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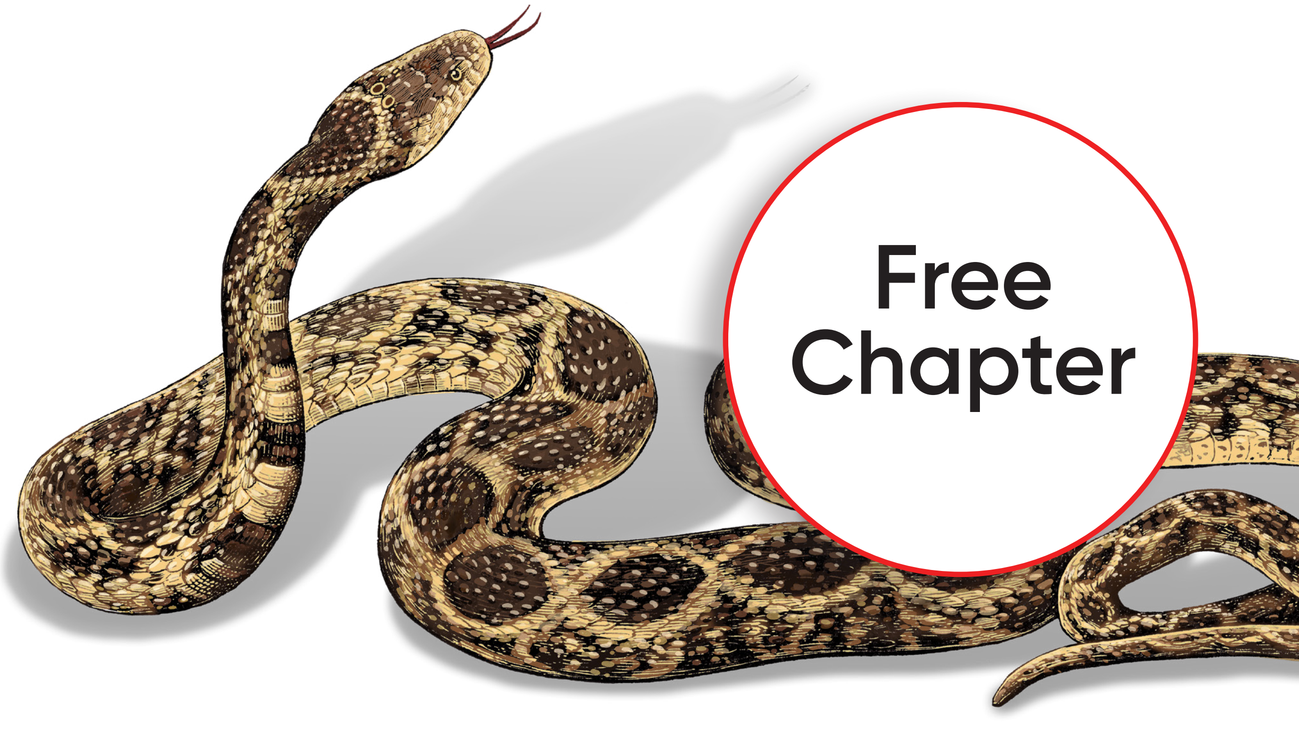
Getting Started with Reading, Cleaning, and Analyzing Data



Free Chapter

Susan E. McGregor

Practical Python Data Wrangling and Data Quality

Susan E. McGregor

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by Susan E. McGregor

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CHAPTER 4

Working with File-Based and Feed-Based Data in Python

In Chapter 3, we focused on the many characteristics that contribute to data quality—from the completeness, consistency, and clarity of data *integrity* to the reliability, validity, and representativeness of data *fit*. We discussed the need to both "clean" and standardize data, as well as the need to augment it by combining it with other datasets. But how do we actually accomplish these things in practice?

Obviously, it's impossible to begin assessing the *quality* of a dataset without first reviewing its contents—but this is sometimes easier said than done. For decades, data wrangling was a highly specialized pursuit, leading companies and organizations to create a whole range of distinct (and sometimes proprietary) digital data formats designed to meet their particular needs. Often, these formats came with their own file extensions—some of which you may have seen: *xls*, *csv*, *dbf*, and *spss* are all file formats typically associated with "data" files.[1] While their specific structures and details vary, all of these formats are what I would describe as *file-based*—that is, they contain (more or less) historical data in static files that can be downloaded from a database, emailed by a colleague, or accessed via file-sharing sites. Most significantly, a file-based dataset will, for the most part, contain the same information whether you open it today or a week, a month, or a year from now.

