIndex,          ❷
                 reader: asyncio.StreamReader,
                 writer: asyncio.StreamWriter):
    client = writer.get_extra_info('peername')  ❸
    while True:  ❹
        writer.write(PROMPT)  # can't await!  ❺
        await writer.drain()  # must await!  ❻
        data = await reader.readline()  ❼
        try:
            query = data.decode().strip()  ❽
        except UnicodeDecodeError:  ❾
            query = '\x00'
        print(f' From {client}: {query!r}')  ❿
        if query:
            if ord(query[:1]) < 32:  ⓫
                break
            results = await search(query, index, writer)  ⓬
            print(f'   To {client}: {results} results.')  ⓭

    writer.close()  ⓮
    await writer.wait_closed()  ⓯
    print(f'Close {client}.')  ⓰
```

❶

`format_results` is useful to display the results of `InvertedIndex.search` in a text-based UI such as the command line or a Telnet session.

❷ To pass `finder` to `asyncio.start_server` I wrapped it with `functools.partial`, because the server expects a coroutine or function that takes only the `reader` and `writer` arguments.

❸ Get the remote client address to which the socket is connected.

❹ This loop handles a dialog that lasts until a control character is received from the client.

❺ The `StreamWriter.write` method is not a coroutine, just a plain function; this line sends the `?>` prompt.

❻ `StreamWriter.drain` flushes the `writer` buffer; it is a coroutine, so it must be driven with `await`.

❼ `StreamWriter.readline` is a coroutine that returns `bytes`.

❽ Decode the `bytes` to `str`, using the default UTF-8 encoding.

❾ A `UnicodeDecodeError` may happen when the user hits `CTRL-C` and the Telnet client sends control bytes; if that happens, replace the query with a null character, for simplicity.

❿ Log the query to the server console.

⓫ Exit the loop if a control or null character was received.

⓬ Do the actual `search`; code presented next.

⓭ Log the response to the server console.

⓮ Close the `StreamWriter`.

⓯ Wait for the `StreamWriter` to close. This is recommended in the `.close()` method documentation.

⓰ Log the end of this client's session to the server console.

The last piece of this example is the `search` coroutine:

Example 22-15. tcp_mojifinder.py: search coroutine.

```
async def search(query: str,  ❶
                 index: InvertedIndex,
                 writer: asyncio.StreamWriter) -> int:
    chars = index.search(query)  ❷
    lines = (line.encode() + CRLF for line  ❸
             in format_results(chars))
    writer.writelines(lines)  ❹
    await writer.drain()      ❺
    status_line = f'{"─" * 66} {len(chars)} found'  ❻
    writer.write(status_line.encode() + CRLF)
    await writer.drain()
    return len(chars)
```

❶ `search` must be a coroutine because it writes to a `StreamWriter` and must use its `.drain()` coroutine method.

❷ Query the inverted index.

❸ This generator expression will yield byte strings encoded in UTF-8 with the Unicode codepoint, the actual character, its name and a `CRLF` sequence—e.g. `b'U+0039\t9\tDIGIT NINE\r\n'`).

❹ Send the `lines`. Surprisingly, `writer.writelines` is not a coroutine.

❺ But `writer.drain()` is a coroutine. Don't forget the `await`!

❻ Build a status line, then send it.

Note that all network I/O in *tcp_mojifinder.py* is in `bytes`: we need to decode the `bytes` received from the network, and encode strings before sending them out. In Python 3, the default encoding is UTF-8, and that's what I used implicitly in all `encode` and `decode` calls in this example.

> **WARNING**
>
> Note that some of the I/O methods are coroutines and must be driven with `await`, while others are simple functions. For example, `StreamWriter.write` is a plain function, because it writes to a buffer. On the other hand, `StreamWriter.drain`—which flushes the buffer and performs the network I/O—is a coroutine, as is `StreamReader.readline`—but not `StreamWriter.writelines`! While I was writing the first edition of this book, the `asyncio` API docs were improved with clear labeling of coroutines as such.

The *tcp_mojifinder.py* code leverages the high-level `asyncio` Streams API that provides a ready-to-use server so you only need to implement a handler function, which can be a plain callback or a coroutine. There is also a lower-level Transports and Protocols API, inspired by the transport and protocols abstractions in the *Twisted* framework. Refer to the `asyncio` documentation for more information, including TCP and UDP echo servers and clients implemented with that lower-level API.

Our next topic is `async for` and the objects that make it work.

Asynchronous iteration and asynchronous iterables

We saw in "Asynchronous Context Managers" how `async with` works with objects implementing the `__aenter__` and `__aexit__` methods returning awaitables—usually in the form of coroutine objects.

Similarly, `async for` works with *asynchronous iterables*: objects that implement `__aiter__`. However, `__aiter__` must be a regular method—not a coroutine-method—and it must return an *asynchronous iterator*.

An asynchronous iterator provides an `__anext__` coroutine-method that returns an awaitable—often a coroutine object. They are also expected to implement `__aiter__`, which usually returns `self`. This mirrors the important distinction of iterables and iterators we discussed in "Don't make the iterable an iterator for itself".

The *aiopg* asynchronous PostgreSQL driver documentation has an example that illustrates the use of `async for` to iterate over the rows of a database cursor:

```
async def go():
    pool = await aiopg.create_pool(dsn)
    async with pool.acquire() as conn:
        async with conn.cursor() as cur:
            await cur.execute("SELECT 1")
            ret = []
            async for row in cur:
                ret.append(row)
            assert ret == [(1,)]
```

In this example the query will return a single row, but in a realistic scenario you may have thousands of rows in response to a `SELECT` query. For large responses, the cursor will not be loaded with all the rows in a single batch. Therefore it is important that `async for row in cur:` does not block the event loop while the cursor may be waiting for additional rows. By implementing the cursor as an asynchronous iterator, *aiopg* may yield to the event loop at each `__anext__` call, and resume later when more rows arrive from PostgreSQL.

Asynchronous Generator Functions

You can implement an asynchronous iterator by writing a class with `__anext__` and `__aiter__`, but there is a simpler way: write a function declared with `async def` and use `yield` in its body. This parallels how generator functions simplify the classic iterator pattern.

Let's study a simple example using `async for` and implementing an asynchronous generator. In Example 22-1 we saw *blogdom.py*, a script that probed domain names. Now suppose we find other uses for the `probe` coroutine we defined there, and decide to put it into a new module—*domainlib.py*—together with a new `multi_probe` asynchronous generator that takes a list of domain names and yields results as they are probed.

We'll look at the implementation of *domainlib.py* soon, but first let's see how it is used with Python's new asynchronous console.

Experimenting with Python's Async Console

Since Python 3.8 you can run the interpreter with the `-m asyncio` command-line option to get an "async REPL": a Python console that imports `asyncio`, provides a running event loop, and accepts `await`, `async for` and `async with` at the top level prompt—which otherwise are syntax errors when used outside of native coroutines.[12]

To experiment with *domainlib.py*, go to the *22-async/domains/asyncio/* directory in your local copy of the *Fluent Python 2e* code repository. Then run:

```
$ python -m asyncio
```

You'll see the console start, similar to this:

```
asyncio REPL 3.9.1 (v3.9.1:1e5d33e9b9, Dec  7 2020, 12:10:52)
[Clang 6.0 (clang-600.0.57)] on darwin
Use "await" directly instead of "asyncio.run()".
Type "help", "copyright", "credits" or "license" for more
information.
>>> import asyncio
>>>
```

Note how it says you can use `await` instead of `asyncio.run()`—to drive coroutines and other awaitables. The `asyncio` module is automatically imported.

Now let's import *domainlib.py* and play with its two coroutines: `probe` and `multi_probe`.

Example 22-16. Experimenting with domainlib.py after running `python3 -m asyncio`.

```
>>> await asyncio.sleep(3, 'Rise and shine!')  ❶
'Rise and shine!'
>>> from domainlib import *
>>> await probe('python.org')  ❷
Result(domain='python.org', found=True)  ❸
>>> names = 'python.org rust-lang.org golang.org
n05uch1an9.org'.split()  ❹
>>> async for result in multi_probe(names):  ❺
...      print(*result, sep='\t')
...
golang.org      True    ❻
n05uch1an9.org  False
python.org      True
rust-lang.org   True
>>>
```

❶ Try a simple `await` to see the asynchronous console in action. Fun fact: `asyncio.sleep()` takes an optional second argument that is returned when you `await` it.

❷ Drive the `probe` coroutine.

❸ The `domainlib` version of `probe` returns a `Result` named tuple.

❹ Make a list of domains.

❺ Iterate with `async for` over the `multi_probe` asynchronous generator to display the results.

❻ Note that the results are not in the order the domains were given to `multiprobe`. They appear as each DNS response comes back.

Example 22-16 shows that `multi_probe` is an asynchronous generator because it is compatible with `async for`. Now let's do a few more experiments, continuing from that example.

Example 22-17. More experiments, continuing from Example 22-16.

```
>>> probe('python.org')  ❶
<coroutine object probe at 0x10e313740>
>>> multi_probe(names)  ❷
<async_generator object multi_probe at 0x10e246b80>
>>> for r in multi_probe(names):  ❸
...     print(r)
...
Traceback (most recent call last):
  ...
TypeError: 'async_generator' object is not iterable
```

❶ Calling a native coroutine gives you a coroutine object.

❷ Calling an asynchronous generator gives you an `async_generator` object.

❸ We can't use a regular `for` loop with asynchronous generators because they implement `__aiter__` instead of `__iter__`.

Asynchronous generators are driven by `async for`, which can be a block statement (as seen in Example 22-16), and it also appears in asynchronous comprehensions, which we'll cover soon.

Implementing an Asynchronous Generator

Now let's study the code for *domainlib.py*, with the `multi_probe` asynchronous generator.

Example 22-18. domainlib.py: functions for probing domains

```
import asyncio
import socket
from collections.abc import Iterable, AsyncIterator
from typing import NamedTuple, Optional


class Result(NamedTuple):  ❶
    domain: str
    found: bool


OptionalLoop = Optional[asyncio.AbstractEventLoop]  ❷
```

```
async def probe(domain: str, loop: OptionalLoop = None) -> Result:
❸
    if loop is None:
        loop = asyncio.get_running_loop()
    try:
        await loop.getaddrinfo(domain, None)
    except socket.gaierror:
        return Result(domain, False)
    return Result(domain, True)


async def multi_probe(domains: Iterable[str]) ->
AsyncIterator[Result]:  ❹
    loop = asyncio.get_running_loop()
    coros = [probe(domain, loop) for domain in domains]  ❺
    for coro in asyncio.as_completed(coros):  ❻
        result = await coro  ❼
        yield result  ❽
```

❶ `NamedTuple` makes the result from `probe` easier to read and debug.

❷ This type alias is to avoid making the next line too long for a book listing.

❸ `probe` now gets an optional `loop` argument, to save repeated calls to `get_running_loop` when this coroutine is driven by `multi_probe`.

❹ An asynchronous generator function produces an asynchronous generator object, which can be annotated as `AsyncIterator[SomeType]`.

❺ Build list of `probe` coroutine objects, each with a different `domain` but all with the same `loop`.

❻ Note that this is not `async for` because `asyncio.as_completed` is a classic generator.

❼ Await on the coroutine object to retrieve the result.

❽ Yield `result`. This is the line that makes `multi_probe` an asynchronous generator.

> **NOTE**
>
> The `for` loop in Example 22-18 could be shorter:
>
> ```
> for coro in asyncio.as_completed(coros):
>     yield await coro
> ```
>
> Python parses that as `yield (await coro)`, so it works. But I thought it could be confusing to use that shortcut in the first asynchronous generator example in the book, so I split it in two lines.

Given *domainlib.py*, we can demonstrate the use of the `multi_probe` asynchronous generator in *domaincheck.py*: a script that takes a domain suffix and searches for domais made from short Python keywords. Here is a sample output of *domaincheck.py*:

```
$ ./domaincheck.py net
FOUND                NOT FOUND
=====                =========
in.net
del.net
true.net
for.net
is.net
                     none.net
try.net
                     from.net
and.net
or.net
else.net
with.net
if.net
as.net
                     elif.net
                     pass.net
                     not.net
                     def.net
```

Thanks to *domainlib*, the code for *domaincheck.py* is straightforward.

Example 22-19. domaincheck.py: utility for probing domains using domainlib

```
#!/usr/bin/env python3
import asyncio
import sys
from keyword import kwlist

from domainlib import multi_probe


async def main(tld: str) -> None:
    tld = tld.strip('.')
    names = (kw for kw in kwlist if len(kw) <= 4)  ❶
    domains = (f'{name}.{tld}'.lower() for name in names)  ❷
    print('FOUND\t\tNOT FOUND')  ❸
    print('=====\t\t=========')
    async for domain, found in multi_probe(domains):  ❹
        indent = '' if found else '\t\t'  ❺
        print(f'{indent}{domain}')


if __name__ == '__main__':
    if len(sys.argv) == 2:
        asyncio.run(main(sys.argv[1]))  ❻
    else:
        print('Please provide a TLD.', f'Example: {sys.argv[0]}
COM.BR')
```

❶ Generate keywords with length up to 4.

❷ Generate domain names with the given suffix as TLD.

❸ Format a header for the tabular output.

❹ Asynchronously iterate over `multi_probe(domains)`.

❺ Set `indent` to zero or two tabs to put the result in the proper column.

❻ Run the `main` coroutine with the given command-line argument.

Generators have one extra use unrelated to iteration: they can be made into context managers. This also applies to asynchronous generators.

Asynchronous Generators as Context Managers

Writing our own asynchronous context managers is not a frequent programming task, but if you need to write one, consider using the `@asynccontextmanager` decorator added to the `contextlib` module in Python 3.7. That's very similar to the `@contextmanager` decorator we studied in "Using @contextmanager".

An interesting example combining `@asynccontextmanager` with `loop.run_in_executor` appears in Caleb Hattingh's book *Using Asyncio in Python*. Example 22-20 is Caleb's code—with a single change and added callouts.

Example 22-20. Example using `@asynccontextmanager` and `loop.run_in_executor`

```
from contextlib import asynccontextmanager

@asynccontextmanager
async def web_page(url):  ❶
    loop = asyncio.get_running_loop()   ❷
    data = await loop.run_in_executor(  ❸
        None, download_webpage, url)
    yield data                          ❹
    await loop.run_in_executor(None, update_stats, url)  ❺

async with web_page('google.com') as data:  ❻
    process(data)
```

❶ The decorated function must be an asynchronous generator.

❷ Minor update to Caleb's code: use the lightweight `get_running_loop` instead of `get_event_loop`.

❸ Suppose `download_webpage` is a blocking function using the *requests* library; we run it in a separate thread to avoid blocking the event loop.

❹ All lines before this `yield` expression will become the `__aenter__` coroutine-method of the asynchronous context manager built by the decorator. The value of `data` will be bound to the `data` variable after the `as` clause in the `async with` statement below.

❺ Lines after the `yield` will become the `__aexit__` coroutine-method. Here another blocking call is delegated to the thread executor.

❻ Use `web_page` with `async with`.

This is very similar to the sequential `@contextmanager` decorator. Please see "Using @contextmanager" for more details, including error handling at the `yield` line. For another example of `@asynccontextmanager`, see the `contextlib` documentation.

Now let's wrap up our coverage of asynchronous generator functions by contrasting them with native coroutines.

Asynchronous Generators Versus Native Coroutines

Here are some key similarities and differences between a native coroutine and an asynchronous generator functions:

- Both are declared with `async def`.
- An asynchronous generator always has a `yield` expression in its body—that's what makes it a generator. A native coroutine never has `yield`.
- A native coroutine may `return` some value other than `None`. An asynchronous generator can only use empty `return` statements.
- Native coroutines are awaitable: they can be driven by `await` expressions or passed to one of the many `asyncio` functions that take awaitable arguments, such as `create_task`. Asynchronous

generators are not awaitable. They are asynchronous iterables, driven by `async for` or by asynchronous comprehensions.

Time to talk about asynchronous comprehensions.

Async Comprehensions and Async Generator Expressions

PEP 530—Asynchronous Comprehensions introduced the use of `async for` and `await` in the syntax of comprehensions and generator expressions, starting with Python 3.6.

The only construct defined by PEP 530 that can appear outside an `async def` body is an asynchronous generator expression.

Defining and Using an Asynchronous Generator Expression

Given the `multi_probe` asynchronous generator from Example 22-18, we could write another asynchronous generator returning only the names of the domains found. Here is how—again using the asynchronous console launched with `-m asyncio`:

Example 22-21. domaincheck.py: utility for probing domains using domainlib

```
>>> import asyncio
>>> from domainlib import multi_probe
>>> names = 'python.org rust-lang.org golang.org
n05uch1an9.org'.split()
>>> gen_found = (domain async for domain, found in
multi_probe(names) if found)  ❶
>>> gen_found
<async_generator object <genexpr> at 0x10a8f9700>  ❷
>>> async for name in gen_found:  ❸
...     print(name)
...
golang.org
python.org
rust-lang.org
```

❶

The use of `async for` makes this an asynchronous generator expression. It can be defined anywhere in a Python module.

❷ The asynchronous generator expression builds an `async_generator` object—exactly the same type of object returned by an asynchronous generator function like `multi_probe`.

❸ The asynchronous generator object is driven by the `async for` statement—which in turn can only appear inside an `async def` body —or in the magic asynchronous console I used in this example.

To summarize: an asynchronous generator expression can be defined anywhere in your program, but it can only be used inside a native coroutine or asynchronous generator function.

The remaining constructs introduced by PEP 530 can only be defined and used inside native coroutines or asynchronous generator functions.

Asynchronous Comprehensions

Yuri Selivanov—the author of PEP 530—justifies the need for asynchronous comprehensions with three short code snippets reproduced next.

We can all agree that we should be able to rewrite this code:

```
result = []
async for i in aiter():
    if i % 2:
        result.append(i)
```

Like this:

```
result = [i async for i in aiter() if i % 2]
```

In addition, given a native coroutine `fun`, we should be able to write this:

```
result = [await fun() for fun in funcs]
```

Using `await` in a list comprehension does the same job as `asyncio.gather`. Back to the magic asynchronous console:

```
>>> names = 'python.org rust-lang.org golang.org
n05uch1an9.org'.split()
>>> names = sorted(names)
>>> coros = [probe(name) for name in names]
>>> await asyncio.gather(*coros)
[Result(domain='golang.org', found=True),
Result(domain='n05uch1an9.org', found=False),
Result(domain='python.org', found=True), Result(domain='rust-
lang.org', found=True)]
>>> [await probe(name) for name in names]
[Result(domain='golang.org', found=True),
Result(domain='n05uch1an9.org', found=False),
Result(domain='python.org', found=True), Result(domain='rust-
lang.org', found=True)]
>>>
```

Note that I sorted the list of names to show that the results come out in the order they were submitted, in both cases.

PEP 530 allows the use of `async for` and `await` in list comprehensions as well as in `dict` and `set` comprehensions. For example, here is a `dict` comprehension to store the results of `multi_probe`—in the asynchronous console:

```
>>> {name: found async for name, found in multi_probe(names)}
{'golang.org': True, 'python.org': True, 'n05uch1an9.org': False,
'rust-lang.org': True}
```

We can use the `await` keyword in the expression before the `for` or `async for` clause, and also in the expression after the `if` clause. Here is a set comprehension in the asynchronous console, collecting only the domains that were found:

```
>>> {name for name in names if (await probe(name)).found}
{'rust-lang.org', 'python.org', 'golang.org'}
```

I had to put extra parenthesis around the `await` expression due to the higher precedence of the `__getattr__` operator `.` (dot).

Again, all of these comprehensions can only appear inside an `async def` body or in the enchanted asynchronous console.

Now let's briefly discuss type hints for asynchronous types.

Generic Asynchronous Types

The following types were introduced in Python 3.5 and 3.6 to annotate asynchronous objects:

```
class typing.AsyncContextManager(Generic[T_co]):
    ...
class typing.AsyncIterable(Generic[T_co]):
    ...
class typing.AsyncIterator(AsyncIterable[T_co]):
    ...
class typing.AsyncGenerator(AsyncIterator[T_co], Generic[T_co,
T_contra]):
    ...
class typing.Awaitable(Generic[T_co]):
    ...
class typing.Coroutine(Awaitable[V_co], Generic[T_co, T_contra,
V_co]):
    ...
```

With Python 3.9, we should use the `collections.abc` equivalents of the above.

I want to highlight three aspects of those generic types.

First: they are all covariant on the first type parameter, which is the type of the items yielded from these objects. Recall rule #1 of "Variance Rules of Thumb":

> *If a formal type parameter defines a type for data that comes out of the object, it can be covariant.*

Second: `AsyncGenerator` and `Coroutine` are contravariant on the second to last parameter. That's the type of the argument of the low-level `.send()` method that the event loop calls to drive asynchronous generators and coroutines. As such, it is an "input" type. Therefore, it can be contravariant, per *Variance Rule of Thumb #2*:

> *If a formal type parameter defines a type for data that goes into the object after its initial construction, it can be contravariant.*

Third: `AsyncGenerator` has no return type, in contrast with `typing.Generator` which we saw in "Generic Type Hints for Classic Coroutines". Returning a value by raising `StopIteration(value)` was one of the hacks that enabled generators to operate as coroutines and support `yield from`, as we saw in Chapter 19. There is no such overlap among the asynchronous objects: `AsyncGenerators` objects don't return values, and are completely separate from native coroutine objects, which are annotated with `typing.Coroutine`.

Now let's talk about a very important feature of the `async` statements, `async` expressions, and the objects they create: they are often used with `asyncio` but, they are actually library-independent.

Async beyond asyncio: Curio

Python's `async/await` language constructs are not tied to any specific event loop or library.[13] Thanks to the hackable API provided by special methods, anyone sufficiently motivated can write their own asynchronous runtime environment and framework to drive native coroutines, asynchronous generators etc.

That's what David Beazley did in his *Curio* project. He was interested in rethinking how these new language features could be used in a framework built from scratch. Recall that `asyncio` was released in Python 3.4, and it used `yield from` instead of `await`, so its API could not leverage asynchronous context managers, asynchronous iterators, and everything else that the `async/await` keywords made possible. As a result, *Curio* has a cleaner API and a simpler implementation, compared to `asyncio`.

Example 22-22 shows the *blogdom.py* script (Example 22-1) rewritten to use *Curio*.

Example 22-22. blogdom.py: Example 22-1, now using Curio.

```
#!/usr/bin/env python3
from curio import run, TaskGroup
import curio.socket as socket
from keyword import kwlist

MAX_KEYWORD_LEN = 4


async def probe(domain: str) -> tuple[str, bool]:  ❶
    try:
        await socket.getaddrinfo(domain, None)  ❷
    except socket.gaierror:
        return (domain, False)
    return (domain, True)

async def main() -> None:
    names = (kw for kw in kwlist if len(kw) <= MAX_KEYWORD_LEN)
    domains = (f'{name}.dev'.lower() for name in names)
    async with TaskGroup() as group:  ❸
        for domain in domains:
            await group.spawn(probe, domain)  ❹
        async for task in group:  ❺
            domain, found = task.result
            mark = '+' if found else ' '
            print(f'{mark} {domain}')

if __name__ == '__main__':
    run(main())  ❻
```

❶ `probe` doesn't need to get the event loop, because…

❷ `getaddrinfo` is a top-level function of `curio.socket`, not a method of a `loop` object—as it is in `asyncio`.

❸ A `TaskGroup` is a core concept in *Curio*, to monitor and control several coroutines, and to make sure they are all executed and cleaned up.

❹ `TaskGroup.spawn` is how you start a coroutine, managed by a specific `TaskGroup` instance. The coroutine is wrapped by a `Task`.

❺ Iterating with `async for` over a `TaskGroup` yields `Task` instances as each is completed. This corresponds to the line in Example 22-1 using `for … as_completed(…):`.

❻ *Curio* pioneered this sensible way to start an asynchronous program in Python.

To expand on the last point: if you look at the `asyncio` code examples for *Fluent Python, First Edition* you'll see lines like these, repeated over and over:

```
loop = asyncio.get_event_loop()
loop.run_until_complete(main())
loop.close()
```

A *Curio* `TaskGroup` is an asynchronous context manager that replaces several ad-hoc APIs and coding patterns in `asyncio`. We just saw how iterating over a `TaskGroup` makes the `asyncio.as_completed(…)` function unnecessary. Another example: instead of a special `gather` function, this snippet from the *Task Groups* docs collects the results of all tasks in the group:

```
async with TaskGroup(wait=all) as g:
    await g.spawn(coro1)
    await g.spawn(coro2)
    await g.spawn(coro3)
print('Results:', g.results)
```

Task groups support *structured concurrency*: a form of concurrent programming that constrains all the activity of a group of asynchronous tasks to a single entry and exit point. This is analogous to structured programming, which eschewed the GOTO command and introduced block statements to limit the entry and exit points of loops and subroutines. When used as an asynchronous context manager, a `TaskGroup` ensures that all tasks spawned inside are completed or cancelled, and any exceptions raised, upon exiting the enclosed block.

> **NOTE**
>
> Structured concurrency will probably be adopted by `asyncio` in upcoming Python releases. A strong indication appears in PEP 654–Exception Groups and except*, which is under consideration for Python 3.10—as of March 2021. The *Motivation* section mentions *Trio's* "nurseries", their name for task groups: "Implementing a better task spawning API in asyncio, inspired by Trio nurseries, was the main motivation for this PEP."

Another important feature of *Curio* is better support for programming with coroutines and threads in the same codebase—a necessity in most non-trivial asynchronous programs. Starting a thread with `await spawn_thread(func, …)` returns an `AsyncThread` object with a `Task`-like interface. Threads can call coroutines thanks to a special `AWAIT(coro)` function—named in all-caps because `await` is now a keyword.

Curio also provides a `UniversalQueue` that can be used to coordinate the work among threads, *Curio* coroutines, and `asyncio` coroutines. That's right, *Curio* has features that allow it to run in a thread along with `asyncio` in another thread, in the same process, communicating via `UniversalQueue` and `UniversalEvent`. The API for these "universal" classes is the same inside and outside of coroutines, but in a coroutine you need to prefix calls with `await`.

As I write this in March 2021, there are no asynchronous HTTP or database libraries compatible with *Curio*, so its usage "out of the box" is limited to low-level network programming. In the *Curio* repository there is an impressive set network programming examples, including one using

WebSocket, and another implementing the RFC 8305—Happy Eyeballs concurrent algorithm for connecting to IPv6 endpoints with fast fallback to IPv4 if needed.

The design of *Curio* has been influential. The *Trio* framework started by Nathaniel J. Smith was heavily inspired by *Curio*. *Curio* may also have prompted Python contributors to improve the usability of the `asyncio` API. For example, in its earliest releases, `asyncio` users very often had to get and pass around a `loop` object because some essential functions were either `loop` methods or required a `loop` argument. As of Python 3.9, direct access to the loop is not needed as often, and in fact several functions that accepted an optional `loop` are now deprecating that argument.

Now let's talk about the advantages and challenges of asynchronous programming.

How Async Works and How It Doesn't

The sections closing this chapter discuss high-level ideas around asynchronous programming, regardless of the language or library you are using.

Let's begin by explaining the #1 reason why asynchronous programming is appealing, followed by a popular myth, and how to deal with it.

Running Circles Around Blocking Calls

Ryan Dahl, the inventor of *Node.js*, introduces the philosophy of his project by saying "We're doing I/O completely wrong.[14]" He defines a *blocking function* as one that does file or network I/O, and argues that we can't treat them as we treat nonblocking functions. To explain why, he presents the numbers in the second column of Table 22-1.

Table 22-1. Modern computer latency for *reading data from different devices; thi*

r
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o
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a
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s

Device	CPU cycles	Proportional “human” scale
L1 cache	3	3 seconds
L2 cache	14	14 seconds
RAM	250	250 seconds
disk	41,000,000	1.3 years
network	240,000,000	7.6 years

To make sense of Table 22-1, bear in mind that modern CPUs with GHz clocks run billions of cycles per second. Let’s say that a CPU runs exactly 1 billion cycles per second. That CPU can make more than 333 million L1 cache reads in one second, or 4 (four!) network reads in the same time. The third column of Table 22-1 puts those numbers in perspective by multiplying the second column by a constant factor. So, in an alternate universe, if one read from L1 cache took 3 seconds, then a network read would take 7.6 years!

Table 22-1 explains why a disciplined approach to asynchronous programming can lead to high performance servers. The challenge is achieving that discipline. The first step is to recognize that “I/O bound system” is a fantasy.

The Myth of I/O Bound Systems

A commonly repeated meme is that asynchronous programming is good for “I/O bound systems”. I learned the hard way that there are no “I/O bound systems”. You may have I/O bound *functions*. Perhaps the vast majority of the functions in your system are I/O bound, i.e. they spend more time waiting for I/O than crunching data. While waiting, they cede control to the event loop which can then drive some other pending task. But inevitably, any non-trivial system will have some parts that are CPU-bound. Even trivial systems reveal that, under stress. In "Soapbox" I tell the story of two asynchronous programs that struggled with CPU-bound functions slowing down the event loop with severe impact on performance.

Given that any non-trivial system will have CPU-bound functions, dealing with them is the key to success in asynchronous programming.

Avoiding CPU-bound Traps

If you're using Python at scale, you should have some automated tests designed specifically to detect performance regressions as soon as they appear. This is critically important with asynchronous code, but also relevant to threaded Python code—because of the GIL. If you wait until the slowdown starts bothering the development team, it's too late. The fix will probably require some major make over.

Here are some options for when you identify a CPU-hogging bottleneck:

- delegate the task to a Python process pool;
- delegate the task to an external task queue;
- rewrite the relevant code in Cython, C, Rust or some other language that compiles to machine code and interfaces with the Python/C API, preferably releasing the GIL;
- decide that you can afford the performance hit and do nothing—but record the decision to make it easier to revert it later.

The external task queue should be chosen and integrated as soon as possible at the start of the project, so that nobody in the team hesitates to use it when needed.

The last option—do nothing—falls in the category of technical debt.

Concurrent programming is a fascinating topic, and I would like to write a lot more about it. But it is not the main focus of the book, and this is already one of the longest chapters, so let's wrap it up.

Chapter Summary

> *The problem with normal approaches to asynchronous programming as that they're all-or-nothing propositions. You rewrite all your code so none of it blocks or you're just wasting your time.*
>
> —Alvaro Videla & Jason J. W. Williams, RabbitMQ in Action

I chose that epigraph for this chapter for two reasons. At a high level, it reminds us to avoid blocking the event loop by delegating slow tasks to a different processing unit, from a simple thread all the way to a distributed task queue. At a lower level, it is also a warning: once you write your first `async def`, your program is inevitably going to have more and more `async def`, `await`, `async with` and `async for`. And using non-asynchronous libraries suddenly becomes a challenge.

After the simple *spinner* examples in Chapter 20, here we really focused on asynchronous programing with native coroutines, starting with the *blogdom.py* DNS probing example, followed by the concept of *awaitables*. While reading the source code of *flags_asyncio.py*, we found the first example of an *asynchronous context manager*.

The more advanced variations of the flag downloading program introduced two powerful functions: the `asyncio.as_completed` generator and the `loop.run_in_executor` coroutine. We also saw the concept and application of a semaphore to limit the number of concurrent downloads—as expected from well-behaved HTTP clients.

Server-side asynchronous programming was presented through the *mojifinder* examples: a *FastAPI* Web service and *tcp_mojifinder.py*—the latter using just `asyncio` and the TCP protocol.

Asynchronous iteration and asynchronous iterables were the next major topic, with sections on `async for`, Python's async console, asynchronous generators, asynchronous generator expressions, and asynchronous comprehensions.

The last example in the chapter was *blogdom.py* rewritten with the *Curio* framework, to demonstrate how Python's asynchronous features are not tied to the `asyncio` package. *Curio* also showcases the concept of *structured concurrency* which may have an industry-wide impact, bringing more clarity to concurrent code.

Finally, the sections under "How Async Works and How It Doesn't" discuss the main appeal of asynchronous programming, the misconception of "I/O bound systems", and dealing with the inevitable CPU-bound parts of your program.

Further Reading

David Beazley's PyOhio 2016 keynote *Fear and Awaiting in Async* is a fantastic, live coded introduction to the potential of the language features made possible by Yuri Selivanov's contribution of the `async/await` keywords in Python 3.5. At one point, Beazley complains that `await` can't be used in list comprehensions, but that was fixed by Selivanov in *PEP 530—Asynchronous Comprehensions*, implemented in Python 3.6 later in that same year. Apart from that, everything else in Beazley's keynote is timeless, as he demonstrates how the asynchronous objects we saw in this chapter work, without the help of any framework—just a simple `run` function using `.send(None)` to drive coroutines. Only at the very end Beazley shows *Curio*, which he started that year as an experiment to see how far can you go doing asynchronous programming without a foundation of callbacks or futures, just coroutines. As it turns out, you can go very far—as demonstrated by the evolution of *Curio* and the later creation of *Trio* by Nathaniel J. Smith. *Curio's* documentation has links to more talks by Beazley on the subject.

Besides starting *Trio*, Nathaniel J. Smith wrote two deep blog posts that I highly recommend: *Some thoughts on asynchronous API design in a post-async/await world*—contrasting the design of *Curio* with that of *asyncio*—and *Notes on structured concurrency, or: Go statement considered harmful*—about structured concurrency. Smith also gave a long and informative answer to the question *What is the core difference between asyncio and trio?* on StackOverflow.

To learn more about the *asyncio* package, I've mentioned the best written resources I know at the start of this chapter: the official documentation after the outstanding overhaul started by Yuri Selivanov in 2018, and Caleb Hattingh's book *Using Asyncio in Python* (O'Reilly, 2020). In the official documentation, make sure to read *Developing with asyncio*: documenting the *asyncio* debug mode, and also discussing "common mistakes and traps" and "how to avoid them".

For a very accessible, 30-minute introduction to asynchronous programming in general and also *asyncio*, watch Miguel Grinberg's *Asynchronous Python for the Complete Beginner*, presented at PyCon 2017. Another great introduction is *Demystifying Python's Async and Await Keywords* presented by Michael Kennedy—where among other things I learned about the *unsync* library that provides a decorator to delegate the execution of coroutines, I/O bound functions and CPU-bound functions to `asyncio`, `threading` or `multiprocessing` as needed.

At EuroPython 2019, Lynn Root—a global leader of *PyLadies*—presented the excellent *Advanced asyncio: Solving Real-world Production Problems*, informed by her experience using Python as a Staff Engineer at Spotify.

In 2020, Łukasz Langa recorded a series of great videos about *asyncio*, starting with *Learn Python's AsyncIO #1 - The Async Ecosystem*. Langa also made the super cool video *AsyncIO + Music* for PyCon 2020 that not only shows *asyncio* applied in a very concrete of event-oriented domain, but also explains it from the ground up.

Another area dominated by event-oriented programming is embedded systems. That's why Damien George added support for `async/await` in his *MicroPython* interpreter for microcontrollers. At PyCon Australia 2018, Matt Trentini demonstrated the *uasyncio* library, a subset of *asyncio* that is part of *MicroPython's* standard library.

For higher level thinking about async programming in Python, read the blog post *Python async frameworks—Beyond developer tribalism* by Tom

Christie.

Finally, I highly recommend *What Color Is Your Function?* by Bob Nystrom, discussing the incompatible execution models of plain functions versus async functions—a.k.a. coroutines—in JavaScript, Python, C#, and other languages. Spoiler alert—Nystrom's conclusion is: the language that got this right is Go, where all functions are the same color. I like that about Go. But I also think Nathaniel J. Smith has a point when he wrote *Go statement considered harmful*. Nothing is perfect, and concurrent programming is always complicated.

SOAPBOX

How a Slow Function Almost Spoiled The `uvloop` Benchmarks

In 2016, Yuri Selivanov released *uvloop*, "a fast, drop-in replacement of the built-in `asyncio` event loop". The benchmarks presented in Selivanov's blog post announcing the library in 2016 are very impressive. He wrote: "it is at least 2x faster than nodejs, gevent, as well as any other Python asynchronous framework. The performance of uvloop-based asyncio is close to that of Go programs."

However, the post reveals that *uvloop* is able to match the performance of Go under two conditions:

1. Go is configured to use a single thread. That makes the Go runtime behave similarly to `asyncio`: concurrency is achieved via multiple coroutines driven by an event loop, all in a single thread.[15]

2. The Python 3.5 code uses *httptools* in addition to *uvloop* itself.

Selivanov explains that he wrote *httptools* after benchmarking *uvloop* with *aiohttp*—one of the first full-featured HTTP libraries built on `asyncio`:

> *However, the performance bottleneck in aiohttp turned out to be its HTTP parser, which is so slow, that it matters very little how fast the underlying I/O library is. To make things more interesting, we created a Python binding for http-parser (nodejs HTTP parser C library, originally developed for Nginx). The library is called httptools, and is available on Github and PyPI.*

Now think about that: Selivanov's HTTP performance tests consisted of a simple echo server written in the different languages/libraries, pounded by the *wrk* benchmarking tool. Most developers would consider a simple echo server an "I/O bound system", right? But it turned out that parsing HTTP headers is CPU-bound, and it had a slow

Python implementation in *aiohttp* in when Selivanov did the benchmarks in 2016.[16] Whenever a Python function was parsing headers in Python, the event loop was blocked. The impact was so significant that Selivanov went to the extra trouble of writing *httptools*. Without optimizing the CPU-bound code, the performance gains of a faster event loop were lost.

Death by a Thousand Cuts

Instead of a simple echo server, imagine a complex and evolving Python system with tens of thousands of lines of asynchronous code, interfacing with many external libraries. Years ago I was asked to help diagnose performance problems in a system like that. It was written in Python 2.7 with the *Twisted* framework—a solid library and in many ways a precursor to `asyncio` itself.

Python was used to build a façade for the Web UI, integrating functionality provided by pre-existing libraries and command-line tools written in other languages—but not designed for concurrent execution.

The project was ambitious, it had been in development for more than a year already, but it was not in production yet.[17] Over time, the developers noticed that the performance of the whole system was decreasing, and they were having a hard time finding the bottlenecks.

What was happening: with each added feature, more CPU-bound code was slowing down *Twisted*'s event loop. Python's role as a glue language meant there was a lot of data parsing and conversion between data formats. There wasn't a single bottleneck: the problem was spread over countless little functions added over months of development. Fixing that would require rethinking the architecture of the system, rewriting a lot of code, probably leveraging a task queue, perhaps using microservices or custom libraries written in languages better suited for CPU-intensive concurrent processing. The stakeholders were not prepared to make that additional investment, and the project was cancelled shortly afterwards.

When I told this story to Glyph Lefkowitz—founder the *Twisted* project—he said that one of his priorities at the start of an asynchronous programming project is to decide which tools he will use to farm-out the CPU-intensive tasks. This conversation with Glyph was the inspiration for “Avoiding CPU-bound Traps”.

Smarter Clients for Better Concurrency

Dealing with slow clients is a major challenge for server-side programmers. Asynchronous programming is a good general strategy to deal with slow clients precisely because it is much cheaper to have a coroutine than a thread waiting for each client, therefore you can handle many more slow clients.

But you can also help your server-side system handle more clients if they are smarter. For example, in *web_mojifinder.py*, there is no pagination. If you search for “CJK”, you’ll get more than 90,000 Chinese, Japanese, and Korean characters (that’s what CJK stands for). Nobody will read more than a few dozen lines, so it is a waste of computing power and bandwidth to send so many results. Implementing pagination or “infinite scroll” can drastically reduce this waste, but it does require more code on the client and the server.

Pagination is just one example. The main point is: consider how to split the task of the server in smaller chunks, so that it can handle more clients at one time. If you’re used to the full-page-at-time style of Web development, this requires a new mindset, a lot more front-end code, and—sometimes—the use of new technology such as *WebSockets*, which an asynchronous server-side framework is better prepared to handle. That’s the reason why the ASGI specification was started by *Django* developers, and they are adding asynchronous features with every new release since *Django 3.0*.

---

1 Videla & Williams, *RabbitMQ in Action (Manning, 2012)*, Chapter 4, *Solving Problems with Rabbit: coding and patterns*, p. 61

2 Selivanov implemented `async/await` in Python, and wrote the related PEPs 492, 525, and 530.

3 There is one exception to this rule: if you run Python with the `-m asyncio` option you can use `await` directly at the `>>>` prompt to drive a native coroutine. This is explained in "Experimenting with Python's Async Console".

4 Sorry, I could not resist it.

5 `true.dev` is available for USD 360/year as I write this. I see that `for.dev` is registered, but has no DNS configured.

6 Thanks to Guto Maia who noted that the concept of a semaphore was not explained when he read the first edition draft for this chapter.

7 A detailed discussion about this can be found in a thread I started in the python-tulip group, titled "Which other futures my come out of asyncio.as_completed?". Guido responds, and gives insight on the implementation of `as_completed` as well as the close relationship between futures and coroutines in `asyncio`.

8 Instead of *uvicorn*, you may use another ASGI server, such as *hypercorn* or *Daphne*. See the official ASGI documentation page about implementations for more

9 As mentioned in Chapter 8, *pydantic* enforces type hints at runtime, for data validation.

10 Thanks for tech reviewer Miroslav Šedivý for highlighting good places to use `pathlib` in code examples.

11 Tech reviewer Leonardo Rochael pointed out that building the index could be delegated to another thread using `loop.run_with_executor()` in the `supervisor` coroutine, so the server would be ready to take requests immediately while the index is built. That's true, but querying the index is the only thing this server does, so it would not be a big win in this example.

12 This is great for experimentation, like the *Node.js* console. Thanks Yuri Selivanov for yet another excellent contribution to asynchronous Python.

13 That's in contrast with JavaScript, where `async/await` is hardwired to the built-in event loop and runtime environment, i.e. a browser, *Node.js*, or *Deno*.

14 Video: Introduction to *Node.js* at 4:55.

15 Using a single thread was the default setting until Go 1.5 was released. Years before, Go had already earned a well deserved reputation for enabling highly concurrent networked systems. One more evidence that concurrency doesn't require multiple threads or CPU cores.

16 Maybe that part of *aiohttp* has been optimized since then; I haven't checked.

17 Regardless of technical choices, this was probably the biggest mistake in this project: the stakeholders did not go for an MVP approach—delivering a Minimum Viable Product as soon as possible, and then adding features at a steady pace.

Chapter 23. Dynamic Attributes and Properties

A NOTE FOR EARLY RELEASE READERS

With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.

This will be the 23rd chapter of the final book. Please note that the GitHub repo will be made active later on.

If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *The crucial importance of properties is that their existence makes it perfectly safe and indeed advisable for you to expose public data attributes as part of your class’s public interface.*[1]
>
> —Martelli, Ravenscroft & Holden, Why properties are important

Data attributes and methods are collectively known as *attributes* in Python. A method is an attribute that is *callable*. Besides data attributes and methods, we can also create properties, which replace a public data attribute with *accessor methods* (i.e., getter/setter), without changing the class interface. This follows Bertrand Meyer’s *Uniform access principle*:

> *All services offered by a module should be available through a uniform notation, which does not betray whether they are implemented through storage or through computation.*[2]

Besides the `property` decorator, Python provides a rich API for controlling attribute access and implementing dynamic attributes. The interpreter calls the `__getattr__` and `__setattr__` special methods to handle attribute access or assignment using dot notation (e.g., `obj.attr`) or via the built-in functions `getattr` and `setattr`. A user-defined class implementing `__getattr__` can implement "virtual attributes" by computing values on the fly whenever somebody tries to read a nonexistent attribute like `obj.no_such_attr`.

Coding dynamic attributes is the kind of metaprogramming that framework authors do. However, in Python the basic techniques are straightforward, so we can use them in everyday data wrangling tasks. That's how we'll start this chapter.

What's new in this chapter

Most updates to this chapter were motivated by a discussion of `@functools.cached_property` (introduced in Python 3.8), as well as the combined use `@property` with `@functools.cache` (new in 3.9). This affected the code for the `Record` and `Event` classes that appear in "Computed Properties". I also added a refactoring to leverage the PEP 412—Key-Sharing Dictionary optimization.

To highlight more relevant features while keeping the examples readable, I removed some nonessential code—merging the old `DbRecord` class into `Record`, replacing `shelve.Shelve` with a `dict`, and deleting the logic to download the OSCON dataset—which the examples now read from a local file included in the *Fluent Python, Second Edition* code repository.

Data Wrangling with Dynamic Attributes

In the next few examples, we'll leverage dynamic attributes to work with a JSON dataset published by O'Reilly for the OSCON 2014 conference. Example 23-1 shows four records from that dataset.[3]

Example 23-1. Sample records from osconfeed.json; some field contents abbreviated

```
{ "Schedule":
  { "conferences": [{"serial": 115 }],
    "events": [
      { "serial": 34505,
        "name": "Why Schools Don´t Use Open Source to Teach
Programming",
        "event_type": "40-minute conference session",
        "time_start": "2014-07-23 11:30:00",
        "time_stop": "2014-07-23 12:10:00",
        "venue_serial": 1462,
        "description": "Aside from the fact that high school
programming...",
        "website_url":
"http://oscon.com/oscon2014/public/schedule/detail/34505",
        "speakers": [157509],
        "categories": ["Education"] }
    ],
    "speakers": [
      { "serial": 157509,
        "name": "Robert Lefkowitz",
        "photo": null,
        "url": "http://sharewave.com/",
        "position": "CTO",
        "affiliation": "Sharewave",
        "twitter": "sharewaveteam",
        "bio": "Robert ´r0ml´ Lefkowitz is the CTO at Sharewave, a
startup..." }
    ],
    "venues": [
      { "serial": 1462,
        "name": "F151",
        "category": "Conference Venues" }
    ]
  }
}
```

Example 23-1 shows 4 of the 895 records in the JSON file. The entire dataset is a single JSON object with the key `"Schedule"`, and its value is another mapping with four keys: `"conferences"`, `"events"`, `"speakers"`, and `"venues"`. Each of those four keys maps to a list of records. In the full dataset the `"events"`, `"speakers"`, and `"venues"` lists have dozens or hundreds of records, while `"conferences"` has only that one record shown in Example 23-1. Every record has a `"serial"` field, which is a unique identifier for the record within the list.

I used Python's console to explore the dataset, as shown in Example 23-2.

Example 23-2. Interactive exploration of osconfeed.json

```
>>> import json
>>> with open('data/osconfeed.json') as fp:
...     feed = json.load(fp)  ❶
>>> sorted(feed['Schedule'].keys())  ❷
['conferences', 'events', 'speakers', 'venues']
>>> for key, value in sorted(feed['Schedule'].items()):
...     print(f'{len(value):3} {key}')  ❸
...
  1 conferences
484 events
357 speakers
 53 venues
>>> feed['Schedule']['speakers'][-1]['name']  ❹
'Carina C. Zona'
>>> feed['Schedule']['speakers'][-1]['serial']  ❺
141590
>>> feed['Schedule']['events'][40]['name']
'There *Will* Be Bugs'
>>> feed['Schedule']['events'][40]['speakers']  ❻
[3471, 5199]
```

❶ `feed` is a `dict` holding nested dicts and lists, with string and integer values.

❷ List the four record collections inside `"Schedule"`.

❸ Display record counts for each collection.

❹ Navigate through the nested dicts and lists to get the name of the last speaker.

❺ Get serial number of that same speaker.

❻ Each event has a `'speakers'` list with zero or more speaker serial numbers.

Exploring JSON-Like Data with Dynamic Attributes

Example 23-2 is simple enough, but the syntax `feed['Schedule']['events'][40]['name']` is cumbersome. In JavaScript, you can get the same value by writing `feed.Schedule.events[40].name`. It's easy to implement a `dict`-like class that does the same in Python—there are plenty of implementations on the Web.[4] I wrote `FrozenJSON`, which is simpler than most recipes because it supports reading only: it's just for exploring the data. `FrozenJSON` is also recursive, dealing automatically with nested mappings and lists.

Example 23-3 is a demonstration of `FrozenJSON` and the source code is in Example 23-4.

Example 23-3. FrozenJSON from Example 23-4 allows reading attributes like `name` and calling methods like `.keys()` and `.items()`

```
>>> import json
>>> raw_feed = json.load(open('data/osconfeed.json'))
>>> feed = FrozenJSON(raw_feed)  ❶
>>> len(feed.Schedule.speakers)  ❷
357
>>> feed.keys()
dict_keys(['Schedule'])
>>> sorted(feed.Schedule.keys())  ❸
['conferences', 'events', 'speakers', 'venues']
>>> for key, value in sorted(feed.Schedule.items()): ❹
...     print(f'{len(value):3} {key}')
...
  1 conferences
484 events
357 speakers
 53 venues
>>> feed.Schedule.speakers[-1].name  ❺
'Carina C. Zona'
>>> talk = feed.Schedule.events[40]
>>> type(talk)  ❻
<class 'explore0.FrozenJSON'>
>>> talk.name
'There *Will* Be Bugs'
>>> talk.speakers  ❼
[3471, 5199]
>>> talk.flavor  ❽
Traceback (most recent call last):
```

```
    ...
KeyError: 'flavor'
```

❶ Build a `FrozenJSON` instance from the `raw_feed` made of nested dicts and lists.

❷ `FrozenJSON` allows traversing nested dicts by using attribute notation; here we show the length of the list of speakers.

❸ Methods of the underlying dicts can also be accessed, like `.keys()`, to retrieve the record collection names.

❹ Using `items()`, we can retrieve the record collection names and their contents, to display the `len()` of each of them.

❺ A `list`, such as `feed.Schedule.speakers`, remains a list, but the items inside are converted to `FrozenJSON` if they are mappings.

❻ Item 40 in the `events` list was a JSON object; now it's a `FrozenJSON` instance.

❼ Event records have a `speakers` list with speaker serial numbers.

❽ Trying to read a missing attribute raises `KeyError`, instead of the usual `AttributeError`.

The keystone of the `FrozenJSON` class is the `__getattr__` method, which we already used in the `Vector` example in "Vector Take #3: Dynamic Attribute Access", to retrieve `Vector` components by letter—`v.x`, `v.y`, `v.z`, etc. It's essential to recall that the `__getattr__` special method is only invoked by the interpreter when the usual process fails to retrieve an attribute (i.e., when the named attribute cannot be found in the instance, nor in the class or in its superclasses).

The last line of Example 23-3 exposes a minor issue with my code: trying to read a missing attribute should raise `AttributeError`, and not

KeyError as shown. When I implemented the error handling to do that, the __getattr__ method became twice as long, distracting from the most important logic I wanted to show. Given that users would know that a FrozenJSON is built from mappings and lists, I think the KeyError is not too confusing.

As shown in Example 23-4, the FrozenJSON class has only two methods (__init__, __getattr__) and a __data instance attribute, so attempts to retrieve an attribute by any other name will trigger __getattr__. This method will first look if the self.__data dict has an attribute (not a key!) by that name; this allows FrozenJSON instances to handle any dict method such as items, by delegating to self.__data.items(). If self.___data doesn't have an attribute with the given name, __getattr__ uses name as a key to retrieve an item from self.__dict, and passes that item to FrozenJSON.build. This allows navigating through nested structures in the JSON data, as each nested mapping is converted to another FrozenJSON instance by the build class method.

Example 23-4. explore0.py: turn a JSON dataset into a FrozenJSON holding nested FrozenJSON objects, lists, and simple types

```
from collections import abc


class FrozenJSON:
    """A read-only façade for navigating a JSON-like object
       using attribute notation
    """

    def __init__(self, mapping):
        self.__data = dict(mapping)  ❶

    def __getattr__(self, name):  ❷
        try:
            return getattr(self.__data, name)  ❸
        except AttributeError:
            return FrozenJSON.build(self.__data[name])  ❹

    @classmethod
    def build(cls, obj):  ❺
```

```
        if isinstance(obj, abc.Mapping):  ❻
            return cls(obj)
        elif isinstance(obj, abc.MutableSequence):  ❼
            return [cls.build(item) for item in obj]
        else:  ❽
            return obj
```

❶ Build a `dict` from the `mapping` argument. This ensures we got a mapping or something that can be converted to one.

❷ `__getattr__` is called only when there's no attribute with that `name`.

❸ If `name` matches an attribute of the instance `__data`, return that. This is how calls like `feed.keys()` are handled: the `keys` method is an attribute of the `__data` `dict`.

❹ Otherwise, fetch the item with the key `name` from `self.__data`, and return the result of calling `FrozenJSON.build()` on that.[5]

❺ This is an alternate constructor, a common use for the `@classmethod` decorator.

❻ If `obj` is a mapping, build a `FrozenJSON` with it. This is an example of *goose typing*.

❼ If it is a `MutableSequence`, it must be a list,[6] so we build a `list` by passing each item in `obj` recursively to `.build()`.

❽ If it's not a `dict` or a `list`, return the item as it is. It should be a `str` or an `int`, given the contents of the JSON file.

Note that no caching or transformation of the original dataset is done. As the dataset is traversed, the nested data structures are converted again and again into `FrozenJSON`. That's OK for a dataset of this size, and for a script that will only be used to explore or convert the data.

Any script that generates or emulates dynamic attribute names from arbitrary sources must deal with one issue: the keys in the original data may not be suitable attribute names. The next section addresses this.

The Invalid Attribute Name Problem

The `FrozenJSON` code doesn't handle attribute names that are Python keywords. For example, if you build an object like this:

```
>>> student = FrozenJSON({'name': 'Jim Bo', 'class': 1982})
```

You won't be able to read `student.class` because `class` is a reserved keyword in Python:

```
>>> student.class
  File "<stdin>", line 1
    student.class
         ^
SyntaxError: invalid syntax
```

You can always do this, of course:

```
>>> getattr(student, 'class')
1982
```

But the idea of `FrozenJSON` is to provide convenient access to the data, so a better solution is checking whether a key in the mapping given to `FrozenJSON.__init__` is a keyword, and if so, append an _ to it, so the attribute can be read like this:

```
>>> student.class_
1982
```

This can be achieved by replacing the one-liner `__init__` from Example 23-4 with the version in Example 23-5.

Example 23-5. explore1.py: append a _ to attribute names that are Python keywords

```
    def __init__(self, mapping):
        self.__data = {}
        for key, value in mapping.items():
            if keyword.iskeyword(key):  ❶
                key += '_'
            self.__data[key] = value
```

❶ The `keyword.iskeyword(…)` function is exactly what we need; to use it, the `keyword` module must be imported, which is not shown in this snippet.

A similar problem may arise if a key in the JSON is not a valid Python identifier:

```
>>> x = FrozenJSON({'2be':'or not'})
>>> x.2be
  File "<stdin>", line 1
    x.2be
      ^
SyntaxError: invalid syntax
```

Such problematic keys are easy to detect in Python 3 because the `str` class provides the `s.isidentifier()` method, which tells you whether `s` is a valid Python identifier according to the language grammar. But turning a key that is not a valid identifier into valid attribute name is not trivial. Two simple solutions would be raising an exception or replacing the invalid keys with generic names like `attr_0`, `attr_1`, and so on. For the sake of simplicity, I will not worry about this issue.

After giving some thought to the dynamic attribute names, let's turn to another essential feature of `FrozenJSON`: the logic of the `build` class method, which is used by `__getattr__` to return a different type of object depending on the value of the attribute being accessed, so that nested structures are converted to `FrozenJSON` instances or lists of `FrozenJSON` instances.

Instead of a class method, the same logic could be implemented as the `__new__` special method, as we'll see next.

Flexible Object Creation with __new__

We often refer to `__init__` as the constructor method, but that's because we adopted jargon from other languages. In Python, `__init__` gets `self` as the first argument, therefore the object already exists when `__init__` is called by the interpreter. Also, `__init__` cannot return anything. So it's really an initializer, not a constructor.

The special method that Python calls to construct an instance is `__new__`: it's a class method, but gets special treatment, so the `@classmethod` decorator is not used. Python takes the instance returned by `__new__` and passes it as the first argument `self` of `__init__`. We rarely need to code `__new__`, because the implementation inherited from `object` suffices for the vast majority of use cases.

If necessary, the `__new__` method can also return an instance of a different class. When that happens, the interpreter does not call `__init__`. In other words, Python's logic for building an object is similar to this pseudocode:

```
# pseudo-code for object construction
def make(the_class, some_arg):
    new_object = the_class.__new__(some_arg)
    if isinstance(new_object, the_class):
        the_class.__init__(new_object, some_arg)
    return new_object

# the following statements are roughly equivalent
x = Foo('bar')
x = make(Foo, 'bar')
```

Example 23-6 shows a variation of `FrozenJSON` where the logic of the former `build` class method was moved to `__new__`.

Example 23-6. explore2.py: using new instead of build to construct new objects that may or may not be instances of FrozenJSON

```
from collections import abc
import keyword

class FrozenJSON:
    """A read-only façade for navigating a JSON-like object
```

```
    using attribute notation
    """

    def __new__(cls, arg):  ❶
        if isinstance(arg, abc.Mapping):
            return super().__new__(cls)  ❷
        elif isinstance(arg, abc.MutableSequence):  ❸
            return [cls(item) for item in arg]
        else:
            return arg

    def __init__(self, mapping):
        self.__data = {}
        for key, value in mapping.items():
            if keyword.iskeyword(key):
                key += '_'
            self.__data[key] = value

    def __getattr__(self, name):
        if hasattr(self.__data, name):
            return getattr(self.__data, name)
        else:
            return FrozenJSON(self.__data[name])  ❹
```

❶ As a class method, the first argument `__new__` gets is the class itself, and the remaining arguments are the same that `__init__` gets, except for `self`.

❷ The default behavior is to delegate to the `__new__` of a super class. In this case, we are calling `__new__` from the `object` base class, passing `FrozenJSON` as the only argument.

❸ The remaining lines of `__new__` are exactly as in the old `build` method.

❹ This was where `FrozenJSON.build` was called before; now we just call the `FrozenJSON` class, which Python handles by calling `FrozenJSON.__new__`.

The `__new__` method gets the class as the first argument because, usually, the created object will be an instance of that class. So, in `FrozenJSON.__new__`, when the expression `super().__new__(cls)` effectively calls `object.__new__(FrozenJSON)`, the instance built by the `object` class is actually an instance of `FrozenJSON`—i.e., the `__class__` attribute of the new instance will hold a reference to `FrozenJSON`—even though the actual construction is performed by `object.__new__`, implemented in C, in the guts of the interpreter.

The OSCON JSON dataset is structured in a way that is not helpful. For example, the event at index `40`, titled `'There *Will* Be Bugs'` has two speakers, `3471` and `5199`. Finding the names of the speakers is awkward, because those are serial numbers and the `Schedule.speakers` list is not indexed by them. To get each speaker, we must iterate over that list until we find a record with a matching serial number. Our next task is restructuring the data, to prepare for automatic retrieval of linked records.

Computed Properties

> **NOTE**
>
> We first saw the `@property` decorator in Chapter 11, section "A Hashable Vector2d". In Example 11-7, I used two properties in `Vector2d` just to make the `x` and `y` attributes read-only. Here we will see properties that compute values, leading to a discussion of how to cache such values.

The records in the `'events'` list of the OSCON JSON data contain integer serial numbers pointing to records in the `'speakers'` and `'venues'` lists. For example, this is the record for a conference talk (with an elided description):

```
{ "serial": 33950,
  "name": "There *Will* Be Bugs",
  "event_type": "40-minute conference session",
  "time_start": "2014-07-23 14:30:00",
  "time_stop": "2014-07-23 15:10:00",
  "venue_serial": 1449,
  "description": "If you're pushing the envelope of
programming...",
  "website_url":
"http://oscon.com/oscon2014/public/schedule/detail/33950",
  "speakers": [3471, 5199],
  "categories": ["Python"] }
```

We will implement an `Event` class with `venue` and `speakers` properties to return the linked data automatically—in other words, “dereferencing” the serial number. Given an `Event` instance, this is the desired behavior:

Example 23-7.