Today, these file-based formats stand in contrast to the data formats and interfaces that have emerged alongside real-time web services over the past 20 years. Web-based data today is available for everything from news to weather monitoring to social media sites, and these feed-style data sources have their own unique formats and

1 Contrast these with some others you might know, like *mp4* or *png*, which are usually associated with music and images, respectively.

structures. Extensions like *xml*, *json*, and *rss* indicate this type of real-time data, which often needs to be accessed via specialized application programming interfaces, or APIs. Unlike file-based formats, accessing the same web-based data location or "endpoint" via an API will always show you the most *recent* data available—and that data may change in days, hours, or even seconds.

These aren't perfect distinctions, of course. There are many organizations (especially government departments) that provide file-based data for download—but then overwrite those files with new ones that have the same name whenever the source data is updated. At the same time, feed-style data formats *can* be downloaded and saved for future reference—but their source location online will not generally provide access to older versions. Despite these sometimes unconventional uses for each class of data format, however, in most cases you can use the high-level differences between file-based and feed-based data formats to help you choose the most appropriate sources for a given data wrangling project.

How do you know if you want file-based or feed-based data? In many cases, you won't have a choice. Social media companies, for example, provide ready access to their data feeds through their APIs but don't generally provide retrospective data. Other types of data—especially data that is itself synthesized from other sources or heavily reviewed before release—are much more likely to be made available in file-based formats. If you *do* have a choice between file-based and feed-based formats, then which you choose will really depend on the nature of your data wrangling question: if it hinges on having the most *recent* data available, then a feed-style format will probably be preferable. But if you're concerned about *trends*, file-based data, which is more likely to contain information collected over time, will probably be your best bet. That said, even when both formats are available, there's no guarantee they contain the same fields, which once again might make your decision for you.

One Data Source, Two Ways

We've actually already worked with a data source that is available in both a file-based and a feed-based format: our Citi Bike data from Chapter 2. We used a subset of the file-based data to examine how many "Subscriber" versus "Customer" rides were taken by Citi Bike riders on September 1, 2020. For data wrangling questions about trends in ridership and station activity, these retrospective files are invaluable.

At the same time, if we wanted information about how many bikes were available at a particular Citi Bike station *right now*, that file-based data just can't help us. But we *can* access this information using Citi Bike's real-time *json* feed. The wall of text you'll see when you open that link in most web browsers isn't especially user-friendly,[2] but

2 Though you'll know how to wrangle it shortly!

it *does* contain information that the file-based data doesn't—like a count of currently available bikes and parking spots, as well as how many bikes there are not usable, etc. In order to determine the physical location of a particular `station_id`, however, you'd need to *augment* this data with information from either a different Citi Bike data feed or with the file-based data we've already used.

In other words, there are plenty of data sources where it makes sense to have both file-based and feed-based data formats—which is better for you will really depend (as always!) on your particular data wrangling question.

Over the course of this chapter, we'll work through hands-on examples of wrangling data from several of the most common file-based and feed-based data formats, with the goal of making them easier to review, clean, augment, and analyze. We'll also take a look at some of the tougher-to-wrangle data formats that you might need to work with strictly out of necessity. Throughout these processes, we'll rely heavily on the excellent variety of libraries that the Python community has developed for these purposes, including specialty libraries and programs for processing everything from spreadsheets to images. By the time we finish, you'll have the skills and sample scripts you need to tackle a huge variety of data wrangling projects, paving the way forward for your next data wrangling project!

Structured Versus Unstructured Data

Before we dive into writing code and wrangling data, I want to briefly discuss one other key attribute of data sources that can impact the direction (and speed) of your data wrangling projects—working with *structured* versus *unstructured* data.

The goal of most data wrangling projects is to generate insight and, often, to use data to make better decisions. But decisions are time sensitive, so our work with data also requires balancing trade-offs: instead of waiting for the "perfect" dataset, we may combine two or three not-so-perfect ones in order to build a valid approximation of the phenomenon we're investigating, or we may look for datasets that share common identifiers (for example, zip codes), even if that means we need to later derive the particular dimensional structure (like neighborhood) that truly interests us. As long as we can gain these efficiencies without sacrificing too much in terms of data quality, improving the timeliness of our data work can also increase its impact.