```
>>> event  ❶
<Event 'There *Will* Be Bugs'>
>>> event.venue  ❷
<Record serial=1449>
>>> event.venue.name  ❸
'Portland 251'
>>> for spkr in event.speakers:  ❹
...     print(f'{spkr.serial}: {spkr.name}')
...
3471: Anna Martelli Ravenscroft
5199: Alex Martelli
```

❶ Given an `Event` instance…

❷ …reading `event.venue` returns a `Record` object instead of a serial number.

❸ Now it’s easy to get the name of the `venue`.

❹ The `event.speakers` property returns a list of `Record` instances.

As usual, we will build the code step-by-step, starting with the `Record` class and a function to read the JSON data and return a `dict` with `Record` instances.

Step 1: Data-driven Attribute Creation

Here is the `doctest` to guide this first step:

Example 23-8. Test driving schedule_v1.py (Example 23-9)

```
    >>> records = load(JSON_PATH)  ❶
    >>> speaker = records['speaker.3471']  ❷
    >>> speaker  ❸
    <Record serial=3471>
    >>> speaker.name, speaker.twitter  ❹
    ('Anna Martelli Ravenscroft', 'annaraven')
```

❶ `load` a `dict` with the JSON data.

❷ The keys in `records` are strings built from the record type and serial.

❸ `speaker` is an instance of the `Record` class defined in Example 23-9.

❹ Fields from the original JSON can be retrieved as `Record` instance attributes.

The code for *schedule_v1.py* is in Example 23-9.

Example 23-9. schedule_v1.py: reorganizing the OSCON schedule data

```
import json

JSON_PATH = 'data/osconfeed.json'

class Record:
    def __init__(self, **kwargs):
        self.__dict__.update(kwargs)  ❶

    def __repr__(self):
        cls_name = self.__class__.__name__
        return f'<{cls_name} serial={self.serial!r}>'  ❷

def load(path=JSON_PATH):
```

```
    records = {}  ❸
    with open(path) as fp:
        raw_data = json.load(fp)  ❹
    for collection, raw_records in raw_data['Schedule'].items():  ❺
        record_type = collection[:-1]  ❻
        for raw_record in raw_records:
            key = f'{record_type}.{raw_record["serial"]}' ❼
            records[key] = Record(**raw_record)  ❽
    return records
```

❶ This is a common shortcut to build an instance with attributes created from keyword arguments (detailed explanation follows).

❷ Use the `serial` field to build the custom `Record` representation shown in Example 23-8.

❸ `load` will ultimately return a `dict` of `Record` instances.

❹ Parse the JSON, returning native Python objects: lists, dicts, strings, numbers etc.

❺ Iterate over the four top-level lists named `'conferences'`, `'events'`, `'speakers'`, and `'venues'`.

❻ `record_type` is the list name without the last character, so `speakers` becomes `speaker`.

❼ Build the `key` in the format `'speaker.3471'`.

❽ Create a `Record` instance and save it in `records` with the `key`

The `Record.__init__` method illustrates an old Python hack. Recall that the `__dict__` of an object is where its attributes are kept—unless `__slots__` is declared in the class, as we saw in "Saving Memory with `__slots__`". So, updating an instance `__dict__` with a mapping is a quick way to create a bunch of attributes in that instance.[7]

> **NOTE**
>
> Depending on the application, the `Record` class may need to deal with keys that are not valid attribute names, as we saw in "The Invalid Attribute Name Problem". Dealing with that issue would distract from the key idea of this example, and is not a problem in the data set we are reading.

The definition of `Record` in Example 23-9 is so simple that you may be wondering why I did not use it before, instead of the more complicated `FrozenJSON`. There are two reasons. First, `FrozenJSON` works by recursively converting the nested mappings and lists; `Record` doesn't need that because our converted dataset doesn't have mappings nested in mappings or lists. The records contain only strings, integers, lists of strings, and lists of integers. Second reason: `FrozenJSON` provides access to the embedded `__data dict` attributes—which we used to invoke methods like `.keys()`—and now we don't need that functionality either.

> **NOTE**
>
> The Python standard library provides at least two classes similar to `Record`, where each instance has an arbitrary set of attributes built from keyword arguments given to `__init__`: `multiprocessing.Namespace` and `argparse.Namespace`. I wrote the simpler `Record` class to highlight the essential idea: `__init__` updating the instance `__dict__`.

After reorganizing the schedule dataset, we can enhance the `Record` class to automatically retrieve `venue` and `speaker` records referenced in an `event` record. We'll use properties to do that in the next examples.

Step 2: Property to Retrieve a Linked Record

The goal of this next version is: given an `event` record, reading its `venue` property will return a `Record`. This is similar to what the Django ORM does when you access a `ForeignKey` field: instead of the key, you get the linked model object.

We’ll start with the `venue` property. See the partial interaction in Example 23-10 as an example.

Example 23-10. Extract from the doctests of schedule_v2.py

```
>>> event = Record.fetch('event.33950')  ❶
>>> event  ❷
<Event 'There *Will* Be Bugs'>
>>> event.venue  ❸
<Record serial=1449>
>>> event.venue.name  ❹
'Portland 251'
>>> event.venue_serial  ❺
1449
```

❶ The `Record.fetch` static method gets a `Record` or an `Event` from the dataset.

❷ Note that `event` is an instance of the `Event` class.

❸ Accessing `event.venue` returns a `Record` instance.

❹ Now it’s easy to find out the name of an `event.venue`.

❺ The `Event` instance also has a `venue_serial` attribute, from the JSON data.

`Event` is a subclass of `Record` adding a `venue` to retrieve linked records, and a specialized `__repr__` method.

The code for this section is in the *schedule_v2.py* module in the *Fluent Python 2e* code repository. The example has nearly 60 lines, so I’ll present it in parts, starting with the enhanced `Record` class.

Example 23-11. schedule_v2.py: `Record` class with a new `fetch` method.

```
import inspect  ❶
import json
```

```
JSON_PATH = 'data/osconfeed.json'

class Record:

    __index = None  ❷

    def __init__(self, **kwargs):
        self.__dict__.update(kwargs)

    def __repr__(self):
        cls_name = self.__class__.__name__
        return f'<{cls_name} serial={self.serial!r}>'

    @staticmethod  ❸
    def fetch(key):
        if Record.__index is None:  ❹
            Record.__index = load()
        return Record.__index[key]  ❺
```

❶ `inspect` will be used in `load`, listed in Example 23-13.

❷ The `__index` private class attribute will eventually hold a reference to the `dict` returned by `load`.

❸ `fetch` is a `staticmethod` to make it explicit that its effect is always exactly the same, no matter how it's called.

❹ Populate the `Record.__index` if needed.

❺ Use it to retrieve the record with the given `key`.

> **TIP**
>
> This is one example where the use of `staticmethod` makes sense. The `fetch` method always acts on the `Record.__index` class attribute, even if invoked as `Event.fetch()`. It would be misleading to code it as a class method because the `cls` first argument would not be used.

Now we get to the use of a property in the `Event` class, listed in Example 23-12.

Example 23-12. schedule_v2.py: the Event class

```
class Event(Record):  ❶

    def __repr__(self):
        if hasattr(self, 'name'):  ❷
            cls_name = self.__class__.__name__
            return f'<{cls_name} {self.name!r}>'
        else:
            return super().__repr__()

    @property
    def venue(self):
        key = f'venue.{self.venue_serial}'
        return self.__class__.fetch(key)  ❸
```

❶ `Event` extends `Record`.

❷ If the instance has a `name` attribute, it is used to produce a custom representation. Otherwise, delegate to the `__repr__` from `Record`.

❸ The `venue` property builds a `key` from the `venue_serial` attribute, and passes it to the `fetch` class method, inherited from `Record` (the reason for using `self.__class__` is explained shortly).

The second line of the `venue` method of Example 23-12, returns `self.__class__.fetch(key)`. Why not simply call `self.fetch(key)`? The simpler form works with the specific OSCON dataset because there is no event record with a `'fetch'` key. But, if an event record had a key named `'fetch'`, then within that specific `Event` instance, the reference `self.fetch` would retrieve the value of that field, instead of the `fetch` class method that `Event` inherits from `Record`. This is a subtle bug, and it could easily sneak through testing because it depends on the dataset.

WARNING

When creating instance attribute names from data, there is always the risk of bugs due to shadowing of class attributes—such as methods—or data loss through accidental overwriting of existing instance attributes. These problems may explain why Python dicts are not like JavaScript objects in the first place.

If the `Record` class behaved more like a mapping, implementing a dynamic `__getitem__` instead of a dynamic `__getattr__`, there would be no risk of bugs from overwriting or shadowing. A custom mapping is probably the Pythonic way to implement `Record`. But if I took that road, we'd not be studying the tricks and traps of dynamic attribute programming.

The final piece of this example is the revised `load` function in Example 23-13.

Example 23-13. schedule_v2.py: the load function

```
def load(path=JSON_PATH):
    records = {}
    with open(path) as fp:
        raw_data = json.load(fp)
    for collection, raw_records in raw_data['Schedule'].items():
        record_type = collection[:-1]  ❶
        cls_name = record_type.capitalize()  ❷
        cls = globals().get(cls_name, Record)  ❸
        if inspect.isclass(cls) and issubclass(cls, Record):  ❹
            factory = cls  ❺
        else:
            factory = Record  ❻
        for raw_record in raw_records:  ❼
            key = f'{record_type}.{raw_record["serial"]}'
            records[key] = factory(**raw_record)  ❽
    return records
```

❶ So far, no changes from the `load` in *schedule_v1.py* (Example 23-9).

❷ Capitalize the `record_type` to get a possible class name; e.g., `'event'` becomes `'Event'`.

❸ Get an object by that name from the module global scope; get the `Record` class if there's no such object.

❹ If the object just retrieved is a class, and is a subclass of `Record`…

❺ …bind the `factory` name to it. This means `factory` may be any subclass of `Record`, depending on the `record_type`.

❻ Otherwise, bind the `factory` name to `Record`.

❼ The `for` loop that creates the `key` and saves the records is the same as before, except that…

❽ …the object stored in `records` is constructed by `factory`, which may be `Record` or a subclass like `Event` selected according to the `record_type`.

Note that the only `record_type` that has a custom class is `Event`, but if classes named `Speaker` or `Venue` are coded, `load` will automatically use those classes when building and saving records, instead of the default `Record` class.

We'll now apply the same idea to a new `speakers` property in the `Events` class.

Step 3: Property Overriding an Existing Attribute

The name of the `venue` property in Example 23-12 does not match a field name in the `Event` records. Its data comes from a `venue_serial` attribute. In contrast, each `Event` instance has `speaker` attribute with a list of serial numbers, and we want to expose that information as a `speaker` property returning a list of `Record` instances. This name clash requires some special attention, as Example 23-14 reveals.

Example 23-14. schedule_v3.py: the `speakers` property

```
    @property
    def speakers(self):
        spkr_serials = self.__dict__['speakers']  ❶
        fetch = self.__class__.fetch
        return [fetch(f'speaker.{key}')
                for key in spkr_serials]  ❷
```

❶ The data we want is in a `speakers` attribute, but we must retrieve it directly from the instance `__dict__` to avoid a recursive call to the `speakers` property.

❷ Return a list of all records with keys corresponding to the numbers in `spkr_serials`.

Inside the `speakers` method, trying to read `self.speakers` will invoke the property itself, quickly raising a `RecursionError`. However if we read the same data via the `self.__dict__['speakers']`, Python's usual algorithm for retrieving attributes is bypassed, the property is not called, and the recursion is avoided. For this reason, reading or writing data directly to an object's `__dict__` is a common Python metaprogramming trick.

> **WARNING**
>
> The interpreter evaluates `obj.my_attr` by first looking at the class of `obj`. If the class has a property with the `my_attr` name, that property shadows an instance attribute by the same name. Examples in "Properties Override Instance Attributes" will demonstrate this, and Chapter 24 will reveal that a property is implemented as a descriptor—a more powerful and general abstraction.

As I coded the list comprehension in Example 23-14, my programmer's lizard brain thought "This may be expensive." Not really, because events in the OSCON dataset have few speakers, so coding anything more complicated would be premature optimization. However, caching a property is a common need—and there are caveats. So let's see how to do that in the next examples.

Step 4: Bespoke Property Cache

Caching properties is a common need because there is an expectation that an expression like `event.venue` should be inexpensive.[8] Some form of caching could become necessary if the `Record.fetch` method behind the `Event` properties needed to query a database or a Web API.

In *Fluent Python, First Edition*, I coded the custom caching logic for the `speakers` method as shown in Example 23-15.

Example 23-15. Custom caching logic using hasattr disables key-sharing optimization.

```
    @property
    def speakers(self):
        if not hasattr(self, '__speaker_objs'):  ❶
            spkr_serials = self.__dict__['speakers']
            fetch = self.__class__.fetch
            self.__speaker_objs = [fetch(f'speaker.{key}')
                    for key in spkr_serials]
        return self.__speaker_objs  ❷
```

❶ If the instance doesn't have an attribute named `__speaker_objs`, fetch the speaker objects and store them there.

❷ Return `self.__speaker_objs`.

The handmade caching in Example 23-15 is straightforward, but creating an attribute after the instance is initialized defeats the PEP 412—Key-Sharing Dictionary optimization, as explained in [Link to Come]. Depending on the size of the dataset, the difference in memory usage may be important.

A similar hand-rolled solution that works well with the key-sharing optimization requires coding an `__init__` for the `Event` class, to create the necessary `__speaker_objs` initialized to `None`, and then checking for that in the `speakers` method. See Example 23-16.

Example 23-16. Storage defined in `__init__` to leverage key-sharing optimization.

```python
class Event(Record):

    def __init__(self, **kwargs):
        self.__speaker_objs = None
        super().__init__(**kwargs)

# 15 lines omitted...
    @property
    def speakers(self):
        if self.__speaker_objs is None:
            spkr_serials = self.__dict__['speakers']
            fetch = self.__class__.fetch
            self.__speaker_objs = [fetch(f'speaker.{key}')
                    for key in spkr_serials]
        return self.__speaker_objs
```

Example 23-15 and Example 23-16 illustrate simple caching techniques that are fairly common in legacy Python codebases. However, in multi-threaded programs handmade caches like those introduce race conditions that may lead to corrupted data. If two threads are reading a property that was not previously cached, the first thread will need to compute the data for the cache attribute (`__speaker_objs` in the examples) and the second thread may read a cached value that is not yet complete.

Fortunately, Python 3.8 introduced `@functools.cached_property` decorator which is thread-safe. Unfortunately, it comes with a couple of caveats, explained next.

Step 5: Caching Properties with functools

The `functools` module provides three decorators for caching. We saw `@cache` and `@lru_cache` in "Memoization with functools.cache" (Chapter 9). Python 3.8 introduced `@cached_property`.

The `functools.cached_property` decorator caches the result of the method in an instance attribute with the same name. For example, in Example 23-17, the value computed by the `venue` method is stored in a `venue` attribute in `self`. After that, when client code tries to read `venue`, the newly created `venue` instance attribute is used instead of the method.

Example 23-17. Simple use of a `@cached_property`.

```
    @cached_property
    def venue(self):
        key = f'venue.{self.venue_serial}'
        return self.__class__.fetch(key)
```

In "Step 3: Property Overriding an Existing Attribute", we saw that a property shadows an instance attribute by the same name. If that is true, how can `@cached_property` work? If the property overrides the instance attribute, the `venue` attribute will be ignored and the `venue` method will always be called, computing the `key` and running `fetch` every time!

The answer is a bit sad: `cached_property` is a misnomer. The `@cached_property` decorator does not create a full-fledged property. While `@property` creates an *overriding descriptor*, `@cached_property` creates a *non-overriding descriptor*. We will study both kinds of descriptors in Chapter 24.

For now, let us set aside the underlying implementation and focus on the differences between `cached_property` and `property` from a user point of view. Raymond Hettinger explains them very well in the Python Docs:

> *The mechanics of `cached_property()` are somewhat different from `property()`. A regular property blocks attribute writes unless a setter is defined. In contrast, a `cached_property` allows writes.*
>
> *The `cached_property` decorator only runs on lookups and only when an attribute of the same name doesn't exist. When it does run, the `cached_property` writes to the attribute with the same name. Subsequent attribute reads and writes take precedence over the `cached_property` method and it works like a normal attribute.*
>
> *The cached value can be cleared by deleting the attribute. This allows the `cached_property` method to run again.*[9]

Back to our `Event` class: the specific behavior of `@cached_property` makes it unsuitable to decorate `speakers`, because that method relies on an existing attribute also named `speakers`, containing the serial numbers of the event speakers.

> **WARNING**
>
> `@cached_property` has some important limitations:
>
> - It cannot be used as a drop-in replacement to `@property` if the decorated method already depends on an instance attribute with the same name;
> - It cannot be used in a class that defines `__slots__`;
> - It defeats the key-sharing optimization of the instance `__dict__`, because it creates an instance attribute after `__init__`.

Despite these limitations, `@cached_property` addresses a common need in a simple way, and it is thread-safe. Its Python code is an example of using a reentrant lock.

The `@cached_property` documentation recommends an alternative solution that we can use with `speakers`: stacking `@property` and `@cache` decorators, as shown in Example 23-18

Example 23-18. Stacking `@property` on `@cache`.

```
    @property  ❶
    @cache  ❷
    def speakers(self):
        spkr_serials = self.__dict__['speakers']
        fetch = self.__class__.fetch
        return [fetch(f'speaker.{key}')
                for key in spkr_serials]
```

❶ The order here is important, `@property` goes on top…

❷ …of `@cache`.

Recall from "Stacked decorators" the meaning of that syntax. The top three lines of Example 23-18 are similar to:

```
speakers = property(cache(speakers))
```

The `@cache` is applied to `speakers`, returning a new function. That function then is decorated by `@property`, which replaces it with a newly constructed property.

This wraps up our discussion of read-only properties and caching decorators. In the next section, we will create a read/write property.

Using a Property for Attribute Validation

Besides computing attribute values, properties are also used to enforce business rules by changing a public attribute into an attribute protected by a getter and setter without affecting client code. Let's work through an extended example.

LineItem Take #1: Class for an Item in an Order

Imagine an app for a store that sells organic food in bulk, where customers can order nuts, dried fruit, or cereals by weight. In that system, each order would hold a sequence of line items, and each line item could be represented by a class as in Example 23-19.

Example 23-19. bulkfood_v1.py: the simplest LineItem class

```
class LineItem:

    def __init__(self, description, weight, price):
        self.description = description
        self.weight = weight
        self.price = price

    def subtotal(self):
        return self.weight * self.price
```

That’s nice and simple. Perhaps too simple. Example 23-20 shows a problem.

Example 23-20. A negative weight results in a negative subtotal

```
>>> raisins = LineItem('Golden raisins', 10, 6.95)
>>> raisins.subtotal()
69.5
>>> raisins.weight = -20  # garbage in...
>>> raisins.subtotal()    # garbage out...
-139.0
```

This is a toy example, but not as fanciful as you may think. Here is a true story from the early days of Amazon.com:

> *We found that customers could order a negative quantity of books! And we would credit their credit card with the price and, I assume, wait around for them to ship the books.*[10]
>
> —Jeff Bezos, Founder and CEO of Amazon.com

How do we fix this? We could change the interface of `LineItem` to use a getter and a setter for the `weight` attribute. That would be the Java way, and it’s not wrong.

On the other hand, it’s natural to be able set the `weight` of an item by just assigning to it; and perhaps the system is in production with other parts already accessing `item.weight` directly. In this case, the Python way would be to replace the data attribute with a property.

LineItem Take #2: A Validating Property

Implementing a property will allow us to use a getter and a setter, but the interface of `LineItem` will not change (i.e., setting the `weight` of a `LineItem` will still be written as `raisins.weight = 12`).

Example 23-21 lists the code for a read/write `weight` property.

Example 23-21. bulkfood_v2.py: a LineItem with a weight property

```
class LineItem:

    def __init__(self, description, weight, price):
```

```
        self.description = description
        self.weight = weight  ❶
        self.price = price

    def subtotal(self):
        return self.weight * self.price

    @property  ❷
    def weight(self):  ❸
        return self.__weight  ❹

    @weight.setter  ❺
    def weight(self, value):
        if value > 0:
            self.__weight = value  ❻
        else:
            raise ValueError('value must be > 0')  ❼
```

❶ Here the property setter is already in use, making sure that no instances with negative `weight` can be created.

❷ `@property` decorates the getter method.

❸ The methods that implement a property all have the name of the public attribute: `weight`.

❹ The actual value is stored in a private attribute `__weight`.

❺ The decorated getter has a `.setter` attribute, which is also a decorator; this ties the getter and setter together.

❻ If the value is greater than zero, we set the private `__weight`.

❼ Otherwise, `ValueError` is raised.

Note how a `LineItem` with an invalid weight cannot be created now:

```
>>> walnuts = LineItem('walnuts', 0, 10.00)
Traceback (most recent call last):
    ...
ValueError: value must be > 0
```

Now we have protected `weight` from users providing negative values. Although buyers usually can't set the price of an item, a clerical error or a bug may create a `LineItem` with a negative `price`. To prevent that, we could also turn `price` into a property, but this would entail some repetition in our code.

Remember the Paul Graham quote from Chapter 17: "When I see patterns in my programs, I consider it a sign of trouble." The cure for repetition is abstraction. There are two ways to abstract away property definitions: using a property factory or a descriptor class. The descriptor class approach is more flexible, and we'll devote Chapter 24 to a full discussion of it. Properties are in fact implemented as descriptor classes themselves. But here we will continue our exploration of properties by implementing a property factory as a function.

But before we can implement a property factory, we need to have a deeper understanding of properties.

A Proper Look at Properties

Although often used as a decorator, the `property` built-in is actually a class. In Python, functions and classes are often interchangeable, because both are callable and there is no `new` operator for object instantiation, so invoking a constructor is no different than invoking a factory function. And both can be used as decorators, as long as they return a new callable that is a suitable replacement of the decorated function.

This is the full signature of the `property` constructor:

```
property(fget=None, fset=None, fdel=None, doc=None)
```

All arguments are optional, and if a function is not provided for one of them, the corresponding operation is not allowed by the resulting property object.

The `property` type was added in Python 2.2, but the @ decorator syntax appeared only in Python 2.4, so for a few years, properties were defined by passing the accessor functions as the first two arguments.

The "classic" syntax for defining properties without decorators is illustrated in Example 23-22.

Example 23-22. bulkfood_v2b.py: same as Example 23-21 but without using decorators

```
class LineItem:

    def __init__(self, description, weight, price):
        self.description = description
        self.weight = weight
        self.price = price

    def subtotal(self):
        return self.weight * self.price

    def get_weight(self):  ❶
        return self.__weight

    def set_weight(self, value):  ❷
        if value > 0:
            self.__weight = value
        else:
            raise ValueError('value must be > 0')

    weight = property(get_weight, set_weight)  ❸
```

❶ A plain getter.

❷ A plain setter.

❸ Build the `property` and assign it to a public class attribute.

The classic form is better than the decorator syntax in some situations; the code of the property factory we'll discuss shortly is one example. On the other hand, in a class body with many methods, the decorators make it explicit which are the getters and setters, without depending on the convention of using `get` and `set` prefixes in their names.

The presence of a property in a class affects how attributes in instances of that class can be found in a way that may be surprising at first. The next section explains.

Properties Override Instance Attributes

Properties are always class attributes, but they actually manage attribute access in the instances of the class.

In "Overriding Class Attributes" we saw that when an instance and its class both have a data attribute by the same name, the instance attribute overrides, or shadows, the class attribute—at least when read through that instance. Example 23-23 illustrates this point.

Example 23-23. Instance attribute shadows class data attribute

```
>>> class Class:  ❶
...     data = 'the class data attr'
...     @property
...     def prop(self):
...         return 'the prop value'
...
>>> obj = Class()
>>> vars(obj)  ❷
{}
>>> obj.data  ❸
'the class data attr'
>>> obj.data = 'bar' ❹
>>> vars(obj)  ❺
{'data': 'bar'}
>>> obj.data  ❻
'bar'
>>> Class.data  ❼
'the class data attr'
```

❶ Define `Class` with two class attributes: the `data` data attribute and the `prop` property.

❷ `vars` returns the `__dict__` of `obj`, showing it has no instance attributes.

❸ Reading from `obj.data` retrieves the value of `Class.data`.

❹ Writing to `obj.data` creates an instance attribute.

❺ Inspect the instance to see the instance attribute.

❻ Now reading from `obj.data` retrieves the value of the instance attribute. When read from the `obj` instance, the instance `data` shadows the class `data`.

❼ The `Class.data` attribute is intact.

Now, let's try to override the `prop` attribute on the `obj` instance. Resuming the previous console session, we have Example 23-24.

Example 23-24. Instance attribute does not shadow class property (continued from Example 23-23)

```
>>> Class.prop  ❶
<property object at 0x1072b7408>
>>> obj.prop  ❷
'the prop value'
>>> obj.prop = 'foo'  ❸
Traceback (most recent call last):
  ...
AttributeError: can't set attribute
>>> obj.__dict__['prop'] = 'foo'  ❹
>>> vars(obj)  ❺
{'data': 'bar', 'prop': 'foo'}
>>> obj.prop  ❻
'the prop value'
>>> Class.prop = 'baz'  ❼
>>> obj.prop  ❽
'foo'
```

❶ Reading `prop` directly from `Class` retrieves the property object itself, without running its getter method.

❷ Reading `obj.prop` executes the property getter.

❸ Trying to set an instance `prop` attribute fails.

❹ Putting `'prop'` directly in the `obj.__dict__` works.

❺ We can see that `obj` now has two instance attributes: `data` and `prop`.

❻ However, reading `obj.prop` still runs the property getter. The property is not shadowed by an instance attribute.

❼ Overwriting `Class.prop` destroys the property object.

❽ Now `obj.prop` retrieves the instance attribute. `Class.prop` is not a property anymore, so it no longer overrides `obj.prop`.

As a final demonstration, we'll add a new property to `Class`, and see it overriding an instance attribute. Example 23-25 picks up where Example 23-24 left off.

Example 23-25. New class property shadows existing instance attribute (continued from Example 23-24)

```
>>> obj.data  ❶
'bar'
>>> Class.data  ❷
'the class data attr'
>>> Class.data = property(lambda self: 'the "data" prop value')  ❸
>>> obj.data  ❹
'the "data" prop value'
>>> del Class.data  ❺
>>> obj.data  ❻
'bar'
```

❶ `obj.data` retrieves the instance `data` attribute.

❷ `Class.data` retrieves the class `data` attribute.

❸ Overwrite `Class.data` with a new property.

❹ `obj.data` is now shadowed by the `Class.data` property.

❺ Delete the property.

❻ `obj.data` now reads the instance `data` attribute again.

The main point of this section is that an expression like `obj.data` does not start the search for `data` in `obj`. The search actually starts at `obj.__class__`, and only if there is no property named `data` in the class, Python looks in the `obj` instance itself. This applies to *overriding descriptors* in general, of which properties are just one example. Further treatment of descriptors must wait for Chapter 24.

Now back to properties. Every Python code unit—modules, functions, classes, methods—can have a docstring. The next topic is how to attach documentation to properties.

Property Documentation

When tools such as the console `help()` function or IDEs need to display the documentation of a property, they extract the information from the `__doc__` attribute of the property.

If used with the classic call syntax, `property` can get the documentation string as the `doc` argument:

```
    weight = property(get_weight, set_weight, doc='weight in
kilograms')
```

When `property` is deployed as a decorator, the docstring of the getter method—the one with the `@property` decorator itself—is used as the documentation of the property as a whole. Figure 23-1 shows the help screens generated from the code in Example 23-26.

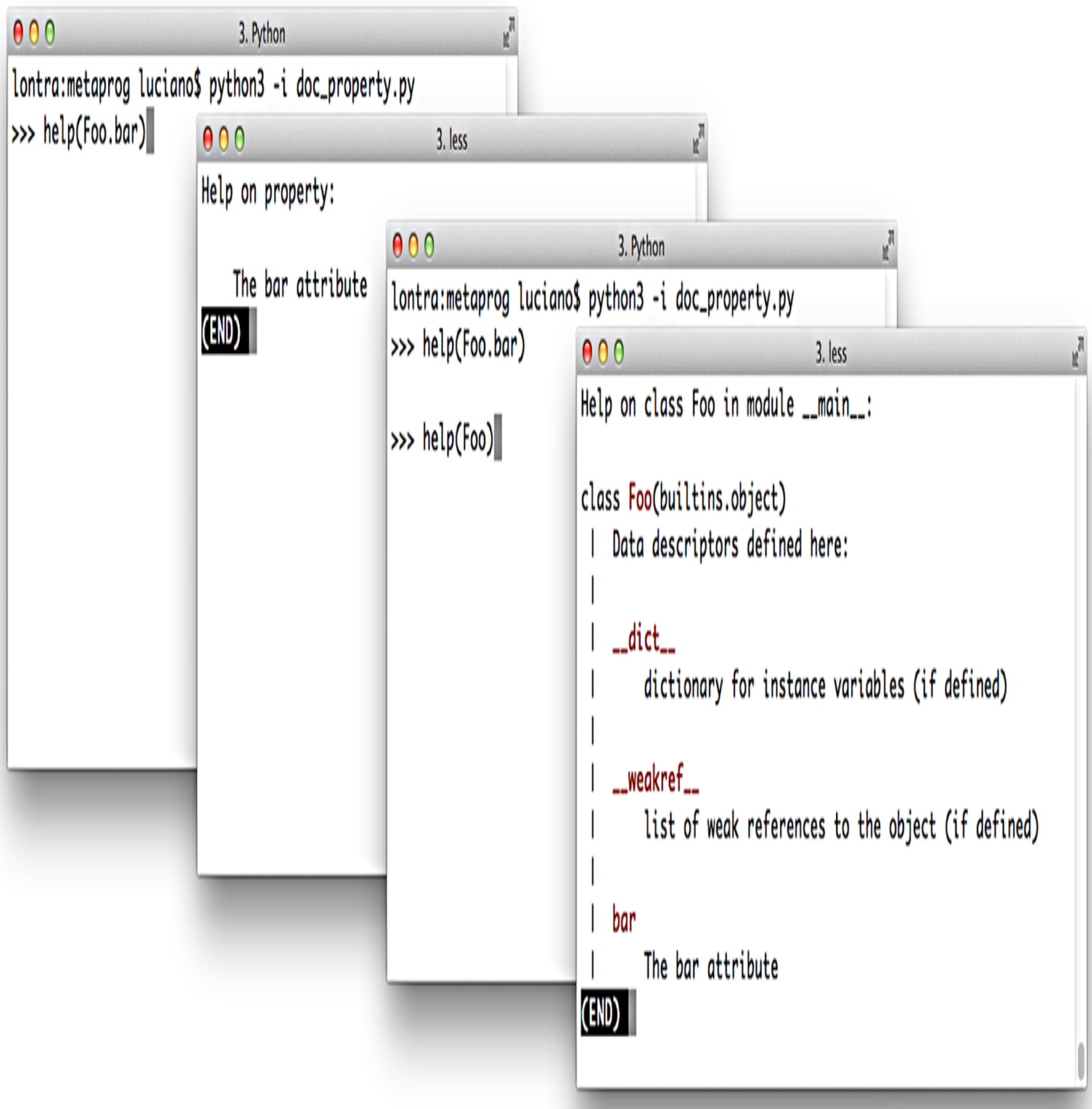

Figure 23-1. Screenshots of the Python console when issuing the commands help(Foo.bar) and help(Foo). Source code in Example 23-26.

Example 23-26. Documentation for a property

```
class Foo:

    @property
    def bar(self):
        '''The bar attribute'''
        return self.__dict__['bar']
```

```
    @bar.setter
    def bar(self, value):
        self.__dict__['bar'] = value
```

Now that we have these property essentials covered, let's go back to the issue of protecting both the `weight` and `price` attributes of `LineItem` so they only accept values greater than zero—but without implementing two nearly identical pairs of getters/setters by hand.

Coding a Property Factory

We'll create a factory to create `quantity` properties—so named because the managed attributes represent quantities that can't be negative or zero in the application. Example 23-27 shows the clean look of the `LineItem` class using two instances of `quantity` properties: one for managing the `weight` attribute, the other for `price`.

Example 23-27. bulkfood_v2prop.py: the quantity property factory in use

```
class LineItem:
    weight = quantity('weight')  ❶
    price = quantity('price')  ❷

    def __init__(self, description, weight, price):
        self.description = description
        self.weight = weight  ❸
        self.price = price

    def subtotal(self):
        return self.weight * self.price  ❹
```

❶ Use the factory to define the first custom property, `weight`, as a class attribute.

❷ This second call builds another custom property, `price`.

❸ Here the property is already active, making sure a negative or `0` `weight` is rejected.

❹

The properties are also in use here, retrieving the values stored in the instance.

Recall that properties are class attributes. When building each `quantity` property, we need to pass the name of the `LineItem` attribute that will be managed by that specific property. Having to type the word `weight` twice in this line is unfortunate:

```
weight = quantity('weight')
```

But avoiding that repetition is complicated because the property has no way of knowing which class attribute name will be bound to it. Remember: the right-hand side of an assignment is evaluated first, so when `quantity()` is invoked, the `weight` class attribute doesn't even exist.

> **NOTE**
>
> Improving the `quantity` property so that the user doesn't need to retype the attribute name is a nontrivial metaprogramming problem. We'll see a workaround in Chapter 24, but real solutions will have to wait until Chapter 25, because they require either a class decorator or a metaclass.

Example 23-28 lists the implementation of the `quantity` property factory.[11]

Example 23-28. bulkfood_v2prop.py: the quantity property factory

```
def quantity(storage_name):  ❶

    def qty_getter(instance):  ❷
        return instance.__dict__[storage_name]  ❸

    def qty_setter(instance, value):  ❹
        if value > 0:
            instance.__dict__[storage_name] = value  ❺
        else:
            raise ValueError('value must be > 0')

    return property(qty_getter, qty_setter)  ❻
```

❶ The `storage_name` argument determines where the data for each property is stored; for the `weight`, the storage name will be `'weight'`.

❷ The first argument of the `qty_getter` could be named `self`, but that would be strange because this is not a class body; `instance` refers to the `LineItem` instance where the attribute will be stored.

❸ `qty_getter` references `storage_name`, so it will be preserved in the closure of this function; the value is retrieved directly from the `instance.__dict__` to bypass the property and avoid an infinite recursion.

❹ `qty_setter` is defined, also taking `instance` as first argument.

❺ The `value` is stored directly in the `instance.__dict__`, again bypassing the property.

❻ Build a custom property object and return it.

The bits of Example 23-28 that deserve careful study revolve around the `storage_name` variable. When you code each property in the traditional way, the name of the attribute where you will store a value is hardcoded in the getter and setter methods. But here, the `qty_getter` and `qty_setter` functions are generic, and they depend on the `storage_name` variable to know where to get/set the managed attribute in the instance `__dict__`. Each time the `quantity` factory is called to build a property, the `storage_name` must be set to a unique value.

The functions `qty_getter` and `qty_setter` will be wrapped by the `property` object created in the last line of the factory function. Later when called to perform their duties, these functions will read the `storage_name` from their closures, to determine where to retrieve/store the managed attribute values.

In Example 23-29, I create and inspect a `LineItem` instance, exposing the storage attributes.

Example 23-29. bulkfood_v2prop.py: the quantity property factory

```
    >>> nutmeg = LineItem('Moluccan nutmeg', 8, 13.95)
    >>> nutmeg.weight, nutmeg.price  ❶
    (8, 13.95)
    >>> sorted(vars(nutmeg).items())  ❷
    [('description', 'Moluccan nutmeg'), ('price', 13.95),
('weight', 8)]
```

❶ Reading the `weight` and `price` through the properties shadowing the namesake instance attributes.

❷ Using `vars` to inspect the `nutmeg` instance: here we see the actual instance attributes used to store the values.

Note how the properties built by our factory leverage the behavior described in "Properties Override Instance Attributes": the `weight` property overrides the `weight` instance attribute so that every reference to `self.weight` or `nutmeg.weight` is handled by the property functions, and the only way to bypass the property logic is to access the instance `__dict__` directly.

The code in Example 23-29 may be a bit tricky, but it's concise: it's identical in length to the decorated getter/setter pair defining just the `weight` property in Example 23-21. The `LineItem` definition in Example 23-27 looks much better without the noise of the getter/setters.

In a real system, that same kind of validation may appear in many fields, across several classes, and the `quantity` factory would be placed in a utility module to be used over and over again. Eventually that simple factory could be refactored into a more extensible descriptor class, with specialized subclasses performing different validations. We'll do that in Chapter 24.

Now let us wrap up the discussion of properties with the issue of attribute deletion.

Handling Attribute Deletion

Recall from the Python tutorial that object attributes can be deleted using the `del` statement:

```
del my_object.an_attribute
```

In practice, deleting attributes is not something we do every day in Python, and the requirement to handle it with a property is even more unusual. But it is supported, and I can think of a silly example to demonstrate it.

In a property definition, the `@my_property.deleter` decorator wraps the method in charge of deleting the attribute managed by the property. As promised, Example 23-30 is a silly example showing how to code a property deleter.

Example 23-30. blackknight.py: inspired by the Black Knight character of "Monty Python and the Holy Grail"

```
class BlackKnight:

    def __init__(self):
        self.phrases = [
            ('an arm', "'Tis but a scratch."),
            ('another arm', "It's just a flesh wound."),
            ('a leg', "I'm invincible!"),
            ('another leg', "All right, we'll call it a draw.")
        ]

    @property
    def member(self):
        print('next member is:')
        return self.phrases[0][0]

    @member.deleter
    def member(self):
        member, text = self.phrases.pop(0)
        print(f'BLACK KNIGHT (loses {member}) -- {text}')
```

The doctests in *blackknight.py* are in Example 23-31.

Example 23-31. blackknight.py: doctests for Example 23-30 (the Black Knight never concedes defeat)

```
>>> knight = BlackKnight()
>>> knight.member
next member is:
'an arm'
>>> del knight.member
BLACK KNIGHT (loses an arm) -- 'Tis but a scratch.
>>> del knight.member
BLACK KNIGHT (loses another arm) -- It's just a flesh wound.
>>> del knight.member
BLACK KNIGHT (loses a leg) -- I'm invincible!
>>> del knight.member
BLACK KNIGHT (loses another leg) -- All right, we'll call it a
draw.
```

Using the classic call syntax instead of decorators, the `fdel` argument configures the deleter function. For example, the `member` property would be coded like this in the body of the `BlackKnight` class:

```
member = property(member_getter, fdel=member_deleter)
```

If you are not using a property, attribute deletion can also be handled by implementing the lower-level `__delattr__` special method, presented in "Special Methods for Attribute Handling". Coding a silly class with `__delattr__` is left as an exercise to the procrastinating reader.

Properties are a powerful feature, but sometimes simpler or lower-level alternatives are preferable. In the final section of this chapter, we'll review some of the core APIs that Python offers for dynamic attribute programming.

Essential Attributes and Functions for Attribute Handling

Throughout this chapter, and even before in the book, we've used some of the built-in functions and special methods Python provides for dealing with dynamic attributes. This section gives an overview of them in one place, because their documentation is scattered in the official docs.

Special Attributes that Affect Attribute Handling

The behavior of many of the functions and special methods listed in the following sections depend on three special attributes:

`__class__`

A reference to the object's class (i.e., `obj.__class__` is the same as `type(obj)`). Python looks for special methods such as `__getattr__` only in an object's class, and not in the instances themselves.

`__dict__`

A mapping that stores the writable attributes of an object or class. An object that has a `__dict__` can have arbitrary new attributes set at any time. If a class has a `__slots__` attribute, then its instances may not have a `__dict__`. See `__slots__` (next).

`__slots__`

An attribute that may be defined in a class to limit the attributes its instances can have. `__slots__` is a `tuple` of strings naming the allowed attributes.[12] If the `'__dict__'` name is not in `__slots__`, then the instances of that class will not have a `__dict__` of their own, and only the named attributes will be allowed in them.

Built-In Functions for Attribute Handling

These five built-in functions perform object attribute reading, writing, and introspection:

`dir([object])`

Lists most attributes of the object. The official docs say `dir` is intended for interactive use so it does not provide a comprehensive list of attributes, but an "interesting" set of names. `dir` can inspect objects implemented with or without a `__dict__`. The `__dict__` attribute itself is not listed by `dir`, but the `__dict__` keys are listed. Several special attributes of classes, such as `__mro__`, `__bases__`, and `__name__` are not listed by `dir` either. If the optional `object` argument is not given, `dir` lists the names in the current scope.

`getattr(object, name[, default])`

Gets the attribute identified by the `name` string from the `object`. This may fetch an attribute from the object's class or from a superclass. If no such attribute exists, `getattr` raises `AttributeError` or returns the `default` value, if given.

`hasattr(object, name)`

Returns `True` if the named attribute exists in the `object`, or can be somehow fetched through it (by inheritance, for example). The documentation explains: "This is implemented by calling getattr(object, name) and seeing whether it raises an AttributeError or not."

`setattr(object, name, value)`

Assigns the `value` to the named attribute of `object`, if the `object` allows it. This may create a new attribute or overwrite an existing one.

`vars([object])`

Returns the `__dict__` of `object`; `vars` can't deal with instances of classes that define `__slots__` and don't have a `__dict__` (contrast with `dir`, which handles such instances). Without an argument, `vars()` does the same as `locals()`: returns a `dict` representing the local scope.

Special Methods for Attribute Handling

When implemented in a user-defined class, the special methods listed here handle attribute retrieval, setting, deletion, and listing.

Attribute access using either dot notation or the built-in functions `getattr`, `hasattr`, and `setattr` trigger the appropriate special methods listed here. Reading and writing attributes directly in the instance `__dict__` does not trigger these special methods—and that's the usual way to bypass them if needed.

"Section 3.3.9. Special method lookup" of the "Data model" chapter warns:

> *For custom classes, implicit invocations of special methods are only guaranteed to work correctly if defined on an object's type, not in the object's instance dictionary.*

In other words, assume that the special methods will be retrieved on the class itself, even when the target of the action is an instance. For this reason, special methods are not shadowed by instance attributes with the same name.

In the following examples, assume there is a class named `Class`, `obj` is an instance of `Class`, and `attr` is an attribute of `obj`.

For every one of these special methods, it doesn't matter if the attribute access is done using dot notation or one of the built-in functions listed in "Built-In Functions for Attribute Handling". For example, both `obj.attr` and `getattr(obj, 'attr', 42)` trigger `Class.__getattribute__(obj, 'attr')`.

`__delattr__(self, name)`

Always called when there is an attempt to delete an attribute using the `del` statement; e.g., `del obj.attr` triggers `Class.__delattr__(obj, 'attr')`.

`__dir__(self)`

Called when `dir` is invoked on the object, to provide a listing of attributes; e.g., `dir(obj)` triggers `Class.__dir__(obj)`.

`__getattr__(self, name)`

Called only when an attempt to retrieve the named attribute fails, after the `obj`, `Class`, and its superclasses are searched. The expressions `obj.no_such_attr`, `getattr(obj, 'no_such_attr')`, and `hasattr(obj, 'no_such_attr')` may trigger `Class.__getattr__(obj, 'no_such_attr')`, but only if an attribute by that name cannot be found in `obj` or in `Class` and its superclasses.

`__getattribute__(self, name)`

Always called when there is an attempt to retrieve the named attribute, except when the attribute sought is a special attribute or method. Dot notation and the `getattr` and `hasattr` built-ins trigger this method. `__getattr__` is only invoked after `__getattribute__`, and only when `__getattribute__` raises `AttributeError`. To retrieve attributes of the instance `obj` without triggering an infinite recursion, implementations of `__getattribute__` should use `super().__getattribute__(obj, name)`.

`__setattr__(self, name, value)`

Always called when there is an attempt to set the named attribute. Dot notation and the `setattr` built-in trigger this method; e.g., both `obj.attr = 42` and `setattr(obj, 'attr', 42)` trigger `Class.__setattr__(obj, 'attr', 42)`.

> **TIP**
>
> In practice, because they are unconditionally called and affect practically every attribute access, the `__getattribute__` and `__setattr__` special methods are harder to use correctly than `__getattr__`—which only handles nonexisting attribute names. Using properties or descriptors is less error prone than defining these special methods.

This concludes our dive into properties, special methods, and other techniques for coding dynamic attributes.

Chapter Summary

We started our coverage of dynamic attributes by showing practical examples of simple classes to make it easier to deal with a JSON dataset. The first example was the `FrozenJSON` class that converted nested dicts and lists into nested `FrozenJSON` instances and lists of them. The `FrozenJSON` code demonstrated the use of the `__getattr__` special method to convert data structures on the fly, whenever their attributes were read. The last version of `FrozenJSON` showcased the use of the `__new__` constructor method to transform a class into a flexible factory of objects, not limited to instances of itself.

We then converted the JSON dataset to a `dict` storing instances of a `Record` class. The first rendition of `Record` was a few lines long and introduced the "bunch" idiom: using `self.__dict__.update(**kwargs)` to build arbitrary attributes from keyword arguments passed to `__init__`. The second iteration added the `Event` class implementing automatic retrieval of linked records through properties. Computed property values sometimes require caching, and we covered a few ways of doing that. After realizing that `@functools.cached_property` does not implement the basic behavior expected of methods decorated with the `@property` built-in, we finally settled on the use of `@cached_property` in one method, and `@functools.cache` decorated with `@property` in the other method.

Coverage of properties continued with the `LineItem` class, where a property was deployed to protect a `weight` attribute from negative or zero values that make no business sense. After a deeper look at property syntax and semantics, we created a property factory to enforce the same validation on `weight` and `price`, without coding multiple getters and setters. The property factory leveraged subtle concepts—such as closures and the instance attribute overriding by properties—to provide an elegant generic solution using the same number of lines as a single hand-coded property definition.

Finally, we had a brief look at handling attribute deletion with properties, followed by an overview of the key special attributes, built-in functions, and special methods that support attribute metaprogramming in the core Python language.

Further Reading

The official documentation for the attribute handling and introspection built-in functions is Chapter 2, "Built-in Functions" of *The Python Standard Library*. The related special methods and the `__slots__` special attribute are documented in The Python Language Reference in "3.3.2. Customizing attribute access". The semantics of how special methods are invoked bypassing instances is explained in "3.3.9. Special method lookup". In Chapter 4, "Built-in Types," of the Python Standard Library, "4.13. Special Attributes" covers `__class__` and `__dict__` attributes.

Python Cookbook, 3E by David Beazley and Brian K. Jones (O'Reilly) has several recipes covering the topics of this chapter, but I will highlight three that are outstanding: "Recipe 8.8. Extending a Property in a Subclass" addresses the thorny issue of overriding the methods inside a property inherited from a superclass; "Recipe 8.15. Delegating Attribute Access" implements a proxy class showcasing most special methods from "Special Methods for Attribute Handling" in this book; and the awesome "Recipe 9.21. Avoiding Repetitive Property Methods," which was the basis for the property factory function presented in Example 23-28.

Python in a Nutshell, 3E (O'Reilly), by Alex Martelli, Anna Ravenscroft, and Steve Holden is rigorous and objective. They devote only three pages to properties, but that's because the book follows an axiomatic presentation style: the preceding 15 pages or so provide a thorough description of the semantics of Python classes from the ground up, including descriptors, which are how properties are actually implemented under the hood. So by the time Martelli et.al. get to properties, they can pack a lot of insights in those three pages—including that which I selected to open this chapter.

Bertrand Meyer—quoted in the *Uniform Access Principle* definition in this chapter opening—pioneered the Design by Contract methodology, designed the Eiffel language, and wrote the excellent *Object-Oriented Software Construction, 2E* (Prentice-Hall). The book is more than 1,250 pages long, and I confess I did not read it all, but the first six chapters provide one of the best conceptual introductions to OO analysis and design I've seen. Chapter 11 presents Design by Contract, and Chapter 35 offers his assessments of some influential OO languages: Simula, Smalltalk, CLOS (the Common Lisp Object System), Objective-C, C++, and Java, with brief comments on some others. Only in the last page of the book he reveals that the highly readable "notation" he uses as pseudocode is Eiffel.

SOAPBOX

Meyer's *Uniform Access Principle* is aesthetically appealing. As a programmer using an API, I shouldn't have to care whether `product.price` simply fetches a data attribute or performs a computation. As a consumer and a citizen, I do care: in e-commerce today the value of `product.price` often depends on who is asking, so it's certainly not a mere data attribute. In fact, it's common practice that the price is lower if the query comes from outside the store—say, from a price-comparison engine. This effectively punishes loyal customers who like to browse within a particular store. But I digress.

The previous digression does raise a relevant point for programming: although the Uniform Access Principle makes perfect sense in an ideal world, in reality users of an API may need to know whether reading `product.price` is potentially too expensive or time-consuming. That's a problem with programming abstractions in general: they make it hard to reason about the runtime cost of evaluating an expression. On the other hand, abstractions let users accomplish more with less code. It's a trade-off. As usual in matters of software engineering, Ward Cunningham's original Wiki hosts insightful arguments about the merits of the Uniform Access Principle.

In object-oriented programming languages, application or violations of the Uniform Access Principle usually revolve around the syntax of reading public data attributes versus invoking getter/setter methods.

Smalltalk and Ruby address this issue in a simple and elegant way: they don't support public data attributes at all. Every instance attribute in these languages is private, so every access to them must be through methods. But their syntax makes this painless: in Ruby, `product.price` invokes the `price` getter; in Smalltalk, it's simply `product price`.

At the other end of the spectrum, the Java language allows the programmer to choose among four access level modifiers.[13]

The general practice does not agree with the syntax established by the Java designers, though. Everybody in Java-land agrees that attributes should be `private`, and you must spell it out every time, because it's not the default. When all attributes are private, all access to them from outside the class must go through accessors. Java IDEs include shortcuts for generating accessor methods automatically. Unfortunately, the IDE is not so helpful when you must read the code six months later. It's up to you to wade through a sea of do-nothing accessors to find those that add value by implementing some business logic.

Alex Martelli speaks for the majority of the Python community when he calls accessors "goofy idioms" and then provides these examples that look very different but do the same thing:[14]

```
someInstance.widgetCounter += 1
# rather than...
someInstance.setWidgetCounter(someInstance.getWidgetCounter()
+ 1)
```

Sometimes when designing APIs, I've wondered whether every method that does not take an argument (besides `self`), returns a value (other than `None`), and is a pure function (i.e., has no side effects) should be replaced by a read-only property. In this chapter, the `LineItem.subtotal` method (as in Example 23-27) would be a good candidate to become a read-only property. Of course, this excludes methods that are designed to change the object, such as `my_list.clear()`. It would be a terrible idea to turn that into a property, so that merely accessing `my_list.clear` would delete the contents of the list!

In the Pingo.io GPIO library (mentioned in "The `__missing__` Method"), much of the user-level API is based on properties. For example, to read the current value of an analog pin, the user writes `pin.value`, and setting a digital pin mode is written as `pin.mode = OUT`. Behind the scenes, reading an analog pin value or setting a digital pin mode may involve a lot of code, depending on the specific board driver. We decided to use properties in Pingo because we want the API to be comfortable to use even in interactive environments like iPython Notebook, and we feel `pin.mode = OUT` is easier on the eyes and on the fingers than `pin.set_mode(OUT)`.

Although I find the Smalltalk and Ruby solution cleaner, I think the Python approach makes more sense than the Java one. We are allowed to start simple, coding data members as public attributes, because we know they can always be wrapped by properties (or descriptors, which we'll talk about in the next chapter).

`__new__` Is Better Than `new`

Another example of the Uniform Access Principle (or a variation of it) is the fact that function calls and object instantiation use the same syntax in Python: `my_obj = foo()`, where `foo` may be a class or any other callable.

Other languages influenced by C++ syntax have a `new` operator that makes instantiation look different than a call. Most of the time, the user of an API doesn't care whether `foo` is a function or a class. Until recently, I was under the impression that `property` was a function. In normal usage, it makes no difference.

There are many good reasons for replacing constructors with factories.[15] A popular motive is limiting the number of instances, by returning previously built ones (as in the Singleton pattern). A related use is caching expensive object construction. Also, sometimes it's convenient to return objects of different types depending on the arguments given.

Coding a constructor is simpler; providing a factory adds flexibility at the expense of more code. In languages that have a `new` operator, the designer of an API must decide in advance whether to stick with a simple constructor or invest in factory. If the initial choice is wrong, the correction may be costly—all because `new` is an operator.

Sometimes it may also be convenient to go the other way, and replace a simple function with a class.

In Python, classes and functions are interchangeable in many situations. Not only because there's no `new` operator, but also because there is the `__new__` special method, which can turn a class into a factory producing objects of different kinds (as we saw in "Flexible Object Creation with __new__") or returning prebuilt instances instead of creating a new one every time.

This function-class duality would be easier to leverage if PEP 8 — Style Guide for Python Code did not recommend `CamelCase` for class names. On the other hand, dozens of classes in the standard library have lowercase names (e.g., `property`, `str`, `defaultdict`, etc.). So maybe the use of lowercase class names is a feature, and not a bug. But however we look at it, the inconsistent capitalization of classes in the Python standard library poses a usability problem.

Although calling a function is not different than calling a class, it's good to know which is which because of another thing we can do with a class: subclassing. So I personally use `CamelCase` in every class that I code, and I wish all classes in the Python standard library used the same convention. I am looking at you, `collections.OrderedDict` and `collections.defaultdict`.

---

1 Alex Martelli, Anna Ravenscroft & Steve Holden, *Python in a Nutshell, 3rd Edition* (O'Reilly), p. 123.

2 Bertrand Meyer, *Object-Oriented Software Construction*, 2E, p. 57.

3 The OSCON conferences were a permanent casualty of the COVID-19 pandemic. The original 744KB JSON file I used for these examples is still online as of December 19, 2020. A copy named *osconfeed.json* can be found in the *23-dyn-attr-prop/oscon/data* directory in the example code repository

4 Two examples are AttrDict and addict.

5 The expression `self.__data[name]` is where a `KeyError` exception may occur. Ideally, it should be handled and an `AttributeError` raised instead, because that's what is

expected from `__getattr__`. The diligent reader is invited to code the error handling as an exercise.

6 The source of the data is JSON, and the only collection types in JSON data are `dict` and `list`.

7 By the way, `Bunch` is the name of the class used by Alex Martelli to share this tip in a recipe from 2001 titled "The simple but handy *collector of a bunch of named stuff* class". The comments on Alex's recipe suggest interesting enhancements.

8 This is actually a downside of Meyer's Uniform Access Principle, which I mentioned in the opening of this chapter. Read the optional "Soapbox" if you're interested in this discussion.

9 Source: @functools.cached_property documentation. I know Raymond Hettinger authored this explanation because he wrote it as a response to an issue I filed: bpo42781—functools.cached_property docs should explain that it is non-overriding. Hettinger is a major contributor to the official Python docs and standard library. He also wrote the excellent Descriptor HowTo Guide, a key resource for Chapter 24.

10 Direct quote by Jeff Bezos in the *Wall Street Journal* story "Birth of a Salesman" (October 15, 2011).

11 This code is adapted from "Recipe 9.21. Avoiding Repetitive Property Methods" from *Python Cookbook, 3E* by David Beazley and Brian K. Jones (O'Reilly).

12 Alex Martelli points out that, although `__slots__` can be coded as a `list`, it's better to be explicit and always use a `tuple`, because changing the list in the `__slots__` after the class body is processed has no effect, so it would be misleading to use a mutable sequence there.

13 Including the no-name default that the Java Tutorial calls "package-private."

14 Alex Martelli, *Python in a Nutshell, 2E* (O'Reilly), p. 101.

15 The reasons I am about to mention are given in the Dr. Dobbs Journal article titled "Java's new Considered Harmful", by Jonathan Amsterdam and in *"Consider static factory methods instead of constructors"*, which is Item 1 of the award-winning book *Effective Java* (Addison-Wesley) by Joshua Bloch.

Chapter 24. Attribute Descriptors

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author’s raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 24th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

> *Learning about descriptors not only provides access to a larger toolset, it creates a deeper understanding of how Python works and an appreciation for the elegance of its design.*[1]
>
> —Raymond Hettinger, Python core developer and guru

Descriptors are a way of reusing the same access logic in multiple attributes. For example, field types in ORMs such as the Django ORM and SQL Alchemy are descriptors, managing the flow of data from the fields in a database record to Python object attributes and vice versa.

A descriptor is a class that implements a dynamic protocol consisting of the `__get__`, `__set__`, and `__delete__` methods. The `property` class implements the full descriptor protocol. As usual with dynamic protocols, partial implementations are OK. In fact, most descriptors we see in real code implement only `__get__` and `__set__`, and many implement only one of these methods.

Descriptors are a distinguishing feature of Python, deployed not only at the application level but also in the language infrastructure. Besides properties, other Python features that leverage descriptors are methods and the `classmethod` and `staticmethod` decorators. Understanding descriptors is key to Python mastery. This is what this chapter is about.

What's new in this chapter

The `Quantity` descriptor example in "LineItem Take #4: Automatic Storage Attribute Names" was dramatically simplified thanks to the `__set_name__` special method added to the descriptor protocol in Python 3.6.

I removed the property factory example formerly in "LineItem Take #4: Automatic Storage Attribute Names" because it became irrelevant: the point was to show an alternative way of solving the `Quantity` problem, but with the addition of `__set_name__` the descriptor solution becomes much simpler.

The `AutoStorage` class that used to appear in "LineItem Take #5: A New Descriptor Type" is also gone because `__set_name__` made it obsolete.

Descriptor Example: Attribute Validation

As we saw in "Coding a Property Factory", a property factory is a way to avoid repetitive coding of getters and setters by applying functional programming patterns. A property factory is a higher-order function that creates a parameterized set of accessor functions and builds a custom property instance from them, with closures to hold settings like the `storage_name`. The object-oriented way of solving the same problem is a descriptor class.

We'll continue the series of `LineItem` examples where we left it, in "Coding a Property Factory", by refactoring the `quantity` property factory into a `Quantity` descriptor class.

LineItem Take #3: A Simple Descriptor

A class implementing a `__get__`, a `__set__`, or a `__delete__` method is a descriptor. You use a descriptor by declaring instances of it as class attributes of another class.

We'll create a `Quantity` descriptor and the `LineItem` class will use two instances of `Quantity`: one for managing the `weight` attribute, the other for `price`. A diagram helps, so take a look at Figure 24-1.

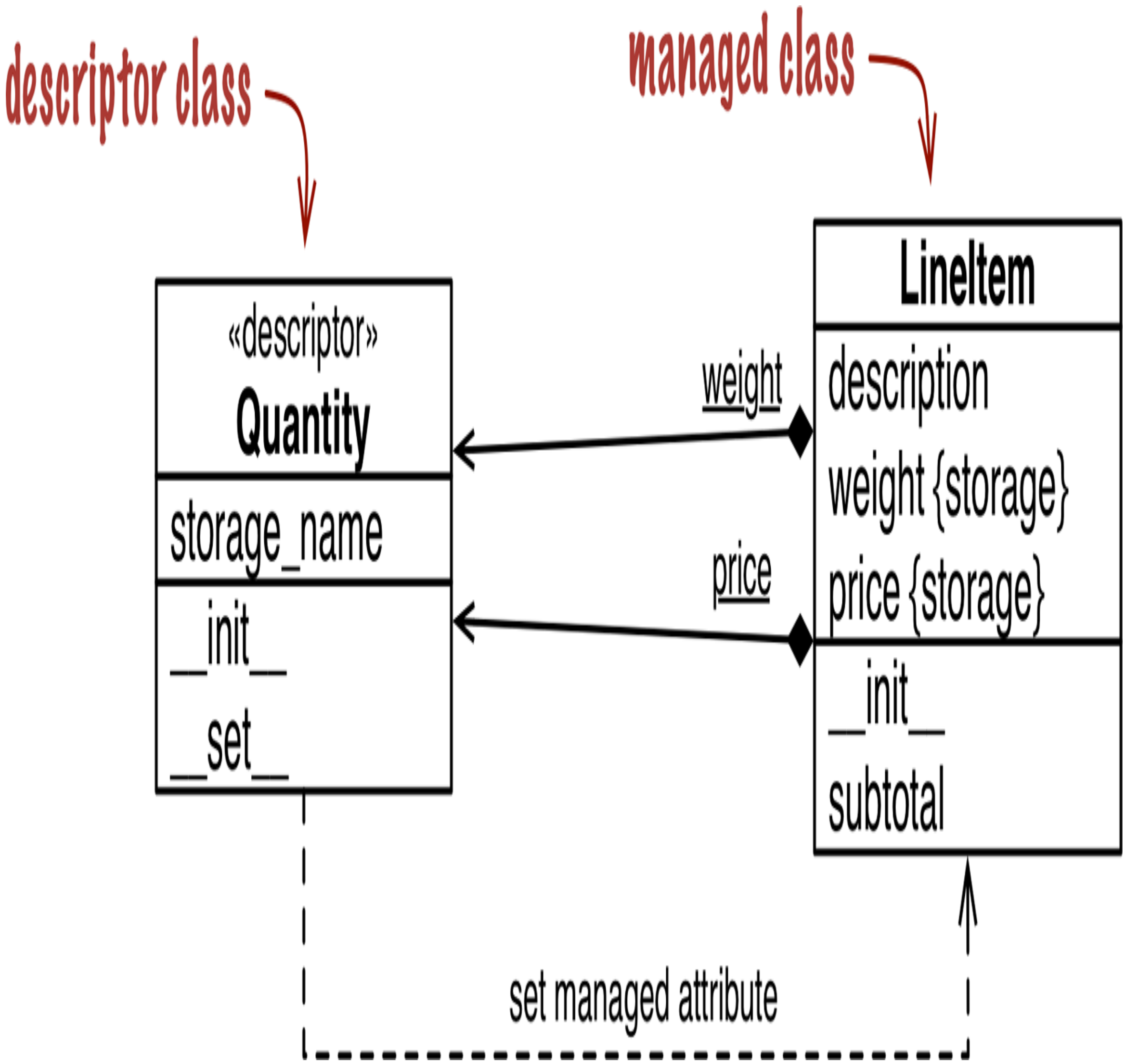

Figure 24-1. UML class diagram for LineItem using a descriptor class named Quantity. Underlined attributes in UML are class attributes. Note that weight and price are instances of Quantity attached to the LineItem class, but LineItem instances also have their own weight and price attributes where those values are stored.

Note that the word `weight` appears twice in Figure 24-1, because there are really two distinct attributes named `weight`: one is a class attribute of `LineItem`, the other is an instance attribute that will exist in each `LineItem` object. This also applies to `price`.

From now on, I will use the following definitions:

Descriptor class

A class implementing the descriptor protocol. That’s `Quantity` in Figure 24-1.

Managed class

The class where the descriptor instances are declared as class attributes —`LineItem` in Figure 24-1.

Descriptor instance

Each instance of a descriptor class, declared as a class attribute of the managed class. In Figure 24-1, each descriptor instance is represented by a composition arrow with an underlined name (the underline means class attribute in UML). The black diamonds touch the `LineItem` class, which contains the descriptor instances.

Managed instance

One instance of the managed class. In this example, `LineItem` instances will be the managed instances (they are not shown in the class diagram).

Storage attribute

An attribute of the managed instance that will hold the value of a managed attribute for that particular instance. In Figure 24-1, the `LineItem` instance attributes `weight` and `price` will be the storage attributes. They are distinct from the descriptor instances, which are always class attributes.

Managed attribute

A public attribute in the managed class that will be handled by a descriptor instance, with values stored in storage attributes. In other words, a descriptor instance and a storage attribute provide the infrastructure for a managed attribute.

It's important to realize that `Quantity` instances are class attributes of `LineItem`. This crucial point is highlighted by the mills and gizmos in Figure 24-2.

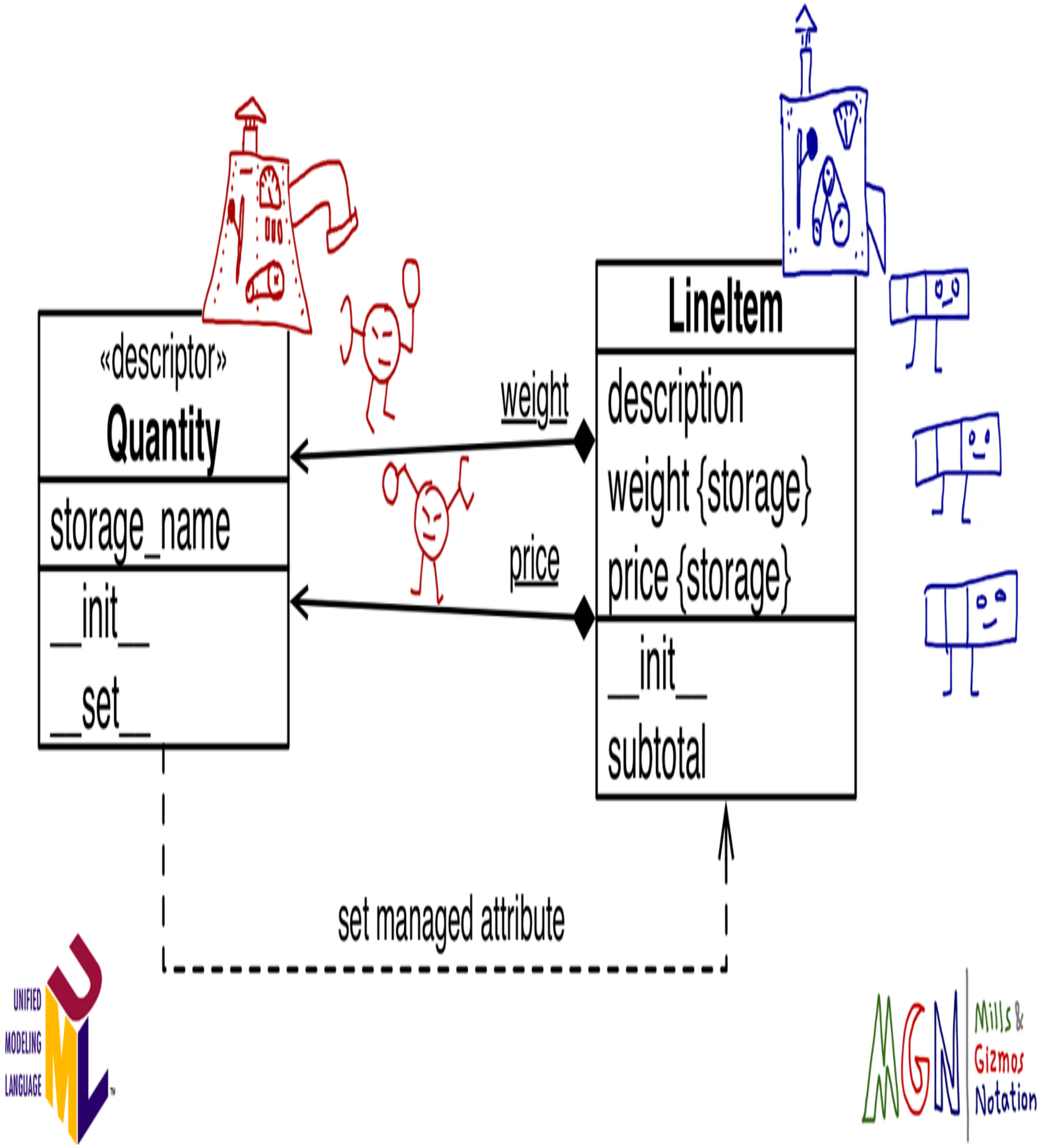

Figure 24-2. UML class diagram annotated with MGN (Mills & Gizmos Notation): classes are mills that produce gizmos—the instances. The Quantity mill produces two gizmos with round heads, which are attached to the LineItem mill: weight and price. The LineItem mill produces rectangular gizmos that have their own weight and price attributes where those values are stored.

INTRODUCING MILLS & GIZMOS NOTATION

After explaining descriptors many times, I realized UML is not very good at showing relationships involving classes and instances, like the relationship between a managed class and the descriptor instances.[2] So I invented my own “language,” the Mills & Gizmos Notation (MGN), which I use to annotate UML diagrams.

MGN is designed to make very clear the distinction between classes and instances. See Figure 24-3. In MGN, a class is drawn as a “mill,” a complicated machine that produces gizmos. Classes/mills are always machines with levers and dials. The gizmos are the instances, and they look much simpler. When this book is rendered in color, gizmos have the same color as the mill that made it.

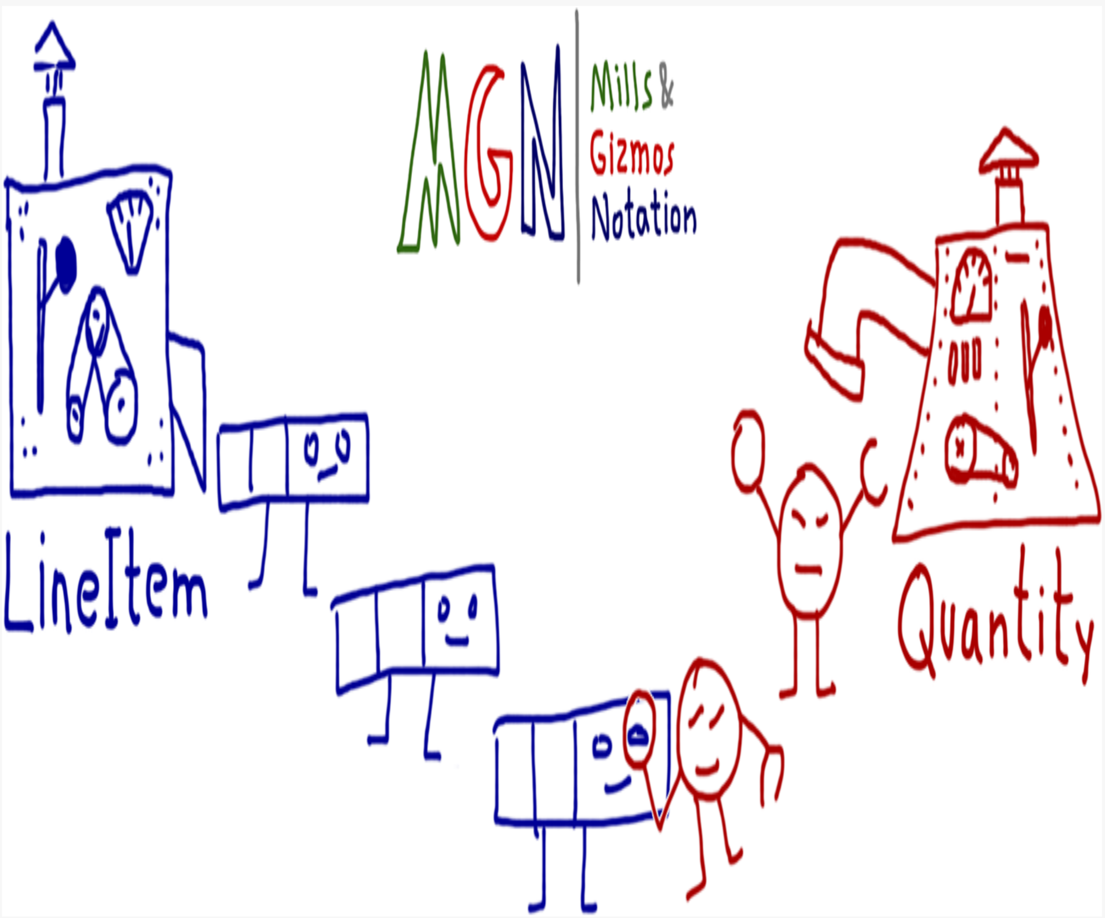

Figure 24-3. MGN sketch showing the LineItem class making three instances, and Quantity making two. One instance of Quantity is retrieving a value stored in a LineItem instance.

For this example, I drew `LineItem` instances as rows in a tabular invoice, with three cells representing the three attributes (`description`, `weight`, and `price`). Because `Quantity` instances are descriptors, they have a magnifying glass to `__get__` values and a claw to `__set__` values. When we get to metaclasses, you'll thank me for these doodles.

Enough doodling for now. Here is the code: Example 24-1 shows the `Quantity` descriptor class, and Example 24-2 lists a new `LineItem` class using two instances of `Quantity`.

Example 24-1. bulkfood_v3.py: Quantity descriptors manage attributes in LineItem

```
class Quantity:  ❶

    def __init__(self, storage_name):
        self.storage_name = storage_name  ❷

    def __set__(self, instance, value):  ❸
        if value > 0:
            instance.__dict__[self.storage_name] = value  ❹
        else:
            msg = f'{self.storage_name} must be > 0'
            raise ValueError(msg)

    def __get__(self, instance, owner):  ❺
        return instance.__dict__[self.storage_name]
```

❶ Descriptor is a protocol-based feature; no subclassing is needed to implement one.

❷ Each `Quantity` instance will have a `storage_name` attribute: that's the name of the storage attribute to hold the value in the managed instances.

❸ `__set__` is called when there is an attempt to assign to the managed attribute. Here, `self` is the descriptor instance (i.e., `LineItem.weight` or `LineItem.price`), `instance` is the managed instance (a `LineItem` instance), and `value` is the value being assigned.

❹ We must store attribute value directly into `__dict__`; calling `setattr(self, self.storage_name)` would trigger the `__set__` method again, leading to infinite recursion.

❺ We need to implement `__get__` because the name of the managed attribute may not the same as the `storage_name`. The `owner` argument will be explained shortly.

Implementing `__get__` is necessary because a user could write something like this:

```
class House:
    rooms = Quantity('number_of_rooms')
```

In the `House` class, the managed attribute is `rooms`, but the storage attribute is `number_of_rooms`.

Note that `__get__` receives three arguments: `self`, `instance`, and `owner`. The `owner` argument is a reference to the managed class (e.g., `LineItem`), and it's useful if you want the descriptor to support retrieving a class attribute—perhaps to emulate Python's default behavior of retrieving a class attribute when the name is not found in the instance.

If a managed attribute, such as `weight`, is retrieved via the class like `LineItem.weight`, the descriptor `__get__` method receives `None` as the value for the `instance` argument.

To support introspection and other metaprogramming tricks by the user, it's a good practice to make `__get__` return the descriptor instance when the managed attribute is accessed through the class. To do that, we'd code `__get__` like this:

```
    def __get__(self, instance, owner):
        if instance is None:
```

```
            return self
        else:
            return instance.__dict__[self.storage_name]
```

Example 24-2 demonstrates the use of `Quantity` in `LineItem`.

Example 24-2. bulkfood_v3.py: Quantity descriptors manage attributes in LineItem

```
class LineItem:
    weight = Quantity('weight')  ❶
    price = Quantity('price')  ❷

    def __init__(self, description, weight, price):  ❸
        self.description = description
        self.weight = weight
        self.price = price

    def subtotal(self):
        return self.weight * self.price
```

❶ The first descriptor instance will manage the `weight` attribute.

❷ The second descriptor instance will manage the `weight` attribute.

❸ The rest of the class body is as simple and clean as the original code in *bulkfood_v1.py* (Example 23-19).

The code in Example 24-2 works as intended, preventing the sale of truffles for $0:[3]

```
>>> truffle = LineItem('White truffle', 100, 0)
Traceback (most recent call last):
    ...
ValueError: value must be > 0
```

WARNING

When coding descriptor `__get__` and `__set__` methods, keep in mind what the `self` and `instance` arguments mean: `self` is the descriptor instance, and `instance` is the managed instance. Descriptors managing instance attributes should store values in the managed instances. That's why Python provides the `instance` argument to the descriptor methods.

It may be tempting, but wrong, to store the value of each managed attribute in the descriptor instance itself. In other words, in the `__set__` method, instead of coding:

```
instance.__dict__[self.storage_name] = value
```

the tempting but bad alternative would be:

```
self.__dict__[self.storage_name] = value
```

To understand why this would be wrong, think about the meaning of the first two arguments to `__set__`: `self` and `instance`. Here, `self` is the descriptor instance, which is actually a class attribute of the managed class. You may have thousands of `LineItem` instances in memory at one time, but you'll only have two instances of the descriptors: the class attributes `LineItem.weight` and `LineItem.price`. So anything you store in the descriptor instances themselves is actually part of a `LineItem` class attribute, and therefore is shared among all `LineItem` instances.

A drawback of Example 24-2 is the need to repeat the names of the attributes when the descriptors are instantiated in the managed class body. It would be nice if the `LineItem` class could be declared like this:

```
class LineItem:
    weight = Quantity()
    price = Quantity()

    # remaining methods as before
```

As it stands, Example 24-2 requires naming each `Quantity` explicitly, which is not only inconvenient but dangerous: if a programmer copy and pasting code forgets to edit both names and writes something like `price = Quantity('weight')`, the program will misbehave badly, clobbering the value of `weight` whenever the `price` is set.

The problem is that—as we saw in Chapter 6—the right-hand side of an assignment is executed before the variable exists. The expression `Quantity()` is evaluated to create a descriptor instance, and there is no way the code in the `Quantity` class can guess the name of the variable to which the descriptor will be bound (e.g., `weight` or `price`).

Thankfully, the descriptor protocol now supports the aptly named `__set_name__` special method. We'll see how to use it next.

> **NOTE**
>
> Automatic naming of a descriptor storage attribute used to be a thorny issue. In *Fluent Python, First Edition* I devoted several pages and lines of code in this chapter and the next to presenting different solutions, including the use of a class decorator and then a metaclasses in Chapter 25. This was greatly simplified in Python 3.6.

LineItem Take #4: Automatic Storage Attribute Names

To avoid retyping the attribute name in the descriptor instances, we'll implement `__set_name__` to create `storage_name` of each `Quantity` instance. The `__set_name__` special method was added to the descriptor protocol in Python 3.6. The interpreter calls `__set_name__` on each descriptor it finds in a `class` body—if the descriptor implements it.[4]

In Example 24-3, the `LineItem` descriptor class doesn't need an `__init__`. Instead, `__set_item__` saves the name of the storage attribute.

Example 24-3. bulkfood_v4.py: `__set_name__` sets the name for each Quantity descriptor instance

```
class Quantity:

    def __set_name__(self, owner, name):  ❶
        self.storage_name = name          ❷

    def __set__(self, instance, value):   ❸
        if value > 0:
            instance.__dict__[self.storage_name] = value
        else:
            msg = f'{self.storage_name} must be > 0'
            raise ValueError(msg)

    # no __get__ needed  ❹

class LineItem:
    weight = Quantity()  ❺
    price = Quantity()

    def __init__(self, description, weight, price):
        self.description = description
        self.weight = weight
        self.price = price

    def subtotal(self):
        return self.weight * self.price
```

❶ `self` is the descriptor instance (not the managed instance); `owner` is the managed class; and `name` is the name of the attribute of `owner` to which this descriptor instance was assigned in the class body of `owner`.

❷ This is what the `__init__` did in Example 24-2.

❸ The `__set__` method here is exactly the same as in Example 24-2.

❹ Implementing `__get__` is not necessary because the name of the storage attribute matches the name of the managed attribute. The expression `product.price` gets the `price` attribute directly from the `LineItem` instance.

❺ Now we don't need to pass the managed attribute name to the `Quantity` constructor. That was the goal for this version.

Looking at Example 24-3, you may think that's a lot of code just for managing a couple of attributes, but it's important to realize that the descriptor logic is now abstracted into a separate code unit: the `Quantity` class. Usually we do not define a descriptor in the same module where it's used, but in a separate utility module designed to be used across the application—even in many applications, if you are developing a framework.

With this in mind, Example 24-4 better represents the typical usage of a descriptor.

Example 24-4. bulkfood_v4c.py: LineItem definition uncluttered; the Quantity descriptor class now resides in the imported model_v4c module

```
import model_v4c as model  ❶


class LineItem:
    weight = model.Quantity()  ❷
    price = model.Quantity()

    def __init__(self, description, weight, price):
        self.description = description
        self.weight = weight
        self.price = price

    def subtotal(self):
        return self.weight * self.price
```

❶ Import the `model_v4c` module where `Quantity` is implemented.

❷ Put `model.Quantity` to use.

Django users will notice that Example 24-4 looks a lot like a model definition. It's no coincidence: Django model fields are descriptors.

Because descriptors are implemented as classes, we can leverage inheritance to reuse some of the code we have for new descriptors. That's what we'll do in the following section.

LineItem Take #5: A New Descriptor Type

The imaginary organic food store hits a snag: somehow a line item instance was created with a blank description and the order could not be fulfilled. To prevent that, we'll create a new descriptor, `NonBlank`. As we design `NonBlank`, we realize it will be very much like the `Quantity` descriptor, except for the validation logic.

This prompts a refactoring, producing `Validated`, an abstract class that overrides the `__set__` method, calling a `validate` method that must be implemented by subclasses.

We'll then rewrite `Quantity` and implement `NonBlank` by inheriting from `Validated` and just coding the `validate` methods.

The relationship between `Validated`, `Quantity`, and `NonBlank` is an application of the *Template Method* as described in the *Design Patterns* classic:

> *A template method defines an algorithm in terms of abstract operations that subclasses override to provide concrete behavior.*[5]

In Example 24-5, `Validated.__set__` is the template method and `self.validate` is the abstract operation.

Example 24-5. model_v5.py: the Validated ABC

```
import abc

class Validated(abc.ABC):

    def __set_name__(self, owner, name):
        self.storage_name = name

    def __set__(self, instance, value):
        value = self.validate(self.storage_name, value)  ❶
        instance.__dict__[self.storage_name] = value  ❷

    @abc.abstractmethod
    def validate(self, name, value):  ❸
        """return validated value or raise ValueError"""
```

❶ `__set__` delegates validation to the `validate` method…

❷ …then uses the returned `value` to update the stored value.

❸ `validate` is an abstract method; this is the template method.

Alex Martelli prefers to call this design pattern *Self-Delegation*, and I agree it's a more descriptive name: the first line of `__set__` self-delegates to `validate`.[6]

The concrete `Validated` subclasses in this example are `Quantity` and `NonBlank`, shown in Example 24-6.

Example 24-6. model_v5.py: Quantity and NonBlank, concrete Validated subclasses

```
class Quantity(Validated):
    """a number greater than zero"""

    def validate(self, name, value):  ❶
        if value <= 0:
            raise ValueError(f'{name} must be > 0')
        return value


class NonBlank(Validated):
    """a string with at least one non-space character"""

    def validate(self, name, value):
        value = value.strip()
        if len(value) == 0:
            raise ValueError(f'{name} cannot be blank')
        return value  ❷
```

Users of *model_v5.py* don't need to know all these details. What matters is that they get to use `Quantity` and `NonBlank` to automate the validation of instance attributes. See the latest `LineItem` class in Example 24-7.

Example 24-7. bulkfood_v5.py: LineItem using Quantity and NonBlank descriptors

```
import model_v5 as model  ❶

class LineItem:
    description = model.NonBlank()  ❷
```

```
    weight = model.Quantity()
    price = model.Quantity()

    def __init__(self, description, weight, price):
        self.description = description
        self.weight = weight
        self.price = price

    def subtotal(self):
        return self.weight * self.price
```

❶ Import the `model_v5` module, giving it a friendlier name.

❷ Put `model.NonBlank` to use. The rest of the code is unchanged.

The `LineItem` examples we've seen in this chapter demonstrate a typical use of descriptors to manage data attributes. Descriptors like `Quantity` are called overriding descriptors because its `__set__` method overrides (i.e., intercepts and overrules) the setting of an instance attribute by the same name in the managed instance. However, there are also non-overriding descriptors. We'll explore this distinction in detail in the next section.

Overriding Versus Non-Overriding Descriptors

Recall that there is an important asymmetry in the way Python handles attributes. Reading an attribute through an instance normally returns the attribute defined in the instance, but if there is no such attribute in the instance, a class attribute will be retrieved. On the other hand, assigning to an attribute in an instance normally creates the attribute in the instance, without affecting the class at all.

This asymmetry also affects descriptors, in effect creating two broad categories of descriptors depending on whether the `__set__` method is implemented. If `__set__` is present, the class is an overriding descriptor;

otherwise, it is a non-overriding descriptor. These terms will make sense as we study descriptor behaviors in the next examples.

Observing the different descriptor categories requires a few classes, so we'll use the code in Example 24-8 as our testbed for the following sections.

> **TIP**
>
> Every `__get__` and `__set__` method in Example 24-8 calls `print_args` so their invocations are displayed in a readable way. Understanding `print_args` and the auxiliary functions `cls_name` and `display` is not important, so don't get distracted by them.

Example 24-8. descriptorkinds.py: simple classes for studying descriptor overriding behaviors

```
### auxiliary functions for display only ###

def cls_name(obj_or_cls):
    cls = type(obj_or_cls)
    if cls is type:
        cls = obj_or_cls
    return cls.__name__.split('.')[-1]

def display(obj):
    cls = type(obj)
    if cls is type:
        return '<class {}>'.format(obj.__name__)
    elif cls in [type(None), int]:
        return repr(obj)
    else:
        return '<{} object>'.format(cls_name(obj))

def print_args(name, *args):
    pseudo_args = ', '.join(display(x) for x in args)
    print('-> {}.__{}__({})'.format(cls_name(args[0]), name,
pseudo_args))


### essential classes for this example ###

class Overriding:  ❶
    """a.k.a. data descriptor or enforced descriptor"""
```

```python
    def __get__(self, instance, owner):
        print_args('get', self, instance, owner)  ❷

    def __set__(self, instance, value):
        print_args('set', self, instance, value)


class OverridingNoGet:  ❸
    """an overriding descriptor without ``__get__``"""

    def __set__(self, instance, value):
        print_args('set', self, instance, value)


class NonOverriding:  ❹
    """a.k.a. non-data or shadowable descriptor"""

    def __get__(self, instance, owner):
        print_args('get', self, instance, owner)


class Managed:  ❺
    over = Overriding()
    over_no_get = OverridingNoGet()
    non_over = NonOverriding()

    def spam(self):  ❻
        print('-> Managed.spam({})'.format(display(self)))
```

❶ An overriding descriptor class with `__get__` and `__set__`.

❷ The `print_args` function is called by every descriptor method in this example.

❸ An overriding descriptor without a `__get__` method.

❹ No `__set__` method here, so this is a non-overriding descriptor.

❺ The managed class, using one instance of each of the descriptor classes.

❻ The `spam` method is here for comparison, because methods are also descriptors.

In the following sections, we will examine the behavior of attribute reads and writes on the `Managed` class and one instance of it, going through each of the different descriptors defined.

Overriding Descriptors

A descriptor that implements the `__set__` method is an *overriding descriptor*, because although it is a class attribute, a descriptor implementing `__set__` will override attempts to assign to instance attributes. This is how Example 24-3 was implemented. Properties are also overriding descriptors: if you don't provide a setter function, the default `__set__` from the `property` class will raise `AttributeError` to signal that the attribute is read-only. Given the code in Example 24-8, experiments with an overriding descriptor can be seen in Example 24-9.

> **WARNING**
>
> Python contributors and authors use different terms when discussing these concepts. I adopted "overriding descriptor" from the book *Python in a Nutshell*. The official Python documentation uses "data descriptor", but "overriding descriptor" highlights the special behavior. Overriding descriptors are also called "enforced descriptors". Synonyms for non-overriding descriptors include "non-data descriptors" or "shadowable descriptors".

Example 24-9. Behavior of an overriding descriptor: obj.over is an instance of Overriding (Example 24-8)

```
    >>> obj = Managed()  ❶
    >>> obj.over  ❷
    -> Overriding.__get__(<Overriding object>, <Managed object>,
        <class Managed>)
    >>> Managed.over  ❸
    -> Overriding.__get__(<Overriding object>, None, <class
Managed>)
    >>> obj.over = 7  ❹
    -> Overriding.__set__(<Overriding object>, <Managed object>, 7)
    >>> obj.over  ❺
    -> Overriding.__get__(<Overriding object>, <Managed object>,
        <class Managed>)
    >>> obj.__dict__['over'] = 8  ❻
```

```
>>> vars(obj)  ❼
{'over': 8}
>>> obj.over  ❽
-> Overriding.__get__(<Overriding object>, <Managed object>,
    <class Managed>)
```

❶ Create `Managed` object for testing.

❷ `obj.over` triggers the descriptor `__get__` method, passing the managed instance `obj` as the second argument.

❸ `Managed.over` triggers the descriptor `__get__` method, passing `None` as the second argument (`instance`).

❹ Assigning to `obj.over` triggers the descriptor `__set__` method, passing the value `7` as the last argument.

❺ Reading `obj.over` still invokes the descriptor `__get__` method.

❻ Bypassing the descriptor, setting a value directly to the `obj.__dict__`.

❼ Verify that the value is in the `obj.__dict__`, under the `over` key.

❽ However, even with an instance attribute named `over`, the `Managed.over` descriptor still overrides attempts to read `obj.over`.

Overriding Descriptor Without __get__

Properties and other overriding descriptors such as Django model fields implement both `__set__` and `__get__`, but it's also possible to implement only `__set__`, as we saw in Example 24-2. In this case, only writing is handled by the descriptor. Reading the descriptor through an instance will return the descriptor object itself because there is no `__get__` to handle that access. If a namesake instance attribute is created with a new value via direct access to the instance `__dict__`, the `__set__` method will still override further attempts to set that attribute, but reading that attribute will simply return the new value from the instance, instead of returning the descriptor object. In other words, the instance attribute will shadow the descriptor, but only when reading. See Example 24-10.

Example 24-10. Overriding descriptor without __get__: obj.over_no_get is an instance of OverridingNoGet (Example 24-8)

```
    >>> obj.over_no_get  ❶
    <__main__.OverridingNoGet object at 0x665bcc>
    >>> Managed.over_no_get  ❷
    <__main__.OverridingNoGet object at 0x665bcc>
    >>> obj.over_no_get = 7  ❸
    -> OverridingNoGet.__set__(<OverridingNoGet object>, <Managed
object>, 7)
    >>> obj.over_no_get  ❹
    <__main__.OverridingNoGet object at 0x665bcc>
    >>> obj.__dict__['over_no_get'] = 9  ❺
    >>> obj.over_no_get  ❻
    9
    >>> obj.over_no_get = 7  ❼
    -> OverridingNoGet.__set__(<OverridingNoGet object>, <Managed
object>, 7)
    >>> obj.over_no_get  ❽
    9
```

❶ This overriding descriptor doesn't have a `__get__` method, so reading `obj.over_no_get` retrieves the descriptor instance from the class.

❷ The same thing happens if we retrieve the descriptor instance directly from the managed class.

❸ Trying to set a value to `obj.over_no_get` invokes the `__set__` descriptor method.

❹ Because our `__set__` doesn't make changes, reading `obj.over_no_get` again retrieves the descriptor instance from the managed class.

❺

Going through the instance `__dict__` to set an instance attribute named `over_no_get`.

❻ Now that `over_no_get` instance attribute shadows the descriptor, but only for reading.

❼ Trying to assign a value to `obj.over_no_get` still goes through the descriptor set.

❽ But for reading, that descriptor is shadowed as long as there is a namesake instance attribute.

Non-overriding Descriptor

A descriptor that does not implement `__set__` is a non-overriding descriptor. Setting an instance attribute with the same name will shadow the descriptor, rendering it ineffective for handling that attribute in that specific instance. Methods and `@functools.cached_property` are implemented as non-overriding descriptors. Example 24-11 shows the operation of a non-overriding descriptor.

Example 24-11. Behavior of a non-overriding descriptor: obj.non_over is an instance of non-overriding (Example 24-8)

```
    >>> obj = Managed()
    >>> obj.non_over  ❶
    -> NonOverriding.__get__(<NonOverriding object>, <Managed
object>,
        <class Managed>)
    >>> obj.non_over = 7  ❷
    >>> obj.non_over  ❸
    7
    >>> Managed.non_over  ❹
    -> NonOverriding.__get__(<NonOverriding object>, None, <class
Managed>)
    >>> del obj.non_over  ❺
    >>> obj.non_over  ❻
    -> NonOverriding.__get__(<NonOverriding object>, <Managed
object>,
        <class Managed>)
```

❶ `obj.non_over` triggers the descriptor `__get__` method, passing `obj` as the second argument.

❷ `Managed.non_over` is a non-overriding descriptor, so there is no `__set__` to interfere with this assignment.

❸ The `obj` now has an instance attribute named `non_over`, which shadows the namesake descriptor attribute in the `Managed` class.

❹ The `Managed.non_over` descriptor is still there, and catches this access via the class.

❺ If the `non_over` instance attribute is deleted…

❻ Then reading `obj.non_over` hits the `__get__` method of the descriptor in the class, but note that the second argument is the managed instance.

In the previous examples, we saw several assignments to an instance attribute with the same name as a descriptor, and different results according to the presence of a `__set__` method in the descriptor.

The setting of attributes in the class cannot be controlled by descriptors attached to the same class. In particular, this means that the descriptor attributes themselves can be clobbered by assigning to the class, as the next section explains.

Overwriting a Descriptor in the Class

Regardless of whether a descriptor is overriding or not, it can be overwritten by assignment to the class. This is a monkey-patching technique, but in Example 24-12 the descriptors are replaced by integers, which would effectively break any class that depended on the descriptors for proper operation.

Example 24-12. Any descriptor can be overwritten on the class itself

```
>>> obj = Managed()  ❶
>>> Managed.over = 1  ❷
>>> Managed.over_no_get = 2
>>> Managed.non_over = 3
>>> obj.over, obj.over_no_get, obj.non_over  ❸
(1, 2, 3)
```

❶ Create a new instance for later testing.

❷ Overwrite the descriptor attributes in the class.

❸ The descriptors are really gone.

Example 24-12 reveals another asymmetry regarding reading and writing attributes: although the reading of a class attribute can be controlled by a descriptor with `__get__` attached to the managed class, the writing of a class attribute cannot be handled by a descriptor with `__set__` attached to the same class.

> **TIP**
>
> In order to control the setting of attributes in a class, you have to attach descriptors to the class of the class—in other words, the metaclass. By default, the metaclass of user-defined classes is `type`, and you cannot add attributes to `type`. But in Chapter 25, we'll create our own metaclasses.

Let's now focus on how descriptors are used to implement methods in Python.

Methods Are Descriptors

A function within a class becomes a bound method because all user-defined functions have a `__get__` method, therefore they operate as descriptors when attached to a class. Example 24-13 demonstrates reading the `spam` method from the `Managed` class introduced in Example 24-8.

Example 24-13. A method is a non-overriding descriptor

```
    >>> obj = Managed()
    >>> obj.spam  ❶
    <bound method Managed.spam of <descriptorkinds.Managed object
at 0x74c80c>>
    >>> Managed.spam  ❷
    <function Managed.spam at 0x734734>
    >>> obj.spam = 7  ❸
    >>> obj.spam
    7
```

❶ Reading from `obj.spam` retrieves a bound method object.

❷ But reading from `Managed.spam` retrieves a function.

❸ Assigning a value to `obj.spam` shadows the class attribute, rendering the `spam` method inaccessible from the `obj` instance.

Functions do not implement `__set__`, therefore they are non-overriding descriptors, as the last line of Example 24-13 shows.

The other key takeaway from Example 24-13 is that `obj.spam` and `Managed.spam` retrieve different objects. As usual with descriptors, the `__get__` of a function returns a reference to itself when the access happens through the managed class. But when the access goes through an instance, the `__get__` of the function returns a bound method object: a callable that wraps the function and binds the managed instance (e.g., `obj`) to the first argument of the function (i.e., `self`), like the `functools.partial` function does (as seen in "Freezing Arguments with functools.partial").

For a deeper understanding of this mechanism, take a look at Example 24-14.

Example 24-14. method_is_descriptor.py: a Text class, derived from UserString

```
import collections
```

```
class Text(collections.UserString):

    def __repr__(self):
        return 'Text({!r})'.format(self.data)

    def reverse(self):
        return self[::-1]
```

Now let's investigate the `Text.reverse` method. See Example 24-15.

Example 24-15. Experiments with a method

```
    >>> word = Text('forward')
    >>> word  ❶
    Text('forward')
    >>> word.reverse()  ❷
    Text('drawrof')
    >>> Text.reverse(Text('backward'))  ❸
    Text('drawkcab')
    >>> type(Text.reverse), type(word.reverse)  ❹
    (<class 'function'>, <class 'method'>)
    >>> list(map(Text.reverse, ['repaid', (10, 20, 30),
Text('stressed')]))  ❺
    ['diaper', (30, 20, 10), Text('desserts')]
    >>> Text.reverse.__get__(word)  ❻
    <bound method Text.reverse of Text('forward')>
    >>> Text.reverse.__get__(None, Text)  ❼
    <function Text.reverse at 0x101244e18>
    >>> word.reverse  ❽
    <bound method Text.reverse of Text('forward')>
    >>> word.reverse.__self__  ❾
    Text('forward')
    >>> word.reverse.__func__ is Text.reverse  ❿
    True
```

❶ The `repr` of a `Text` instance looks like a `Text` constructor call that would make an equal instance.

❷ The `reverse` method returns the text spelled backward.

❸ A method called on the class works as a function.

❹ Note the different types: a `function` and a `method`.

❺

`Text.reverse` operates as a function, even working with objects that are not instances of `Text`.

❻ Any function is a non-overriding descriptor. Calling its `__get__` with an instance retrieves a method bound to that instance.

❼ Calling the function's `__get__` with `None` as the `instance` argument retrieves the function itself.

❽ The expression `word.reverse` actually invokes `Text.reverse.__get__(word)`, returning the bound method.

❾ The bound method object has a `__self__` attribute holding a reference to the instance on which the method was called.

❿ The `__func__` attribute of the bound method is a reference to the original function attached to the managed class.

The bound method object also has a `__call__` method, which handles the actual invocation. This method calls the original function referenced in `__func__`, passing the `__self__` attribute of the method as the first argument. That's how the implicit binding of the conventional `self` argument works.

The way functions are turned into bound methods is a prime example of how descriptors are used as infrastructure in the language.

After this deep dive into how descriptors and methods work, let's go through some practical advice about their use.

Descriptor Usage Tips

The following list addresses some practical consequences of the descriptor characteristics just described:

Use property to Keep It Simple

The `property` built-in creates overriding descriptors implementing both `__set__` and `__get__`, even if you do not define a setter method. The default `__set__` of a property raises `AttributeError: can't set attribute`, so a property is the easiest way to create a read-only attribute, avoiding the issue described next.

Read-only descriptors require __set__

If you use a descriptor class to implement a read-only attribute, you must remember to code both `__get__` and `__set__`, otherwise setting a namesake attribute on an instance will shadow the descriptor. The `__set__` method of a read-only attribute should just raise `AttributeError` with a suitable message.[7]

Validation descriptors can work with __set__ only

In a descriptor designed only for validation, the `__set__` method should check the `value` argument it gets, and if valid, set it directly in the instance `__dict__` using the descriptor instance name as key. That way, reading the attribute with the same name from the instance will be as fast as possible, because it will not require a `__get__`. See the code for Example 24-2.

Caching can be done efficiently with __get__ only

If you code just the `__get__` method, you have a non-overriding descriptor. These are useful to make some expensive computation and then cache the result by setting an attribute by the same name on the instance. The namesake instance attribute will shadow the descriptor, so subsequent access to that attribute will fetch it directly from the instance `__dict__` and not trigger the descriptor `__get__` anymore. The `@functools.cached_property` decorator actually produces a non-overriding descriptor.

Non-special methods can be shadowed by instance attributes

> Because functions and methods only implement `__get__`, they are non-overriding descriptors. A simple assignment like `my_obj.the_method = 7` means that further access to `the_method` through that instance will retrieve the number `7`—without affecting the class or other instances. However, this issue does not interfere with special methods. The interpreter only looks for special methods in the class itself, in other words, `repr(x)` is executed as `x.__class__.__repr__(x)`, so a `__repr__` attribute defined in `x` has no effect on `repr(x)`. For the same reason, the existence of an attribute named `__getattr__` in an instance will not subvert the usual attribute access algorithm.

The fact that non-special methods can be overridden so easily in instances may sound fragile and error-prone, but I personally have never been bitten by this in more than 20 years of Python coding. On the other hand, if you are doing a lot of dynamic attribute creation, where the attribute names come from data you don't control (as we did in the earlier parts of this chapter), then you should be aware of this and perhaps implement some filtering or escaping of the dynamic attribute names to preserve your sanity.

> **NOTE**
>
> The `FrozenJSON` class in Example 23-5 is safe from instance attribute shadowing methods because its only methods are special methods and the `build` class method. Class methods are safe as long as they are always accessed through the class, as I did with `FrozenJSON.build` in Example 23-5—later replaced by `__new__` in Example 23-6. The `Record` and `Event` presented in "Computed Properties" are also safe: they implement only special methods, static methods, and properties. Properties are overriding descriptors, so they are not shadowed by instance attributes.

To close this chapter, we'll cover two features we saw with properties that we have not addressed in the context of descriptors: documentation and handling attempts to delete a managed attribute.

Descriptor docstring and Overriding Deletion

The docstring of a descriptor class is used to document every instance of the descriptor in the managed class. Figure 24-4 shows the help displays for the `LineItem` class with the `Quantity` and `NonBlank` descriptors from Examples 24-6 and 24-7.


1. Python
lontra:descriptors luciano$ python3 -i bulkfood_v5.py
>>> help(LineItem.weight)
1. less
Help on Quantity in module model_v5 object:
class Quantity(Validated)
| a number greater than zero
| Method resol
| Quantity
| Validate
| abc.ABC
| AutoStor
| builtins
| Methods defi
| validate(sel
| Data and oth
| __abstractme
| Methods inhe
1. Python
lontra:descriptors luciano$ python3 -i bulkfood_v5.py
>>> help(LineItem.weight)
>>> help(LineItem)
1. less
Help on class LineItem in module __main__:
class LineItem(builtins.object)
| Methods defined here:
| __init__(self, description, weight, price)
| subtotal(self)
| Data descriptors defined here:
| __dict__
| dictionary for instance variables (if defined)
| __weakref__
| list of weak references to the object (if defined)
| description
| a string with at least one non-space character
| price
| a number greater than zero

Figure 24-4. Screenshots of the Python console when issuing the commands help(LineItem.weight) and help(LineItem)

That is somewhat unsatisfactory. In the case of `LineItem`, it would be good to add, for example, the information that `weight` must be in kilograms. That would be trivial with properties, because each property handles a specific managed attribute. But with descriptors, the same `Quantity` descriptor class is used for `weight` and `price`.[8]

The second detail we discussed with properties but have not addressed with descriptors is handling attempts to delete a managed attribute. That can be done by implementing a `__delete__` method alongside or instead of the usual `__get__` and/or `__set__` in the descriptor class. Coding a silly descriptor class with `__delete__` is left as an exercise to the leisurely reader.

Chapter Summary

The first example of this chapter was a continuation of the `LineItem` examples from Chapter 23. In Example 24-2, we replaced properties with descriptors. We saw that a descriptor is a class that provides instances that are deployed as attributes in the managed class. Discussing this mechanism required special terminology, introducing terms such as managed instance and storage attribute.

In "LineItem Take #4: Automatic Storage Attribute Names", we removed the requirement that `Quantity` descriptors were declared with an explicit `storage_name`, which was redundant and error-prone. The solution was to implement the `__set_name__` special method in `Quantity`, to save the name of the managed property as `self.storage_name`.

"LineItem Take #5: A New Descriptor Type" showed how to subclass an abstract descriptor class to share code while building specialized descriptors with some common functionality.

We then looked at the different behavior of descriptors providing or omitting the `__set__` method, making the crucial distinction between overriding and non-overriding descriptors, a.k.a. data and non-data descriptors. Through detailed testing we uncovered when descriptors are in control and when they are shadowed, bypassed, or overwritten.

Following that, we studied a particular category of non-overriding descriptors: methods. Console experiments revealed how a function attached to a class becomes a method when accessed through an instance, by leveraging the descriptor protocol.

To conclude the chapter, "Descriptor Usage Tips" presented practical tips, and "Descriptor docstring and Overriding Deletion" provided a brief look at how descriptor deletion and documentation work.

> **NOTE**
>
> As noted in "What's new in this chapter", several examples in this chapter became much simpler thanks to the `__set_name__` special method of the descriptor protocol, added in Python 3.6. That's language evolution!

Further Reading

Besides the obligatory reference to the "Data Model" chapter, Raymond Hettinger's Descriptor HowTo Guide is a valuable resource—part of the HowTo collection in the official Python documentation.

As usual with Python object model subjects, Martelli, Ravenscroft & Holden's *Python in a Nutshell*, 3E (O'Reilly) is authoritative and objective. Martelli also has a presentation titled *Python's Object Model*, which covers properties and descriptors in depth (slides, video).

> **WARNING**
>
> Beware that any coverage of descriptors written or recorded before PEP 487 was adopted in 2016 is likely to contain examples that are needlessly complicated today, because `__set_name__` was not supported in Python versions prior to 3.6.

For more practical examples, *Python Cookbook, 3E* by David Beazley and Brian K. Jones (O'Reilly), has many recipes illustrating descriptors, of which I want to highlight "6.12. Reading Nested and Variable-Sized Binary Structures," "8.10. Using Lazily Computed Properties," "8.13. Implementing a Data Model or Type System," and "9.9. Defining Decorators As Classes"—the latter of which addresses deep issues with the interaction of function decorators, descriptors, and methods, explaining how a function decorator implemented as a class with `__call__` also needs to implement `__get__` if it wants to work with decorating methods as well as functions.

PEP 487—Simpler customisation of class creation introduced the `__set_name__` special method, and it includes an example of a validating descriptor.

SOAPBOX

The Design of `self`

"Worse is Better" is a design philosophy described by Richard P. Gabriel in *The Rise of Worse is Better*. The first priority of this philosophy is "Simplicity," which Gabriel presents as:

> *The design must be simple, both in implementation and interface. It is more important for the implementation to be simple than the interface. Simplicity is the most important consideration in a design.*

The requirement to explicitly declare `self` as a first argument in methods is an application of "Worse is Better" in Python. The implementation is simple—elegant even—at the expense of the user interface: a method signature like `def zfill(self, width):` doesn't visually match the invocation `pobox.zfill(8)`.

Modula-3 introduced that convention—and the use of the `self` identifier—but there is a difference: in Modula-3, interfaces are declared separately from their implementation, and in the interface declaration the `self` argument is omitted, so from the user's perspective, a method appears in an interface declaration with the same explicit arguments it takes.

One improvement in this regard has been the error messages: for a user-defined method with one argument besides `self`, if the user invokes `obj.meth()`, Python 2.7 raised `TypeError: meth() takes exactly 2 arguments (1 given)`. In Python 3 the message is clearer: the confusing argument count is not mentioned, but the missing argument is named: `meth() missing 1 required positional argument: 'x'`.

Besides the use of `self` as an explicit argument, the requirement to qualify all access to instance attributes with `self` is also criticized.[9] I personally don't mind typing the `self` qualifier: it's good to distinguish local variables from attributes. My issue is with the use of self in the `def` statement. But I got used to it.

Anyone who is unhappy about the explicit `self` in Python can feel a lot better by considering the baffling semantics of the implicit `this` in JavaScript. Guido had some good reasons to make `self` work as it does, and he wrote about them in "Adding Support for User-Defined Classes", a post on his blog, The History of Python.

---

1 Raymond Hettinger, Descriptor HowTo Guide.

2 Classes and instances are drawn as rectangles in UML class diagrams. There are visual differences, but instances are rarely shown in class diagrams, so developers may not recognize them as such.

3 White truffles cost thousands of dollars per pound. Disallowing the sale of truffles for $0.01 is left as an exercise for the enterprising reader. I know a person who actually bought an $1,800 encyclopedia of statistics for $18 because of an error in an online store (not Amazon.com in this case).

4 More precisely, `__set_name__` is called by `type.__new__`—the constructor of objects representing classes. The `type` built-in is actually a metaclass: the default class of user-defined classes. This is hard to grasp at first, but rest assured: Chapter 25 is devoted to the dynamic configuration of classes, including the concept of metaclasses.

5 Gamma et al., *Design Patterns: Elements of Reusable Object-Oriented Software*, p. 326.

6 Slide #50 of Alex Martelli's *Python Design Patterns* talk. Highly recommended.

7 Python is not consistent in such messages. Trying to change the `c.real` attribute of a `complex` number gets `AttributeError: read-only attribute`, but an attempt to change `c.conjugate` (a method of `complex`), results in `AttributeError: 'complex' object attribute 'conjugate' is read-only`.

8 Customizing the help text for each descriptor instance is surprisingly hard. One solution requires dynamically building a wrapper class for each descriptor instance.

9 See, for example, A. M. Kuchling's famous *Python Warts* post (archived); Kuchling himself is not so bothered by the `self` qualifier, but he mentions it—probably echoing opinions from `comp.lang.python`.

Chapter 25. Class Metaprogramming

> **A NOTE FOR EARLY RELEASE READERS**
>
> With Early Release ebooks, you get books in their earliest form—the author's raw and unedited content as they write—so you can take advantage of these technologies long before the official release of these titles.
>
> This will be the 25th chapter of the final book. Please note that the GitHub repo will be made active later on.
>
> If you have comments about how we might improve the content and/or examples in this book, or if you notice missing material within this chapter, please reach out to the author at fluentpython2e@ramalho.org.

Everyone knows that debugging is twice as hard as writing a program in the first place. So if you're as clever as you can be when you write it, how will you ever debug it?[1]

—Brian W. Kernighan and P. J. Plauger, The Elements of Programming Style

Class metaprogramming is the art of creating or customizing classes at runtime. Classes are first-class objects in Python, so a function can be used to create a new class at any time, without using the `class` keyword. Class decorators are also functions, but designed to inspect, change, and even replace the decorated class with another class. Finally, metaclasses are the most advanced tool for class metaprogramming: they let you create whole new categories of classes with special traits, such as the abstract base classes we've already seen.

Metaclasses are powerful, but hard to justify and even harder to get right. Class decorators solve many of the same problems and are easier to understand. Furthermore, Python 3.6 implemented *PEP 487—Simpler customisation of class creation*, providing special methods supporting tasks that previously required metaclasses or class decorators.[2]

This chapter presents the class metaprogramming techniques in ascending order of complexity.

> **WARNING**
>
> This is an exciting topic, and it's easy to get carried away. So I must offer this advice:
>
> For the sake of readability and maintainability, you should probably avoid the techniques described in this chapter in application code.
>
> On the other hand, these are the tools of the trade if you want to write the next great Python framework.

What's new in this chapter

All the code in the *Class Metaprogramming* chapter of *Fluent Python, First Edition* still runs correctly. However, some of the previous examples no longer represent the simplest solutions, in light of new features added since Python 3.6.

I replaced those examples with different ones, highlighting Python's new metaprogramming features or adding further requirements to justify the use of the more advanced techniques. Some of the new examples leverage type hints to provide class builders similar to the `@dataclass` decorator and `typing.NamedTuple`.

"Metaclasses in the Real world" is a new section with some high level considerations about the applicability of metaclasses.

> **TIP**
>
> Some of the best refactorings are removing code made redundant by newer and simpler ways of solving the same problems. This applies to production code as well as books.

We'll get started by reviewing attributes and methods defined in the Python Data Model for all classes.

Classes as Objects

Like most program entities in Python, classes are also objects. Every class has a number of attributes defined in the Python Data Model, documented in "4.13. Special Attributes" of the "Built-in Types" chapter in the *Library Reference*. Three of those attributes appeared several times in the book already: `__class__`, `__name__`, and `__mro__`. Other class standard attributes are:

`cls.__bases__`

The tuple of base classes of the class.

`cls.__qualname__`

The qualified name of a class or function, which is a dotted path from the global scope of the module to the class definition. This is relevant when the class is defined inside another class. For example, in a Django model class such as `Ox`, there is an inner class called `Meta`. The `__qualname__` of `Meta` is `Ox.Meta`, but its `__name__` is just `Meta`. The specification for this attribute is PEP-3155 — Qualified name for classes and functions.

`cls.__subclasses__()`

This method returns a list of the immediate subclasses of the class. The implementation uses weak references to avoid circular references between the superclass and its subclasses—which hold a strong reference to the superclasses in their `__bases__` attribute. The method lists subclasses currently in memory.

`cls.mro()`

The interpreter calls this method when building a class to obtain the tuple of superclasses that is stored in the `__mro__` attribute of the class. A metaclass can override this method to customize the method resolution order of the class under construction.

> **TIP**
>
> None of the attributes mentioned in this section are listed by the `dir(…)` function.

Now, if a class is an object, what is the class of a class?

type: The Built-in Class Factory

We usually think of `type` as a function that returns the class of an object, because that's what `type(my_object)` does: it returns `my_object.__class__`.

However, `type` is a class that creates a new class when invoked with three arguments.

Consider this simple class:

```
class MyClass(MySuperClass, MyMixin):
    x = 42

    def x2(self):
        return self.x * 2
```

Using the `type` constructor, you can create `MyClass` at runtime with this code:

```
MyClass = type('MyClass', (MySuperClass, MyMixin),
               {'x': 42, 'x2': lambda self: self.x * 2})
```

That `type` call is functionally equivalent to the previous `class MyClass…` block statement.

When Python reads a `class` statement, it calls `type` to build the class object with these parameters:

`name`

The identifier that appears after the `class` keyword; e.g.: `MyClass`.

`bases`

The tuple of superclasses given in parenthesis after the class identifier, or `(object,)` if superclasses are not mentioned in the `class` statement.

`dict`

A mapping of attribute names to values. Callables become methods; other values become class attributes.

> **NOTE**
>
> The `type` constructor accepts optional keyword arguments. That's an advanced feature not covered in this book.

The `type` class is a *metaclass*: a class that builds classes. In other words, instances of the `type` class are classes. The standard library provides a few other metaclasses, but `type` is the default.

```
>>> type(7)
<class 'int'>
>>> type(int)
<class 'type'>
>>> type(OSError)
<class 'type'>
```

```
>>> class Whatever:
...     pass
...
>>> type(Whatever)
<class 'type'>
```

We'll build custom metaclasses in "Metaclasses 101".

Next, we'll use the `type` built-in to make a function that builds classes.

A Class Factory Function

The standard library has a class factory function that appears several times in this book: `collections.namedtuple`. In Chapter 5 we also saw `collections.NamedTuple` and `@dataclass`. All of these class builders leverage techniques covered in this chapter.

We'll start with a super simple factory for classes of mutable objects—the simplest possible replacement for `@dataclass`.

Suppose I'm writing a pet shop application and I want to store data for dogs as simple records. But I don't want to write boilerplate like this:

```
class Dog:
    def __init__(self, name, weight, owner):
        self.name = name
        self.weight = weight
        self.owner = owner
```

Boring… each field name appears three times, and that boilerplate doesn't even buy us a nice `repr`:

```
>>> rex = Dog('Rex', 30, 'Bob')
>>> rex
<__main__.Dog object at 0x2865bac>
```

Taking a hint from `collections.namedtuple`, let's create a `record_factory` that creates simple classes like `Dog` on the fly. Example 25-1 shows how it should work.

Example 25-1. Testing record_factory, a simple class factory

```
>>> Dog = record_factory('Dog', 'name weight owner')  ❶
>>> rex = Dog('Rex', 30, 'Bob')
>>> rex  ❷
Dog(name='Rex', weight=30, owner='Bob')
>>> name, weight, _ = rex  ❸
>>> name, weight
('Rex', 30)
>>> "{2}'s dog weighs {1}kg".format(*rex)  ❹
"Bob's dog weighs 30kg"
>>> rex.weight = 32  ❺
>>> rex
Dog(name='Rex', weight=32, owner='Bob')
>>> Dog.__mro__  ❻
(<class 'factories.Dog'>, <class 'object'>)
```

❶ Factory can be called like `namedtuple`: class name, followed by attribute names separated by spaces in a single strings.

❷ Nice `repr`.

❸ Instances are iterable, so they can be conveniently unpacked on assignment…

❹ …or when passing to functions like `format`.

❺ A record instance is mutable.

❻ The newly created class inherits from `object`—no relationship to our factory.

The code for `record_factory` is in Example 25-2.[3]

Example 25-2. record_factory.py: a simple class factory

```
from typing import Union, Any
from collections.abc import Iterable, Iterator

FieldNames = Union[str, Iterable[str]]  ❶

def record_factory(cls_name: str, field_names: FieldNames) ->
type[tuple]:  ❷
```

```
    slots = parse_identifiers(field_names)  ❸

    def __init__(self, *args, **kwargs) -> None:  ❹
        attrs = dict(zip(self.__slots__, args))
        attrs.update(kwargs)
        for name, value in attrs.items():
            setattr(self, name, value)

    def __iter__(self) -> Iterator[Any]:  ❺
        for name in self.__slots__:
            yield getattr(self, name)

    def __repr__(self):  ❻
        values = ', '.join(
            '{}={!r}'.format(*i) for i in zip(self.__slots__, self)
        )
        cls_name = self.__class__.__name__
        return f'{cls_name}({values})'

    cls_attrs = dict(  ❼
        __slots__=slots,
        __init__=__init__,
        __iter__=__iter__,
        __repr__=__repr__,
    )

    return type(cls_name, (object,), cls_attrs)  ❽


def parse_identifiers(names: FieldNames) -> tuple[str, ...]:
    if isinstance(names, str):
        names = names.replace(',', ' ').split()  ❾
    if not all(s.isidentifier() for s in names):
        raise ValueError('names must all be valid identifiers')
    return tuple(names)
```

❶ User can provide field names as a single string or an iterable of strings.

❷ Accept arguments like the first two of `collections.namedtuple`; return a `type`—i.e. a class—that behaves like a `tuple`.

❸ Build a tuple of attribute names, this will be the `__slots__` attribute of the new class.

❹ This function will become the `__init__` method in the new class. It accepts positional and/or keyword arguments. There's no point in adding type hints to `__init__`, because the actual types are `Any`.

❺ Yield the field values in the order given by `__slots__`.

❻ Produce the nice `repr`, iterating over `__slots__` and `self`.

❼ Assemble dictionary of class attributes.

❽ Build and return the new class, calling the `type` constructor.

❾ Convert `names` separated by spaces or commas to list of `str`.

In summary, the last line of `record_factory` in Example 25-2 builds a class named by the value of `cls_name`, with `object` as its single immediate base class and with a namespace loaded with `__slots__`, `__init__`, `__iter__`, and `__repr__`, of which the last three are instance methods.

We could have named the `__slots__` class attribute anything else, but then we'd have to implement `__setattr__` to validate the names of attributes being assigned, because for our record-like classes we want the set of attributes to be always the same and in the same order. However, recall that the main feature of `__slots__` is saving memory when you are dealing with millions of instances, and using `__slots__` has some drawbacks, discussed in "Saving Memory with `__slots__`".

> **WARNING**
>
> Instances of classes created by `record_factory` are not serializable—that is, they can't be exported with the `dump` function from the `pickle` module. Solving this problem is beyond the scope of this example, which aims to show the `type` class in action in a simple use case. For the full solution, study the source code for `collections.namedtuple`; search for the word "pickling."

Now let's see how to emulate more modern class builders like `typing.NamedTuple`, which takes a user-defined class written as a `class` statement, and automatically enhances it with more functionality.

Introducing `__init_subclass__`

Both `__init_subclass__` and `__set_name__` were proposed in *PEP 487—Simpler customisation of class creation*. We saw the `__set_name__` special method for descriptors for the first time in "LineItem Take #4: Automatic Storage Attribute Names". Now let's study `__init_subclass__`.

In Chapter 5, we saw that `typing.NamedTuple` and `@dataclass` let programmers use the `class` statement to specify attributes for a new class, which is then enhanced by the class builder with the automatic addition of essential methods like `__init__`, `__repr__`, `__eq__` etc.

Both of these class builders read type hints in the user's `class` statement to enhance the class. Those type hints also allow static type checkers to validate code that sets or gets those attributes. However, `NamedTuple` and `@dataclass` do not take advantage of the type hints for attribute validation at runtime. The `Checked` class in next example does.

> **NOTE**
>
> It is not possible to support every conceivable static type hint for runtime type checking, which is probably why `typing.NamedTuple` and `@dataclass` don't even try it. However, some types that are also concrete classes can be used with `Checked`. This includes simple types often used for field contents, such as `str`, `int`, `float` and `bool`, as well as lists of those types.

Example 25-3 shows how to use `Checked` to build a `Movie` class.

Example 25-3. initsub/checkedlib.py: doctest for creating a `Movie` subclass of `Checked`.

```
>>> class Movie(Checked):  ❶
...     title: str  ❷
...     year: int
...     box_office: float
...
>>> movie = Movie(title='The Godfather', year=1972,
box_office=137)  ❸
>>> movie.title
'The Godfather'
>>> movie  ❹
Movie(title='The Godfather', year=1972, box_office=137.0)
```

❶ `Movie` inherits from `Checked`—the subject of this section.

❷ Each attribute is annotated with a constructor. Here I used built-in types.

❸ `Movie` instances must be created using keyword arguments.

❹ In return, you get a nice `__repr__`.

The constructors used as the attribute type hints may be any callable that takes zero or one argument and returns a value suitable for the intended field type, or rejects the argument by raising `TypeError` or `ValueError`.

Using built-in types for the annotations in Example 25-3 means the values must be acceptable by the constructor of the type. For `int`, this means any `x` such that `int(x)` returns an `int`. For `str`, anything goes at runtime, because `str(x)` works with any `x` in Python.[4]

When called with no arguments, the constructor should return a default value of its type.[5]

This is standard behavior for Python’s built-in constructors:

```
>>> int(), float(), bool(), str(), list(), dict(), set()
(0, 0.0, False, '', [], {}, set())
```

In a `Checked` subclass like `Movie`, missing parameters create instances with default values returned by the field constructors. For example:

```
>>> Movie(title='Life of Brian')
Movie(title='Life of Brian', year=0, box_office=0.0)
```

The constructors are used for validation during instantiation and when an attribute is set directly on an instance:

```
>>> blockbuster = Movie(title='Avatar', year=2009,
box_office='billions')
Traceback (most recent call last):
  ...
TypeError: 'billions' is not compatible with box_office:float
>>> movie.year = 'MCMLXXII'
Traceback (most recent call last):
  ...
TypeError: 'MCMLXXII' is not compatible with year:int
```

CHECKED SUBCLASSES AND STATIC TYPE CHECKING

In a *.py* source file with a `movie` instance of `Movie` as defined in Example 25-3, Mypy flags this assignment as a type error:

```
movie.year = 'MCMLXXII'
```

However, Mypy can't detect type errors in this constructor call:

```
blockbuster = Movie(title='Avatar', year='MMIX')
```

That's because `Movie` inherits `Checked.__init__`, and the signature of that method must accept any keyword arguments, to support arbitrary user-defined classes.

On the other hand, if you declare a `Checked` subclass field with the type hint `list[float]`, Mypy can flag assignments of lists with incompatible contents, but `Checked` will ignore the type parameter and treat that the same as `list`.

Now let's look at the implementation of `checkedlib.py`. The first class is the `Field` descriptor:

Example 25-4. initsub/checkedlib.py: the `Field` descriptor class.

```
from collections.abc import Callable  ❶
from typing import Any, NoReturn, get_type_hints


class Field:
    def __init__(self, name: str, constructor: Callable) -> None:
❷
        if not callable(constructor) or constructor is type(None):
❸
            raise TypeError(f'{name!r} type hint must be callable')
        self.name = name
        self.constructor = constructor

    def __set__(self, instance: Any, value: Any) -> None:
        if value is ...:  ❹
            value = self.constructor()
        else:
            try:
                value = self.constructor(value)  ❺
            except (TypeError, ValueError) as e:  ❻
                type_name = self.constructor.__name__
                msg = f'{value!r} is not compatible with
{self.name}:{type_name}'
                raise TypeError(msg) from e
        instance.__dict__[self.name] = value  ❼
```

❶ Recall that since Python 3.9, the `Callable` type for annotations is the ABC in `collections.abc`, and not the deprecated `typing.Callable`.

❷ This is a minimal `Callable` type hint; the `constructor` parameter type and return type are `Any`, so we can omit them.

❸ For runtime checking, we use the `callable` built-in.[6] The test against `type(None)` is necessary because Python reads `None` in a type as `NoneType`, the class of `None` (therefore callable) but a useless constructor that only returns `None`.

❹ If `Checked.__init__` sets the `value` as `...` (the `Ellipsis` built-in object), we call the `constructor` with no arguments.

5. Otherwise, call the `constructor` with the given `value`.

6. If `constructor` raises either of these exceptions, we raise `TypeError` with a helpful message including the names of the field and constructor; e.g. `'MMIX' is not compatible with year:int`.

7. If no exceptions were raised, the `value` is stored in the `instance.__dict__`.

In `__set__` we need to catch `TypeError` and `ValueError` because built-in constructors may raise either of them, depending on the argument. For example: `float(None)` raises `TypeError`, but `float('A')` raises `ValueError`. On the other hand, `float('8')` raises no error and returns `8.0`. I hereby declare that this is feature and not a bug of this toy example.

> **TIP**
>
> In "LineItem Take #4: Automatic Storage Attribute Names" we saw the handy `__set_name__` special method for descriptors. We don't need it in the `Field` class because the descriptors are not instantiated in client source code; the user declares types that are constructors, as we saw in the `Movie` class (Example 25-3). Instead, the `Field` descriptor instances are created at runtime by the `Checked.__init_subclass__` method which we'll see in Example 25-5.

Now let's focus on the `Checked` class. I split it in two listing: Example 25-5 shows the top of the class, which includes the most important methods in this example. The remaining methods are in Example 25-6.

Example 25-5. initsub/checkedlib.py: the most important methods of the `Checked` class.

```
class Checked:
    @classmethod
    def _fields(cls) -> dict[str, type]:  ➊
```

```
        return get_type_hints(cls)

    def __init_subclass__(subclass) -> None:  ❷
        super().__init_subclass__()           ❸
        for name, constructor in subclass._fields().items():   ❹
            setattr(subclass, name, Field(name, constructor))  ❺

    def __init__(self, **kwargs: Any) -> None:
        for name in self._fields():           ❻
            value = kwargs.pop(name, ...)     ❼
            setattr(self, name, value)        ❽
        if kwargs:                            ❾
            self.__flag_unknown_attrs(*kwargs)  ❿
```

❶ I wrote this class method to hide the use of `typing.get_type_hints` from the rest of the class. As explained in "Problems with Annotations at Runtime", that function doesn't always work—but it does handle the simple types the `Checked` and `Field` classes are designed to handle.

❷ `__init_subclass__` is called when a subclass of the current subclass is defined. It gets that new subclass as its first argument—which is why I named the argument `subclass` instead of the usual `cls`. For more on this, see "`__init_subclass__` is not a typical class method".

❸ `super().__init_subclass__()` should be invoked.

❹ Iterate over each field `name` and `constructor`…

❺ …creating an attribute on `subclass` with that `name` bound to a `Field` descriptor parameterized with `name` and `constructor`.

❻ For each `name` in the class fields…

❼ Get the corresponding `value` from `kwargs` and remove it from `kwargs`. Using `...`—the `Ellipsis` object—as default allows us to distinguish between arguments given the value `None` from arguments that were not given.[7]

- ❽ This `setattr` call triggers `Checked.__setattr__`, shown in Example 25-6.

- ❾ If there are remaining items in `kwargs`, their names do not match any of the declared fields, and `__init__` will fail.

- ❿ The error is reported by `__flag_unknown_attrs`, listed in Example 25-6. It takes a `*names` argument with the unknown attribute names. I used a single asterisk in `*kwargs` to pass its keys as a sequence of arguments.

__INIT_SUBCLASS__ IS NOT A TYPICAL CLASS METHOD

The `@classmethod` decorator is never used with `__init_subclass__`, but that doesn't mean much, because the `__new__` special method behaves as a class method even without `@classmethod`. The first argument that Python passes to `__init_subclass__` is a class. However, it is never the class where `__init_subclass__` is implemented: it is a newly defined subclass of that class. That's unlike `__new__` and every other class method that I know about. Therefore, I think `__init_subclass__` is not a class method in the usual sense, and it is misleading to name the first argument `cls`. The `__init_suclass__` documentation names the argument `cls` but explains: "…called whenever the containing class is subclassed. `cls` is then the new subclass."

Now let's see the remaining methods of the `Checked` class, continuing from Example 25-5. Note that I prepended _ to the `_fields` and `_asdict` method names for the same reason the `collections.namedtuple` API does: to reduce the chance of name clashes with user-defined field names.

Example 25-6. initsub/checkedlib.py: remaining methods of the `Checked` class.

```
    def __setattr__(self, name: str, value: Any) -> None:  ❶
        if name in self._fields():                  ❷
            cls = self.__class__
            descriptor = getattr(cls, name)
            descriptor.__set__(self, value)         ❸
        else:                                       ❹
            self.__flag_unknown_attrs(name)

    def __flag_unknown_attrs(self, *names: str) -> NoReturn:  ❺
        plural = 's' if len(names) > 1 else ''
        extra = ', '.join(f'{name!r}' for name in names)
        cls_name = repr(self.__class__.__name__)
        raise AttributeError(f'{cls_name} object has no
attribute{plural} {extra}')

    def _asdict(self) -> dict[str, Any]:  ❻
        return {
            name: getattr(self, name)
            for name, attr in self.__class__.__dict__.items()
            if isinstance(attr, Field)
        }

    def __repr__(self) -> str:  ❼
        kwargs = ', '.join(
            f'{key}={value!r}' for key, value in
self._asdict().items()
        )
        return f'{self.__class__.__name__}({kwargs})'
```

❶ Intercept all attempts to set an instance attribute. This is needed to prevent setting an unknown attribute.

❷ If the attribute `name` is known, fetch the corresponding `descriptor`.

❸ Usually we don't need to call the descriptor `__set__` explicitly; it was necessary in this case because `__setattr__` intercepts all attempts to set an attribute on the instance, including in the presence of an overriding descriptor such as `Field`.[8]

4. Otherwise, the attribute `name` is unknown, and an exception will be raised by `__flag_unknown_attrs`.

5. Build a helpful error message listing all unexpected arguments and raise `AttributeError`. This is a rare example of the `NoReturn` special type, covered in "`NoReturn`".

6. Create a `dict` from the attributes of a `Movie` object. I'd call this method `_as_dict`, but I followed the convention started by the `_asdict` method in `collections.namedtuple`.

7. Implementing a nice `__repr__` is the main reason for having `_asdict` in this example.

The `Checked` example illustrates how to handle overriding descriptors when implementing `__setattr__` to block arbitrary attribute setting after instantiation. It is debatable whether implementing `__setattr__` is worthwhile in this example. Without it, setting `movie.director = 'Greta Gerwig'` would succeed, but the `director` attribute would not be checked in any away, and would not appear in the `__repr__` nor be included in the `dict` returned by `_asdict`—both defined in Example 25-6.

In *record_factory.py* (Example 25-2) I solved this issue using the `__slots__` class attribute. However, this simpler solution is not viable in this case, as explained next.

Why `__init_subclass__` cannot configure `__slots__`

The `__slots__` attribute is only effective if it is one of the entries in the class namespace passed to `type.__new__`. Adding `__slots__` to an existing class has no effect. Python invokes `__init_subclass__` only after the class is built—by then it's too late to configure `__slots__`. A class decorator can't configure `__slots__` either, because it is applied even later than `__init_subclass__`. We'll explore these timing issues in "What Happens When: Import Time Versus Runtime".

To configure `__slots__` at runtime, your own code must build the class namespace passed as the last argument of `type.__new__`. To do that, you can write a class factory function, like `_record_factory.py_`, or you take the nuclear option and implement a metaclass. We will see how to dynamically configure `__slots__` in "Metaclasses 101".

Before PEP 487 simplified the customisation of class creation with `__init_subclass__` in Python 3.7, similar functionality had to be implemented using a class decorator. That's the focus of the next section.

Enhancing Classes with a Class Decorator

A class decorator is a callable that behaves similarly to a function decorator: it gets the decorated class as an argument, and must return a class which will replace the decorated class. Class decorators often return the decorated class itself, after injecting more methods in it via attribute assignment.

Probably the most common reason to chose a class decorator over the simpler `__init_subclass__` is to avoid interfering with other class features such as inheritance and metaclasses.[9]

In this section, we'll study *checkeddeco.py*, which provides the same service as *checkedlib.py*, but using a class decorator. As usual, we'll start by looking at an usage example, extracted from the doctests in *checkeddeco.py*.

Example 25-7. checkeddeco.py: creating a `Movie` class decorated with `@checked`.

```
>>> @checked
... class Movie:
...     title: str
...     year: int
```

```
...     box_office: float
...
>>> movie = Movie(title='The Godfather', year=1972,
box_office=137)
>>> movie.title
'The Godfather'
>>> movie
Movie(title='The Godfather', year=1972, box_office=137.0)
```

The only difference between Example 25-7 and Example 25-3 is the way the `Movie` class is declared: it is decorated with `@checked` instead of subclassing `Checked`. Otherwise, the external behavior is the same, including the type validation and default value assignments shown after Example 25-3 in "Introducing `__init_subclass__`".

Now let's look at the implementation of *checkeddeco.py*. The imports and `Field` class are the same as in *checkedlib.py*, listed in Example 25-4. There is no other class, only functions in *checkeddeco.py*.

The logic previously implemented in `__init_subclass__` is now part of the `checked` function—the class decorator listed in Example 25-8.

Example 25-8. checkeddeco.py: the class decorator.

```
def checked(cls: type) -> type:  ❶
    for name, constructor in _fields(cls).items():    ❷
        setattr(cls, name, Field(name, constructor))  ❸

    cls._fields = classmethod(_fields)  # type: ignore  ❹

    instance_methods = (  ❺
        __init__,
        __repr__,
        __setattr__,
        _asdict,
        __flag_unknown_attrs,
    )
    for method in instance_methods:  ❻
        setattr(cls, method.__name__, method)

    return cls  ❼
```

❶ Recall that classes are instances of `type`. These type hints strongly suggest this is a class decorator: it takes a class, and returns a class.

❷ `_fields` is a module-level function defined later in the module (in Example 25-9).

❸ Replacing each attribute returned by `_fields` with a `Field` descriptor instance is what `__init_subclass__` did in Example 25-5. Here there is more work to do…

❹ Build a class method from `_fields`, and add it to the decorated class. The `type: ignore` comment is needed because Mypy complains that `type` has no `_fields` attribute.

❺ Module-level functions that will become instance methods of the decorated class.

❻ Add each of the `instance_methods` to `cls`.

❼ Return the decorated `cls`, fulfilling the essential contract of a class decorator.

Every top-level function in *checkeddeco.py* is prefixed with an underscore, except the `checked` decorator. This naming convention makes sense for a couple of reasons:

1. `checked` is part of the public interface of the *checkeddeco.py* module, but the other functions are not.
2. The functions in Example 25-9 will be injected in the decorated class, and the leading _ reduces the chance of naming conflicts with user-defined attributes and methods of the decorated class.

The rest of *checkeddeco.py* is listed in Example 25-9. Those module-level functions have the same code as the corresponding methods of the `Checked` class of *checkedlib.py*. They were explained in Example 25-5 and Example 25-6.

Note that the `_fields` function does double duty in *checkeddeco.py*. It is used as a regular function in the first line of the `checked` decorator, and it will also be injected as a class method of the decorated class.

Example 25-9. checkeddeco.py: the methods to be injected in the decorated class.

```
def _fields(cls: type) -> dict[str, type]:
    return get_type_hints(cls)

def __init__(self: Any, **kwargs: Any) -> None:
    for name in self._fields():
        value = kwargs.pop(name, ...)
        setattr(self, name, value)
    if kwargs:
        self.__flag_unknown_attrs(*kwargs)

def __setattr__(self: Any, name: str, value: Any) -> None:
    if name in self._fields():
        cls = self.__class__
        descriptor = getattr(cls, name)
        descriptor.__set__(self, value)
    else:
        self.__flag_unknown_attrs(name)

def __flag_unknown_attrs(self: Any, *names: str) -> NoReturn:
    plural = 's' if len(names) > 1 else ''
    extra = ', '.join(f'{name!r}' for name in names)
    cls_name = repr(self.__class__.__name__)
    raise AttributeError(f'{cls_name} has no attribute{plural}
{extra}')

def _asdict(self: Any) -> dict[str, Any]:
    return {
        name: getattr(self, name)
        for name, attr in self.__class__.__dict__.items()
        if isinstance(attr, Field)
    }

def __repr__(self: Any) -> str:
    kwargs = ', '.join(
        f'{key}={value!r}' for key, value in self._asdict().items()
    )
    return f'{self.__class__.__name__}({kwargs})'
```

The *checkeddeco.py* module implements a simple but usable class decorator. Python's `@dataclass` does a lot more. It supports many configuration options, adds more methods to the decorated class, handles or warns about conflicts with user-defined methods in the decorated class, and even traverses the `__mro__` to collect user-defined attributes declared in the superclasses of the decorated class. The source code of the `dataclasses` package in Python 3.9 is more than 1200 lines long.

For metaprogramming classes, we must be aware of when the Python interpreter evaluates each block of code during the construction of a class. This is covered next.

What Happens When: Import Time Versus Runtime

Python programmers talk about "import time" versus "runtime" but the terms are not strictly defined and there is a gray area between them.

At import time, the interpreter:

1. Parses the source code of a *.py* module in one pass from top to bottom. This is when `SyntaxError` may occur.

2. Compiles the bytecode to be executed.

3. Executes the top-level code of the compiled module.

If there is an up-to-date *.pyc* file available in the local `__pycache__`, parsing and compiling are skipped because the bytecode is ready to run.

Although parsing and compiling are definitely "import time" activities, other things may happen at that time, because almost every statement in Python is executable in the sense that they potentially run user code and may change the state of the user program.

In particular, the `import` statement is not merely a declaration[10] but it actually runs all the top-level code of a module when it is imported for the first time in the process—further imports of the same module will use a cache, and then the only effect will be binding the imported objects to names in the client module. That top-level code may do anything, including actions typical of "runtime", such as writing to a log or connecting to a database.[11] That's why the border between "import time" and "runtime" is fuzzy: the `import` statement can trigger all sorts of "runtime" behavior.

This is all rather abstract and subtle, so let's do some experiments to see what happens when.

Evaluation Time Experiments

Consider an *evaldemo.py* script which uses a class decorator, a descriptor, and a class builder based on `__init_subclass__`, all defined in a *builderlib.py* module. The modules have several `print` calls to show what happens under the covers. Otherwise, they don't perform anything useful. The goal of these experiments is to observe the order in which these `print` calls happen.

> **WARNING**
>
> Applying a class decorator and a class builder with `__init_subclass__` together in single class is likely a sign of overengineering or desperation. This unusual combination is useful in these experiments to show the timing of the changes that a class decorator and `__init_subclass__` can apply to a class.

Let's start by checking out *builderlib.py*, split in two parts: Example 25-10 and Example 25-11.

Example 25-10. builderlib.py: top of the module

```
print('@ builderlib module start')

class Builder:  ❶
    print('@ Builder body')

    def __init_subclass__(cls):  ❷
        print(f'@ Builder.__init_subclass__({cls!r})')
```

```
        def inner_0(self):  ❸
            print(f'@ SuperA.__init_subclass__:inner_0({self!r})')

        cls.method_a = inner_0

    def __init__(self):
        super().__init__()
        print(f'@ Builder.__init__({self!r})')


def deco(cls):  ❹
    print(f'@ deco({cls!r})')

    def inner_1(self):  ❺
        print(f'@ deco:inner_1({self!r})')

    cls.method_b = inner_1
    return cls  ❻
```

❶ This is a class builder to implement…

❷ `__init_subclass__`.

❸ Define a function to be added to the subclass in the assignment below.

❹ A class decorator.

❺ Function to be added to the decorated class.

❻ Return the class received as argument.

Continuing with *builderlib.py*…

Example 25-11. builderlib.py: bottom of the module

```
class Descriptor:  ❶
    print('@ Descriptor body')

    def __init__(self):  ❷
        print(f'@ Descriptor.__init__({self!r})')

    def __set_name__(self, owner, name):  ❸
        args = (self, owner, name)
```

```
        print(f'@ Descriptor.__set_name__{args!r}')

    def __set__(self, instance, value):  ❹
        args = (self, instance, value)
        print(f'@ Descriptor.__set__{args!r}')

    def __repr__(self):
        return '<Descriptor instance>'


print('@ builderlib module end')
```

❶ A descriptor class to demonstrate when…

❷ …a descriptor instance is created, and when…

❸ …`__set_name__` will be invoked during the `owner` class construction.

❹ Like the other methods, this `__set__` doesn't do anything except display its arguments.

If you import *builderlib.py* in the Python console, this is what you get:

```
>>> import builderlib
@ builderlib module start
@ Builder body
@ Descriptor body
@ builderlib module end
```

Note that the lines printed by *builderlib.py* are prefixed with `@`.

Now let's turn to *evaldemo.py*, which will trigger special methods in *builderlib*.

Example 25-12. evaldemo.py: script to experiment with builderlib.py.

```
#!/usr/bin/env python3

from builderlib import Builder, deco, Descriptor

print('# evaldemo module start')
```

```
@deco  ❶
class Klass(Builder):  ❷
    print('# Klass body')

    attr = Descriptor()  ❸

    def __init__(self):
        super().__init__()
        print(f'# Klass.__init__({self!r})')

    def __repr__(self):
        return '<Klass instance>'


def main():  ❹
    obj = Klass()
    obj.method_a()
    obj.method_b()
    obj.attr = 999

if __name__ == '__main__':
    main()

print('# evaldemo module end')
```

❶ Apply decorator.

❷ Subclass `Builder` to trigger its `__init_subclass__`.

❸ Instantiate descriptor.

❹ This will only be called if the module is run as the main program.

The `print` calls in *evaldemo.py* show a # prefix. If you open the console again and import *evaldemo.py*, this is the output:

Example 25-13. Console experiment with evaldemo.py.

```
>>> import evaldemo
@ builderlib module start  ❶
@ Builder body
@ Descriptor body
@ builderlib module end
# evaldemo module start
```

```
# Klass body  ❷
@ Descriptor.__init__(<Descriptor instance>)  ❸
@ Descriptor.__set_name__(<Descriptor instance>,
      <class 'evaldemo.Klass'>, 'attr')                ❹
@ Builder.__init_subclass__(<class 'evaldemo.Klass'>)  ❺
@ deco(<class 'evaldemo.Klass'>)  ❻
# evaldemo module end
```

❶ The top 4 lines are the result of `from builderlib import…`. They will not appear if you didn't close the console after the previous experiment, because *builderlib.py* is already loaded.

❷ This signals that Python started reading the body of `Klass`. At this point, the class object does not exist yet.

❸ The descriptor instance is created and bound to `attr` in the namespace that Python will pass to the default class object constructor: `type.__new__`.

❹ At this point, Python's built-in `type.__new__` has created the `Klass` object and calls `__set_name__` on each descriptor instance of descriptor classes that provide that method, passing `Klass` as the `owner` argument.

❺ `type.__new__` then calls `__init_subclass__` on the superclass of `Klass`, passing `Klass` as the single argument.

❻ When `type.__new__` returns the class object, Python applies the decorator. In this example, the class returned by `deco` is bound to `Klass` in the module namespace.

The implementation of `type.__new__` is written in C. The behavior I just described is documented in the *Creating the class object* section of Python's *Data Model* reference.

Note that the `main()` function of *evaldemo.py* (Example 25-12) was not executed in the console session (Example 25-13), therefore no instance of

`Klass` was created. All the action we saw was triggered by “import time” operations: importing `builderlib` and defining `Klass`.

If you run *evaldemo.py* as a script, you will see the same output as Example 25-13 with extra lines right before the last. The extra lines are the result of running `main()`:

Example 25-14. Running evaldemo.py as a program.

```
$ ./evaldemo.py
[... 9 lines omitted ...]
@ deco(<class '__main__.Klass'>)  ❶
@ Builder.__init__(<Klass instance>)  ❷
# Klass.__init__(<Klass instance>)
@ SuperA.__init_subclass__:inner_0(<Klass instance>)  ❸
@ deco:inner_1(<Klass instance>)  ❹
@ Descriptor.__set__(<Descriptor instance>, <Klass instance>, 999)
❺
# evaldemo module end
```

❶ The top 10 lines—including this one—are the same shown in Example 25-13.

❷ Triggered by `super().__init__()` in `Klass.__init__`.

❸ Triggered by `obj.method_a()` in `main`; `method_a` was injected by `SuperA.__init_subclass__`.

❹ Triggered by `obj.method_b()` in `main`; `method_b` was injected by `deco`.

❺ Triggered by `obj.attr = 999` in `main`.

A base class with `__init_subclass__` and a class decorator are powerful tools, but they are limited to working with a class already built by `type.__new__` under the covers. In the rare occasions when you need to adjust the arguments passed to `type.__new__`, you need a metaclass. That’s the final destination of this chapter—and this book.

Metaclasses 101

> *[Metaclasses] are deeper magic than 99% of users should ever worry about. If you wonder whether you need them, you don't (the people who actually need them know with certainty that they need them, and don't need an explanation about why).*[12]
>
> —Tim Peters, Inventor of the timsort algorithm and prolific Python contributor

A metaclass is a class factory. In contrast with `record_factory` from Example 25-2, a metaclass is written as a class. In other words, a metaclass is class whose instances are classes. Figure 25-1 depicts a metaclass using the Mills & Gizmos Notation: a mill producing another mill.

Figure 25-1. A metaclass is a class that builds classes

Consider the Python object model: classes are objects, therefore each class must be an instance of some other class. By default, Python classes are instances of `type`. In other words, `type` is the metaclass for most built-in and user-defined classes:

```
>>> str.__class__
<class 'type'>
>>> from bulkfood_v5 import LineItem
>>> LineItem.__class__
<class 'type'>
>>> type.__class__
<class 'type'>
```

To avoid infinite regress, the class of `type` is `type`, as the last line shows.

Note that I am not saying that `str` or `LineItem` are subclasses of `type`. What I am saying is that `str` and `LineItem` are instances of `type`. They all are subclasses of `object`. Figure 25-2 may help you confront this strange reality.

Figure 25-2. Both diagrams are true. The left one emphasizes that `str`, `type`, and `LineItem` are subclasses of object. The right one makes it clear that str, object, and `LineItem` are instances `type`, because they are all classes.

> **NOTE**
>
> The classes `object` and `type` have a unique relationship: `object` is an instance of `type`, and `type` is a subclass of `object`. This relationship is "magic": it cannot be expressed in Python because either class would have to exist before the other could be defined. The fact that `type` is an instance of itself is also magical.

The next snippet shows that the class of `collections.Iterable` is `abc.ABCMeta`. Note that `Iterable` is an abstract class, but `ABCMeta` is a concrete class—after all, `Iterable` is an instance of `ABCMeta`:

```
>>> from collections.abc import Iterable
>>> Iterable.__class__
<class 'abc.ABCMeta'>
>>> import abc
>>> from abc import ABCMeta
>>> ABCMeta.__class__
<class 'type'>
```

Ultimately, the class of `ABCMeta` is also `type`. Every class is an instance of `type`, directly or indirectly, but only metaclasses are also subclasses of `type`. That's the most important relationship to understand metaclasses: a metaclass, such as `ABCMeta`, inherits from `type` the power to construct classes. Figure 25-3 illustrates this crucial relationship.

Figure 25-3. Iterable is a subclass of object and an instance of ABCMeta. Both object and ABCMeta are instances of type, but the key relationship here is that ABCMeta is also a subclass of type, because ABCMeta is a metaclass. In this diagram, Iterable is the only abstract class.

The important takeaway here is that metaclasses are subclasses of `type`, and that's what makes them work as class factories. A metaclass can customize its instances by implementing special methods, as the next sections demonstrate.

How a Metaclass Customizes a Class

To use a metaclass, it’s critical to understand how `__new__` works on any class. This was discussed in “Flexible Object Creation with __new__”.

The same mechanics happen at a “meta” level when a metaclass is about to create a new instance, which is a class. Consider this declaration:

```
class Klass(SuperKlass, metaclass=MetaKlass):
    x = 42
    def __init__(self, y):
        self.y = y
```

To process that `class` statement Python calls `MetaKlass.__new__` with these arguments:

`meta_cls`

: the metaclass itself (`MetaKlass`), because `__new__` works as class method;

`cls_name`

: the string `Klass`;

`bases`

: the single-element tuple `(SuperKlass,)`—with more elements in the case of multiple inheritance.

`cls_dict`

: a mapping like `{x: 42, `__init__`: <function *init* at 0x1009c4040>}`

When you implement `MetaKlass.__new__`, you can inspect and change those arguments before passing them to `super().__new__`, which will eventually call `type.__new__` to create the new class object.

After `super().__new__` returns, you can also apply further processing to the newly created class before returning it to Python. Python then calls `SuperKlass.__init_subclass__`, passing the class you created, and then applies a class decorator to it, if one is present. Finally, Python binds the class object to its name in the surrounding namespace—usually the global namespace of a module, if the `class` statement was a top-level statement.

The most common processing made in a metaclass `__new__` is to add or replace items in the `cls_dict`—the mapping that represents the namespace of the class under construction. For instance, before calling `super().__new__`, you can inject methods in the class under construction by adding functions to `cls_dict`. However, note that adding methods can also be done after the class is built, which is why we were able to do it using `__init_subclass__` or a class decorator.

One attribute that you must add to the `cls_dict` before `type.__new__` runs is `__slots__`, as discussed in "Why `__init_subclass__` cannot configure `__slots__`". The `__new__` method of a metaclass is the ideal place to configure `__slots__`. The next section shows how to do that.

A Nice Metaclass Example

The `MetaBunch` metaclass presented here is a variation of the last example in chapter 4 of *Python in a Nutshell, 3rd Edition*, by Alex Martelli, Anna Ravenscroft, and Steve Holden, written to run on Python 2.7 and 3.5.[13] Assuming Python 3.6 or later, I was able to further simplify the code.

First, let's see what the `Bunch` base class provides:

```
>>> class Point(Bunch):
...     x = 0.0
```

```
...     y = 0.0
...     color = 'gray'
...
>>> Point(x=1.2, y=3, color='green')
Point(x=1.2, y=3, color='green')
>>> p = Point()
>>> p.x, p.y, p.color
(0.0, 0.0, 'gray')
>>> p
Point()
```

Instead of the type hints we use to name the fields in `Checked` subclasses, `Bunch` subclasses assign values to class attributes, which then become the default values of the instance attributes. The generated `__repr__` omits the arguments for attributes that are equal to the defaults.

`MetaBunch`—the metaclass of `Bunch`—generates `__slots__` for the new class from the class attributes declared in the user's class. This blocks the instantiation and later assignment of undeclared attributes:

```
>>> Point(x=1, y=2, z=3)
Traceback (most recent call last):
  ...
AttributeError: 'Point' object has no attribute 'z'
>>> p = Point(x=21)
>>> p.y = 42
>>> p
Point(x=21, y=42)
>>> p.flavor = 'banana'
Traceback (most recent call last):
  ...
AttributeError: 'Point' object has no attribute 'flavor'
```

Now let's dive into the elegant code of `Metabunch`:

Example 25-15. metabunch/from3.6/bunch.py: `MetaBunch` metaclass and `Bunch` class.

```
class MetaBunch(type):  ❶
    def __new__(meta_cls, cls_name, bases, cls_dict):  ❷

        defaults = {}  ❸

        def __init__(self, **kwargs):  ❹
```

```
            for name, default in defaults.items():  ❺
                setattr(self, name, kwargs.pop(name, default))
            if kwargs:  ❻
                setattr(self, *kwargs.popitem())

        def __repr__(self):  ❼
            rep = ', '.join(f'{name}={value!r}'
                            for name, default in defaults.items()
                            if (value := getattr(self, name)) !=
default)
            return f'{cls_name}({rep})'

        new_dict = dict(__slots__=[], __init__=__init__,
__repr__=__repr__)  ❽

        for name, value in cls_dict.items():  ❾
            if name.startswith('__') and name.endswith('__'):  ❿
                if name in new_dict:
                    raise AttributeError(f"Can't set {name!r} in
{cls_name!r}")
                new_dict[name] = value
            else:  ⓫
                new_dict['__slots__'].append(name)
                defaults[name] = value
        return super().__new__(meta_cls, cls_name, bases, new_dict)
⓬


class Bunch(metaclass=MetaBunch):  ⓭
    pass
```

❶ To create a new metaclass, inherit from `type`.

❷ `__new__` works as a class method, but the class is a metaclass, so I like to name the first argument `meta_cls` (`mcs` is a common alternative). The remaining three arguments are the same as the three-argument signature for calling `type()` directly to create a class.

❸ `defaults` will hold a mapping of attribute names and their default values.

❹ This will be injected into the new class.

❺ Read the `defaults` and set the corresponding instance attribute with a value popped from `kwargs` or a default.

❻ If there is still any item in `kwargs`, it is unexpected. We believe in *failing fast* as best practice, so we don't want to silently ignore extra items. A quick and effective solution is to pop one item from `kwargs` and try to set it on the instance, triggering an `AttributeError` on purpose.

❼ `__repr__` returns a string that looks like a constructor call—e.g. `Point(x=3)`, omitting the keyword arguments with default values.

❽ Initialize namespace for the new class.

❾ Iterate over namespace of user's class…

❿ If a dunder `name` is found, copy the item to the new class namespace, unless it's already there. This prevents users from overwriting `__init__`, `__repr__` and other attributes set by Python, such as `__qualname__` and `__module__`.

⓫ If not a dunder `name`, append to `__slots__` and save its `value` in `defaults`.

⓬ Build and return the new class.

⓭ Provide a base class, so users don't need to see `MetaBunch`.

`MetaBunch` works because it is able to configure `__slots__` before calling `super().__new__` to build the final class. As usual when metaprogramming, understanding the sequence of actions is key. Let's do another evaluation time experiment, now with a metaclass.

Metaclass Evaluation Time Experiment

This is a variation of "Evaluation Time Experiments", adding a metaclass to the mix. The *builderlib.py* module is the same as before, but the main script is now *evaldemo_meta.py*, listed in Example 25-16.

Example 25-16. evaldemo_meta.py: experimenting with a metaclass.

```
#!/usr/bin/env python3

from builderlib import Builder, deco, Descriptor
from metalib import MetaKlass  ❶

print('# evaldemo_meta module start')

@deco
class Klass(Builder, metaclass=MetaKlass):  ❷
    print('# Klass body')

    attr = Descriptor()

    def __init__(self):
        super().__init__()
        print(f'# Klass.__init__({self!r})')

    def __repr__(self):
        return '<Klass instance>'


def main():
    obj = Klass()
    obj.method_a()
    obj.method_b()
    obj.method_c()  ❸
    obj.attr = 999


if __name__ == '__main__':
    main()

print('# evaldemo_meta module end')
```

❶ Import `MetaKlass`.

❷ Declare `Klass` as subclass of `Builder` and instance of `MetaKlass`.

❸ Method injected by `MetaKlass`.

WARNING

In the interest of science, Example 25-16 defies all reason and applies three different metaprogramming techniques together on `Klass`: a decorator, a base class using `__init_subclass__`, and a custom metaclass. If you do this in production code, please don't blame me. Again, the goal is to observe the order in which the three techniques interfere in the class construction process.

As in the previous evaluation time experiment, this example does nothing but print messages revealing the flow of execution. Next is the code for the top part of *metalib.py*—the rest is in Example 25-18:

Example 25-17. metalib.py: the NosyDict class

```
print('% metalib module start')

import collections

class NosyDict(collections.UserDict):
    def __setitem__(self, key, value):
        args = (self, key, value)
        print(f'% NosyDict.__setitem__{args!r}')
        super().__setitem__(key, value)

    def __repr__(self):
        return '<NosyDict instance>'
```

I wrote the `NosyDict` class to override `__setitem__` to display each `key` and `value` as they are set. The metaclass will use a `NosyDict` instance to hold the namespace of the class under construction, revealing more of Python's inner workings.

The main attraction of *metalib.py* is the metaclass in Example 25-18. It implements the `__prepare__` special method, a class method that Python only invokes on metaclasses. The `__prepare__` method provides the earliest opportunity to influence the process of creating a new class.

> **TIP**
>
> When coding a metaclass, I find it useful to adopt this naming convention for special method arguments:
>
> - Use `cls` instead of `self` for instance methods, because the instance is a class.
> - Use `meta_cls` instead of `cls` for class methods, because the class is a metaclass. Recall that `__new__` behaves as a class method even without `@classmethod`.

Example 25-18. metalib.py: the `MetaKlass`

```
class MetaKlass(type):
    print('% MetaKlass body')

    @classmethod  ❶
    def __prepare__(meta_cls, cls_name, bases):  ❷
        args = (meta_cls, cls_name, bases)
        print(f'% MetaKlass.__prepare__{args!r}')
        return NosyDict()  ❸

    def __new__(meta_cls, cls_name, bases, cls_dict):  ❹
        args = (meta_cls, cls_name, bases, cls_dict)
        print(f'% MetaKlass.__new__{args!r}')
        def inner_2(self):
            print(f'% MetaKlass.__new__:inner_2({self!r})')

        cls = super().__new__(meta_cls, cls_name, bases,
cls_dict.data)  ❺

        cls.method_c = inner_2  ❻

        return cls  ❼

    def __repr__(cls):  ❽
        cls_name = cls.__name__
        return f"<class {cls_name!r} built by MetaKlass>"

print('% metalib module end')
```

❶ `__prepare__` should be declared as a class method. It is not an instance method because the class under construction does not exist yet when Python calls `__prepare__`.

❷ Python calls `__prepare__` on a metaclass to obtain a mapping to hold the namespace of the class under construction.

❸ Return `NosyDict` instance to be used as the namespace.

❹ `cls_dict` is a `NosyDict` instance returned by `__prepare__`.

❺ `type.__new__` requires a real `dict` as the last argument, so I give it the `data` attribute of `NosyDict`, inherited from `UserDict`.

❻ Inject a method in the newly created class.

❼ As usual, `__new__` must return the object just created—in this case, the new class.

❽ Defining `__repr__` on a metaclass allows customizing the `repr()` of class objects.

The main use case for `__prepare__` before Python 3.6 was to provide an `OrderedDict` to hold the attributes of the class under construction, so that the metaclass `__new__` could process those attributes in the order in which they appear in the source code of the user's class definition. Now that `dict` preserves the insertion order, `__prepare__` is rarely needed. You will see a creative use for it in "A Metaclass Hack with `__prepare__`".

Importing *metalib.py* in the Python console is not very exciting. Note the use of `%` to prefix the lines output by this module:

```
>>> import metalib
% metalib module start
% MetaKlass body
% metalib module end
```

Lots of things happen if you import *evaldemo_meta.py*:

Example 25-19. Console experiment with evaldemo_meta.py.

```
>>> import evaldemo_meta
@ builderlib module start
@ Builder body
@ Descriptor body
@ builderlib module end
% metalib module start
% MetaKlass body
% metalib module end
# evaldemo_meta module start  ❶
% MetaKlass.__prepare__(<class 'metalib.MetaKlass'>, 'Klass',  ❷
                        (<class 'builderlib.Builder'>,))
% NosyDict.__setitem__(<NosyDict instance>, '__module__',
'evaldemo_meta')  ❸
% NosyDict.__setitem__(<NosyDict instance>, '__qualname__',
'Klass')
# Klass body
@ Descriptor.__init__(<Descriptor instance>)  ❹
% NosyDict.__setitem__(<NosyDict instance>, 'attr', <Descriptor
instance>)  ❺
% NosyDict.__setitem__(<NosyDict instance>, '__init__',
                       <function Klass.__init__ at …>)  ❻
% NosyDict.__setitem__(<NosyDict instance>, '__repr__',
                       <function Klass.__repr__ at …>)
% NosyDict.__setitem__(<NosyDict instance>, '__classcell__', <cell
at …: empty>)
% MetaKlass.__new__(<class 'metalib.MetaKlass'>, 'Klass',
                    (<class 'builderlib.Builder'>,), <NosyDict
instance>)  ❼
@ Descriptor.__set_name__(<Descriptor instance>,
                          <class 'Klass' built by MetaKlass>,
'attr')  ❽
@ Builder.__init_subclass__(<class 'Klass' built by MetaKlass>)
@ deco(<class 'Klass' built by MetaKlass>)
# evaldemo_meta module end
```

❶ The lines before this are the result of importing *builderlib.py* and *metalib.py*.

❷ Python invokes `__prepare__` to start processing a `class` statement.

❸ Before parsing the class body, Python adds the `__module__` and `__qualname__` entries to the namespace of the class under construction.

❹ The descriptor instance is created…

❺ …and bound to `attr` in the class namespace.

❻ `__init__` and `__repr__` methods are defined and added to the namespace.

❼ Once Python finished processing the class body, it calls `MetaKlass.__new__`.

❽ `__set_name__`, `__init_subclass__`, and the decorator are invoked in this order, after the `__new__` method of the metaclass returns the newly constructed class.

If you run *evaldemo_meta.py* as script, `main()` is called, and a few more things happen:

Example 25-20. Running evaldemo_meta.py as a program.

```
$ ./evaldemo_meta.py
[... 20 lines omitted ...]
@ deco(<class 'Klass' built by MetaKlass>)  ❶
@ Builder.__init__(<Klass instance>)
# Klass.__init__(<Klass instance>)
@ SuperA.__init_subclass__:inner_0(<Klass instance>)
@ deco:inner_1(<Klass instance>)
% MetaKlass.__new__:inner_2(<Klass instance>)  ❷
@ Descriptor.__set__(<Descriptor instance>, <Klass instance>, 999)
# evaldemo_meta module end
```

❶ The top 21 lines—including this one—are the same shown in Example 25-19.

❷ Triggered by `obj.method_c()` in `main`; `method_c` was injected by `MetaKlass.__new__`.

Let’s now go back to the idea of the `Checked` class with the `Field` descriptors implementing runtime type validation, and see how it can be done with a metaclass.

A Metaclass solution for Checked

I don’t want to encourage premature optimization and overengineering, so here is a make-believe scenario to justify rewriting *checkedlib.py* with `__slots__`, which requires the application of a metaclass. Feel free to skip it.

> **A BIT OF STORYTELLING**
>
> Our *checkedlib.py* using `__init_subclass__` is a company-wide success, and our production servers have millions of instances of `Checked` subclasses in memory at any one time.
>
> Profiling a proof-of-concept, we discover that using `__slots__` will reduce the cloud hosting bill for two reasons:
>
> - lower memory usage, as `Checked` instances don’t need their own `__dict__`;
> - higher performance, by removing `__setattr__` which was created just to block unexpected attributes, but is triggered at instantiation and for all attribute setting before `Field.__set__` is called to do its job.

The *metaclass/checkedlib.py* module we’ll study next is a drop-in replacement for *initsub/checkedlib.py*. The doctests embedded in them are identical, as well as the *checkedlib_test.py* files for *pytest*.

The complexity in *checkedlib.py* is abstracted away from the user. Here is the source code of a script using the package:

```
from checkedlib import Checked

class Movie(Checked):
```

```
    title: str
    year: int
    box_office: float

if __name__ == '__main__':
    movie = Movie(title='The Godfather', year=1972,
box_office=137)
    print(movie)
    print(movie.title)
```

That concise `Movie` class definition leverages three instances of `Field` validating descriptors, a `__slots__` configuration, five methods inherited from `Checked`, and a metaclass to put it all together. The only visible part of `checkedlib` is the `Checked` base class.

Consider Figure 25-4. The Mills & Gizmos Notation complements the UML class diagram by making the relationship between classes and instances more visible. For example, a `Movie` class using the new *checkedlib.py* is an instance of `CheckedMeta`, and a subclass of `Checked`. Also, the `title`, `year` and `box_office` class attributes of `Movie` are three separate instances of `Field`. Each `Movie` instance has its own `_title`,`_year`, and `_box_office` attributes, to store the values of the corresponding fields.

Figure 25-4. UML class diagram annotated with MGN: the `CheckedMeta` meta-mill builds the `Movie` mill. The `Field` mill builds the `title`, `year`, and `box_office` descriptors which are class atttributes of `Movie`. The per-instance data for the fields is stored in the `_title`, `_year` and `_box_office` instance attributes of `Movie`. Note the package boundary of `checkedlib`. The developer of `Movie` doesn't need to grok all the machinery inside checkedlib.py.

Now let's study the code, starting with the `Field` class, shown in Example 25-21.

The `Field` descriptor class is now a bit different. In the previous examples, each `Field` descriptor instance stored its value in the managed instance using an attribute of the same name. For example, in the `Movie` class, the `title` descriptor stored the field value in a `title` attribute in the managed instance. This made it unnecessary for `Field` to provide a `__get__` method.

However, when a class like `Movie` uses `__slots__`, it cannot have class attributes and instance attributes with the same name. Each descriptor instance is a class attribute, and now we need separate per-instance storage attributes. The code uses the descriptor name prefixed with a single _. Therefore `Field` instances have separate `name` and `storage_name` attributes, and we implement `Field.__get__`.

Here is the source code for `Field`, with callouts describing only the changes in this version:

Example 25-21. metaclass/checkedlib.py: the `Field` descriptor with `storage_name` and `__get__`.

```
class Field:
    def __init__(self, name: str, constructor: Callable) -> None:
        if not callable(constructor) or constructor is type(None):
            raise TypeError(f'{name!r} type hint must be callable')
        self.name = name
        self.storage_name = '_' + name  ❶
        self.constructor = constructor

    def __get__(self, instance, owner=None):  ❷
        return getattr(instance, self.storage_name)  ❸

    def __set__(self, instance: Any, value: Any) -> None:
```

```
        if value is ...:
            value = self.constructor()
        else:
            try:
                value = self.constructor(value)
            except (TypeError, ValueError) as e:
                type_name = self.constructor.__name__
                msg = f'{value!r} is not compatible with
{self.name}:{type_name}'
                raise TypeError(msg) from e
        setattr(instance, self.storage_name, value)  ❹
```

❶ Compute `storage_name` from the `name` argument.

❷ Implement `__get__`…

❸ Using `getattr` and the `storage_name`.

❹ `__set__` now uses `setattr` to set or update the managed attribute.

Next is the code for the metaclass that drives this example.

Example 25-22. metaclass/checkedlib.py: the `CheckedMeta` metaclass.

```
class CheckedMeta(type):

    def __new__(meta_cls, cls_name, bases, cls_dict):  ❶
        if '__slots__' not in cls_dict:  ❷
            slots = []
            type_hints = cls_dict.get('__annotations__', {})  ❸
            for name, constructor in type_hints.items():  ❹
                field = Field(name, constructor)  ❺
                cls_dict[name] = field  ❻
                slots.append(field.storage_name)  ❼

            cls_dict['__slots__'] = slots  ❽

        return super().__new__(
                meta_cls, cls_name, bases, cls_dict)  ❾
```

❶ `__new__` is the only method implemented in `CheckedMeta`.

❷

Only enhance the class if its `cls_dict` doesn't include `__slots__`. If `__slots__` is already present, assume it is the `Checked` base class and not a user-defined subclass, and build the class as is.

❸ To get the type hints in prior examples we used `typing.get_type_hints`, but that requires an existing class as the first argument. At this point, the class we are configuring does not exist yet, so we need to retrieve the `__annotations__` directly from the `cls_dict`—the namespace of the class under construction, which Python passes as the last argument to the metaclass `__new__`.

❹ iterate over `type_hints` to…

❺ …build a `Field` for each annotated attribute…

❻ …overwrite the corresponding entry in `cls_dict` with the `Field` instance…

❼ …and append the `storage_name` of the field in the list we'll use to…

❽ …populate the `__slots__` entry in `cls_dict`—the namespace of the class under construction.

❾ Finally, we call `super().__new__`.

The last part of *metaclass/checkedlib.py* is the `Checked` base class that users of this library will subclass to enhance their classes, like `Movie`.

The code for this version of `Checked` is the same as `Checked` in *initsub/checkedlib.py* (listed in Example 25-5 and Example 25-6), with three changes:

1. Added an empty `__slots__` to signal to `CheckedMeta.__new__` that this class doesn't require special processing.

2. Removed `__init_subclass__`. Its job is now done by `CheckedMeta.__new__`.

3. Removed `__setattr__`. It became redundant because adding `__slots__` to the user defined class prevents setting undeclared attributes.

Example 25-23 is a complete listing of the final version of `Checked`.

Example 25-23. metaclass/checkedlib.py: the `Checked` base class.

```
class Checked(metaclass=CheckedMeta):
    __slots__ = ()  # skip CheckedMeta.__new__ processing

    @classmethod
    def _fields(cls) -> dict[str, type]:
        return get_type_hints(cls)

    def __init__(self, **kwargs: Any) -> None:
        for name in self._fields():
            value = kwargs.pop(name, ...)
            setattr(self, name, value)
        if kwargs:
            self.__flag_unknown_attrs(*kwargs)

    def __flag_unknown_attrs(self, *names: str) -> NoReturn:
        plural = 's' if len(names) > 1 else ''
        extra = ', '.join(f'{name!r}' for name in names)
        cls_name = repr(self.__class__.__name__)
        raise AttributeError(f'{cls_name} object has no
attribute{plural} {extra}')

    def _asdict(self) -> dict[str, Any]:
        return {
            name: getattr(self, name)
            for name, attr in self.__class__.__dict__.items()
            if isinstance(attr, Field)
        }

    def __repr__(self) -> str:
        kwargs = ', '.join(
            f'{key}={value!r}' for key, value in
self._asdict().items()
        )
        return f'{self.__class__.__name__}({kwargs})'
```

This concludes the third rendering of a class builder with validated descriptors.

The next section covers some general issues related to metaclasses.

Metaclasses in the Real world

Metaclasses are powerful but tricky. Before deciding to implement a metaclass, consider the following points.

Modern Features Simplify or Replace Metaclasses

Over time, several common use cases of metaclasses were made redundant by new language features:

Class decorators

: Simpler to understand than metaclasses, and less likely to cause conflicts with base classes and metaclasses.

`__set_name__`

: Avoids the need for custom metaclass logic to automatically set the name of a descriptor.[14]

`__init_subclass__`

: Provides a way to customize class creation that is transparent to the end-user and even simpler than a decorator—but may introduce conflicts in a complex class hierarchy.

Built-in `dict` preserving key insertion order

: Eliminated the #1 reason to use `__prepare__`: to provide an `OrderedDict` to store the namespace of the class under construction. Python only calls `__prepare__` on metaclasses, so if you needed to process the class namespace in the order it appears in the source code, you had to use a metaclass before Python 3.6.

As of 2021, every actively maintained version of CPython supports all the features above.

I keep advocating these features because I see too much unnecessary complexity in our profession, and metaclasses are a gateway to complexity.

Metaclasses are Stable Language Features

Metaclasses were introduced in Python 2.2 in 2002, together with so-called “new-style classes”, descriptors, and properties.

It is remarkable that the `MetaBunch` example, first posted by Alex Martelli in July 2002, still works in Python 3.9—the only change being the way to specify the metaclass to use, which in Python 3 is done with the syntax `class Bunch(metaclass=MetaBunch):`.

None of the additions I mentioned in “Modern Features Simplify or Replace Metaclasses” broke existing code using metaclasses. But legacy code using metaclasses can often be simplified by leveraging those features, especially if you can drop support to Python versions before 3.6—which are no longer maintained.

A Class Can Only Have One Metaclass

If your class declaration involves two or more metaclasses, you will see this puzzling error message:

```
TypeError: metaclass conflict: the metaclass of a derived class
must be a (non-strict) subclass of the metaclasses of all its
bases
```

This may happen even without multiple inheritance. For example, a declaration like this could trigger that `TypeError`:

```
class Record(abc.ABC, metaclass=PersistentMeta):
    pass
```

We saw that `abc.ABC` is an instance of the `abc.ABCMeta` metaclass. If that `Persistent` metaclass is not itself a subclass of `abc.ABCMeta`, you get a metaclass conflict.

There are two ways of dealing with that error:

- Find some other way of doing what you need to do, while avoiding at least one of the metaclasses involved.
- Write your own `PersistentABCMeta` metaclass as a subclass of both `abc.ABCMeta` and `PersistentMeta`, using multiple inheritance, and use that as the only metaclass for `Record`.[15]

> **TIP**
>
> I can imagine the solution of the metaclass with two base metaclasses implemented to meet a deadline. In my experience, metaclass programming always takes longer than anticipated, which makes this approach risky before a hard deadline. If you do it and make the deadline, the code may contain subtle bugs. Even in the absence of known bugs, you should consider this approach as technical debt simply because it is hard to understand and maintain.

Metaclasses Should be Implementation Details

Besides `type`, there are only six metaclasses in the entire Python 3.9 standard library. The better known are probably `abc.ABCMeta`, `typing.NamedTupleMeta`, and `enum.EnumMeta`. None of them are intended to appear explicitly in user code. We may consider them implementation details.

Although you can do some really whacky metaprograming with metaclasses, it's best to heed the Principle of least astonishment so that most users can indeed regard metaclasses as implementation details.[16]

In recent years, some metaclasses in the Python standard library were replaced by other mechanisms, without breaking the public API of their packages. The simplest way future-proof such APIs is to offer a regular class that users subclass to access the functionality provided by the metaclass, as we've done in our examples.

To wrap up our coverage of class metaprogramming, I will share with you the coolest, small example of metaclass I found as I researched this chapter.

A Metaclass Hack with `__prepare__`

When I updated this chapter for the *Second Edition*, I needed to find simple but illuminating examples to replace the *bulkfood* `LineItem` code that no longer require metaclasses since Python 3.6.

The simplest and most interesting metaclass idea was given to me by João S. O. Bueno—better known as JS in the Brazilian Python community. One application of his idea is to create a class that auto-generates numeric constants.

```
>>> class Flavor(AutoConst):
...     banana
...     coconut
...     vanilla
...
>>> Flavor.vanilla
2
>>> Flavor.banana, Flavor.coconut
(0, 1)
```

Yes, that code works as shown! That's actually a doctest in *autoconst_demo.py*.

Here is the user-friendly `AutoConst` base class and the metaclass behind it, implemented in *autoconst.py*:

```
class AutoConstMeta(type):
    def __prepare__(name, bases, **kwargs):
        return WilyDict()

class AutoConst(metaclass=AutoConstMeta):
    pass
```

That’s it.

Clearly the trick is in `WilyDict`.

When Python processes the namespace of the user’s class and reads `banana`, it looks that name up in the mapping provided by `__prepare__`: an instance of `WilyDict`. `WilyDict` implements `__missing__`—covered in “The `__missing__` Method”. The `WilyDict` instance initially has no `'banana'` key, so the `__missing__` method is triggered. It makes an item on the fly with the key `'banana'` and the value `0`, returning that value. Python is happy with that, then tries to retrieve `'coconut'`. `WilyDict` promptly adds that entry with the value `1`, returning it. The same happens with `'vanilla'`, which is then mapped to `2`.

We’ve seen `__prepare__` and `__missing__` before. The real innovation is how JS put them together.

Here is the source code for `WilyDict`, also from *autoconst.py*:

```
class WilyDict(dict):
    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.__next_value = 0

    def __missing__(self, key):
        if key.startswith('__') and key.endswith('__'):
            raise KeyError(key)
        self[key] = value = self.__next_value
        self.__next_value += 1
        return value
```

While experimenting, I found that Python looked up `__name__` in the namespace of the class under construction, causing `WilyDict` to add a `__name__` entry, and increment `__next_value`. So I added that `if` statement in `__missing__` to raise `KeyError` for keys that look like dunder attributes.

The *autoconst.py* package both requires and illustrates mastery of Python’s dynamic class building machinery.

I had a great time adding more functionality to `AutoConstMeta` and `AutoConst`, but instead of sharing my experiments I will let you have fun playing with JS's ingenious hack.

Here are some ideas:

- Make it possible to retrieve the constant name if you have the value. For example, `Flavor[2]` could return `'vanilla'`. You can to this by implementing `__getitem__` in `AutoConstMeta`. Since Python 3.9, you can implement `__class_getitem__` in `AutoConst` itself.

- Support iteration over the class, by implementing `__iter__` on the metaclass. I would make the `__iter__` yield the constants as `(name, value)` pairs.

- Implement a new `Enum` variant. This would be a major undertaking, because the `enum` package is full of tricks, including the `EnumMeta` metaclass with hundreds of lines of code and a non-trivial `__prepare__` method.

Enjoy!

> **NOTE**
>
> The `__class_getitem__` special method was added in Python 3.9 to support generic types, as part of *PEP 585—Type Hinting Generics In Standard Collections*. Thanks to `__class_getitem__`, Python's core developers did not have to write a new metaclass for the built-in types to implement `__getitem__` so that we could write generic type hints like `list[int]`. This is a narrow feature, but representative of a wider use case for metaclasses: implementing operators and other special methods to work at the class level, such as making the class itself iterable, just like `Enum` subclasses.

Wrapping up

Metaclasses, as well as class decorators and `__init_subclass__` are useful for:

- Subclass registration.
- Subclass structural validation.
- Applying decorators to many methods at once.
- Object serialization.
- Object-relational mapping.
- Object-based persistence.
- Implementing special methods at the class level.
- Implementing class features found in other languages, such as traits and aspect-oriented programming.

Class metaprogramming can also help with performance issues in some cases, by performing tasks at import time that otherwise would execute repeatedly at runtime.

To wrap up, let's recall Alex Martelli's final advice from his essay "Waterfowl and ABCs":

> *And, don't define custom ABCs (or metaclasses) in production code… if you feel the urge to do so, I'd bet it's likely to be a case of "all problems look like a nail"-syndrome for somebody who just got a shiny new hammer—you (and future maintainers of your code) will be much happier sticking with straightforward and simple code, eschewing such depths.*

I believe Martelli's advice applies not only to ABCs and metaclasses, but also to class hierarchies, operator overloading, function decorators, descriptors, class decorators, and class builders using `__init_subclass__`.

Those powerful tools exist primarily to support library and framework development. Applications naturally should *use* those tools, as provided by the Python standard library or external packages. But *implementing* them in application code is often premature abstraction.

> *Good frameworks are extracted, not invented.*[17]
>
> —David Heinemeier Hansson, creator of Ruby on Rails

Chapter Summary

This chapter started with an overview of attributes found in class objects, such as `__qualname__` and the `__subclasses__()` method. Next we saw how the `type` built-in can be used to construct classes at runtime.

The `__init_subclass__` special method was introduced, with the first iteration of a `Checked` base class designed to replace attribute type hints in user-defined subclasses with `Field` instances that apply constructors to enforce the type of those attributes at runtime.

The same idea was implemented with a `@checked` class decorator which adds features to user-defined classes, similar to what `__init_subclass__` allows. We saw that neither `__init_subclass__` nor a class decorator can dynamically configure `__slots__`, because they operate only after a class is created.

The concepts of "import time" and "runtime" were clarified with experiments showing the order in which Python code in executed when modules, descriptors, class decorators, and `__init_subclass__` is involved.

Our coverage of metaclasses began with an overall explanation of `type` as a metaclass, and how user defined metaclasses can implement `__new__` to customize the classes it builds. We then saw our first custom metaclass, the classic `MetaBunch` example using `__slots__`. Next, another evaluation time experiment demonstrated how the `__prepare__` and `__new__` methods of a metaclass are invoked earlier than `__init_subclass__` and class decorators, providing opportunities for deeper class customization.

The third iteration of a `Checked` class builder with `Field` descriptors and custom `__slots__` configuration was presented, followed by some general considerations about metaclass usage in practice.

Finally, we saw the `AutoConst` hack invented by João S. O. Bueno, based on the cunning idea of a metaclass with `__prepare__` returning a mapping that implements `__missing__`. In less than 20 lines of code, *autoconst.py* showcases the power of combining Python metaprograming techniques

I haven't yet found a language that manages to be easy for beginners, practical for professionals, and exciting for hackers in the way that Python is. Thanks, Guido van Rossum and everybody else who makes it so.

Further Reading

The essential references for this chapter in the Python documentation are "3.3.3. Customizing class creation" in the "Data Model" chapter of The Python Language Reference, which covers `__init_subclass__` and metaclasses. The `type` class documentation in the "Built-in Functions" page, and "4.13. Special Attributes" of the "Built-in Types" chapter in the *Library Reference* is also essential reading.

In the *Library Reference*, the `types` module documentation covers two functions added in Python 3.3 that simplify class metaprogramming: `types.new_class` and `types.prepare_class`.

Class decorators were formalized in PEP 3129—Class Decorators, written by Collin Winter, with the reference implementation authored by Jack Diederich. The PyCon 2009 talk "Class Decorators: Radically Simple" (video), also by Jack Diederich, is a quick introduction to the feature. Besides `@dataclass`, an interesting—and much simpler—example of a class decorator in Python's standard library is `functools.total_ordering` that generates special methods for object comparison.

For metaclasses, the main reference in Python's documentation is PEP 3115—Metaclasses in Python 3000, in which the `__prepare__` special method was introduced.

Python in a Nutshell, 3rd Edition by Alex Martelli, Anna Ravenscroft, and Steve Holden is authoritative, but was written before *PEP 487—Simpler* *customization of class creation* came out. The main metaclass example in that book—`MetaBunch`—is still valid, because it can't be written with simpler mechanisms. Brett Slatkin's *Effective Python, Second Edition* (Addison-Wesley, 2019) has several up-to-date examples of class bulding techniques, including metaclasses.

To learn about the origins of class metaprogramming in Python, I recommend Guido van Rossum's paper from 2003, Unifying types and classes in Python 2.2. The text applies to modern Python as well, as it covers what were then called the "new-style" class semantics—the default semantics in in Python 3—including descriptors and metaclasses. One of the references cited by Guido is *Putting Metaclasses to Work: a New Dimension in Object-Oriented Programming*, by Ira R. Forman and Scott H. Danforth (Addison-Wesley, 1998), a book to which he gave 5 stars on Amazon.com, adding the following review:

> ***This book contributed to the design for metaclasses in Python 2.2***
>
> *Too bad this is out of print; I keep referring to it as the best tutorial I know for the difficult subject of cooperative multiple inheritance, supported by Python via the* `super()` *function.*[18]

If you are keen on metaprogramming, you may wish Python had the ultimate metaprogramming feature: syntactic macros, as offered the Lisp family of languages and—more recently—by Elixir and Rust. Syntactic macros are more powerful and less error-prone than the primitive code substitution macros in the C language. They are special functions that rewrite source code using custom syntax into standard code before the compilation step, enabling developers to introduce new language constructs without changing the compiler. Like operator overloading, syntactic macros can be abused. But as long as the community understands and manages the downsides, they support powerful and user-friendly abstractions, like DSLs (Domain-Specific Languages). In September 2020, Python core developer Mark Shannon posted PEP 638—Syntactic Macros advocating just that. Seven months after initially published, PEP 638 is still in draft and there are no ongoing discussions about it. Clearly it's not a top priority for the Python core developers. I would like to see PEP 638 further discussed and eventually approved. Syntactic macros would allow the Python community to experiment with controversial new features, such as the walrus operator (PEP 572), pattern matching (PEP 634), and alternative rules for evaluating type hints (PEPs 563 and 649) before making permanent changes to the core language. Meanwhile, you can get a taste of syntactic macros with the MacroPy package.

SOAPBOX

I will start the last soapbox in the book with a long quote from Brian Harvey and Matthew Wright, two computer science professors from the University of California (Berkeley and Santa Barbara). In their book, *Simply Scheme*, Harvey and Wright wrote:

> *There are two schools of thought about teaching computer science. We might caricature the two views this way:*
>
> 1. ***The conservative view**: Computer programs have become too large and complex to encompass in a human mind. Therefore, the job of computer science education is to teach people how to discipline their work in such a way that 500 mediocre programmers can join together and produce a program that correctly meets its specification.*
>
> 2. ***The radical view**: Computer programs have become too large and complex to encompass in a human mind. Therefore, the job of computer science education is to teach people how to expand their minds so that the programs can fit, by learning to think in a vocabulary of larger, more powerful, more flexible ideas than the obvious ones. Each unit of programming thought must have a big payoff in the capabilities of the program.*[19]
>
> —Brian Harvey and Matthew Wright, Preface to Simply Scheme

Harvey and Wright's exaggerated descriptions are about teaching computer science, but they also apply to programming language design. By now, you should have guessed that I subscribe to the "radical" view, and I believe Python was designed in that spirit.

The property idea is a great step forward compared to the accessors-from-the-start approach practically demanded by Java and supported by Java IDEs generating getters/setters with a keyboard shortcut. The main advantage of properties is to let us start our programs simply exposing attributes as public—in the spirit of *KISS*—knowing a public attribute can become a property at any time without much pain. But the descriptor idea goes way beyond that, providing a framework for abstracting away repetitive accessor logic. That framework is so effective that essential Python constructs use it behind the scenes.

Another powerful idea is functions as first-class objects, paving the way to higher-order functions. Turns out the combination of descriptors and higher-order functions enable the unification of functions and methods. A function's `__get__` produces a method object on the fly by binding the instance to the `self` argument. This is elegant.[20]

Finally, we have the idea of classes as first-class objects. It's an outstanding feat of design that a beginner-friendly language provides powerful abstractions such as class builders, class decorators and full-fledged, user-defined metaclasses. Best of all: the advanced features are integrated in a way that does not complicate Python's suitability for casual programming (they actually help it, under the covers). The convenience and success of frameworks such as Django and SQLAlchemy owes much to metaclasses. Over the years, class metaprogramming in Python is becoming simpler and simpler, at least for common use cases. The best language features are those that benefit everyone, even if some Python users are not aware of them. But they can always learn and create the next great library.

I look forward to learning about your contributions to the Python community and ecosystem!

---

1 Quote from chapter 2, *Expression*, page 10, of *The Elements of Programming Style, Second Edition*.

2 That doesn't mean PEP 487 broke code that used those features. It just means that some code that used class decorators or metaclasses prior to Python 3.6 can now be refactored to use plain classes, resulting in simpler and possibly more efficient code.

3 Thanks to my friend J. S. O. Bueno for contributing to this example.

4 That's true for any object, except when its class overrides the `__str__` or `__repr__` methods inherited from `object` with broken implementations.

5 This solution avoids using `None` as a default. Avoiding null values is a good idea. They are hard to avoid in general, but easy in some cases. In Python as well as SQL, I prefer to represent missing data in a text field with an empty string instead of `None` or `NULL`. Learning Go reinforced this idea: variables and struct fields of primitive types in Go are initialized by default with a "zero value". See Zero values in the online *Tour of Go* if you are curious.

6 I believe that `callable` should be made suitable for type hinting. As of May 6, 2021, this is an open issue.

7 As mentioned in "What's a good poison pill?", the `Ellipsis` object is a convenient and safe sentinel value. It has been around for a long time, but recently people are finding more uses for it, as we see in type hints and NumPy.

8 The subtle concept of an overriding descriptor was explained in "Overriding Descriptors".

9 This rationale appears in the abstract of PEP 557–Data Classes to explain why it was implemented as a class decorator.

10 Contrast with the `import` statement in Java, which is just a declaration to let the compiler know that certain packages are required.

11 I'm not saying opening a database connection just because a module is imported is a good idea, only pointing out it can be done.

12 Message to comp.lang.python, subject: "Acrimony in c.l.p.". This is another part of the same message from December 23, 2002, quoted in the Preface. The TimBot was inspired that day.

13 The authors kindly gave me permission to use their example. `MetaBunch` first appeared in a message posted by Martelli in the *comp.lang.python* group on July 7, 2002, with the subject line *a nice metaclass example (was Re: structs in python)*, following a discussion about record-like data structures in Python. Martelli's original code for Python 2.2 still runs after a single change: to use a metaclass in Python 3, you must use the metaclass keyword argument in the class declaration, e.g. `Bunch(metaclass=MetaBunch)`, instead of the older convention of adding a `__metaclass__` class-level attribute.

14 In *Fluent Python, First Edition*, the more advanced versions of the `LineItem` class used a metaclass just to set the storage name of the attributes. See the code in the metaclasses of bulkfood in the *First Edition* code repository

15 If you just got dizzy considering the implications of multiple inheritance with metaclasses, good for you. I'd stay way from this solution as well.

16 I made a living writing Django code for a few years before I decided to study how Django's model fields were implemented. Only then I learned about descriptors and metaclasses.

17 The phrase is widely quoted. I found an early direct quote in a post in DHH's blog from 2005.

18 I bought a used copy and found it a very challenging read.

19 Brian Harvey and Matthew Wright, *Simply Scheme* (MIT Press, 1999), p. xvii. Full text available at Berkeley.edu.

20 *Machine Beauty* by David Gelernter (Basic Books) opens with an intriguing discussion of elegance and aesthetics in works of engineering, from bridges to software. The later chapters are not great, but the opening is worth the price.

About the Author

Luciano Ramalho became a web developer before the Netscape IPO in 1995, and switched from Perl to Java to Python in 1998. He joined Thoughtworks in 2015, where he is a Principal Consultant in the São Paulo office. He has delivered keynotes, talks and tutorials at Python events in the Americas, Europe and Asia, and also presented at Go and Elixir conferences, focusing on language design topics. Ramalho is a fellow of the Python Software Foundation and cofounder of Garoa Hacker Clube, the first hackerspace in Brazil.