One of the simplest ways to make our data wrangling more efficient is to seek out data formats that are easy for Python and other computational tools to access and understand. Although advances in computer vision, natural language processing, and machine learning have made it easier for computers to analyze data regardless of its underlying structure or format, the fact is that *structured*, *machine-readable* data remains—unsurprisingly, perhaps—the most straightforward type of data to work with. In truth, while anything from interviews to images to the text of books can be used as a data source, when many of us think of "data," we often think of structured, numerical data more than anything else.

What Do We Mean by "Machine-Readable"?

Believe it or not, the United States actually has a legal definition of "machine-readable" data, thanks to the Foundations for Evidence-Based Policymaking Act, which went into effect in early 2019. According to the law, machine-readable data is:

> data in a format that can be easily processed by a computer without human intervention while ensuring no semantic meaning is lost.

Helpful, right? While it may seem a bit formal now, as you continue to work with data (especially if you are requesting it from government agencies), you'll begin to appreciate why this definition is important. Particularly when it comes to dealing with "unstructured" data (like text documents), for example, there is a big difference between data that was generated by a word-processing program and data that was scanned in from a piece of paper. While both are "machine-readable" in the sense that you can view them on a computer, good luck trying to access the underlying text from the scanned document programmatically![3] Since there will be times that the folks providing your data might be a little reluctant to do so, a clear (legal!) definition of what "machine-readable" means is actually very valuable.

Structured data is any type of data that has been organized and classified in some way, into some version of records and fields. In file-based formats, these are usually rows and columns; in feed-based formats they are often (essentially) lists of objects or *dictionaries*.

Unstructured data, by contrast, may consist of a mash-up of different data types, combining text, numbers, and even photographs or illustrations. The contents of a magazine or a novel, or the waveforms of a song, for example, would typically be considered unstructured data.

If right now you're thinking, "Hang on, novels have structure! What about chapters?" then congratulations: you're already thinking like a data wrangler. We can create data about almost anything by collecting information about the world and applying structure to it.[4] And in truth, this is how *all* data is created: the datasets that we access via files and feeds are all the product of someone's decisions about how to collect and

3 Actually, you won't need that much luck—we'll look at how to do this in "Wrangling PDFs with Python" on page 45.

4 In computer science, the terms *data* and *information* are applied in exactly the opposite way: *data* is the raw facts collected about the world, and *information* is the meaningful end product of organizing and structuring it. In recent years, however, as talk about "big data" has dominated many fields, the interpretation I use here has become more common, so I'll stick with it throughout this book for clarity.

organize information. In other words, there is always more than one way to organize information, but the structure chosen influences how it can be analyzed. This is why it's a *little* ridiculous to suggest that data can somehow be "objective"; after all, it's the product of (inherently subjective) human choices.

For example, try conducting this mini-experiment: think about how you organize some collection of yours (it could be a collection of music, books, games, or varieties of tea—you name it). Now ask a friend how they organize their own collection of that item. Do you do it the same way? Which is "better"? Now ask someone else, and maybe even a third person. While you may find similarities among the systems that you and your friends use for organizing your music collections, for example, I would be very surprised if you find that any two of you do it precisely the same way. In fact, you'll probably find that everyone does it a little bit differently but *also* feels passionately that their way is "best." And it is! For *them*.

If this is reminding you of our discussion in Chapter 3, that's no coincidence, because the result of your data wrangling question and efforts will eventually be—you guessed it!—another dataset, which will reflect *your* interests and priorities. It, too, will be structured and organized, which makes working with it in certain ways easier than others. But the takeaway here is not that any given way is right or wrong, just that every choice involves trade-offs. Identifying and acknowledging those trade-offs is a key part of using data honestly and responsibly.

So a key trade-off when using *structured* data is that it requires depending on someone else's judgments and priorities in organizing the underlying information. Obviously, this can be a good—or even great!—thing if that data has been structured according to an open, transparent process that involves well-qualified experts. Thoughtfully applied data structures like this can give us early insight into a subject we may otherwise know little to nothing about. On the other hand, there is also the possibility that we will inherit someone else's biased or poorly designed choices.

Unstructured data, of course, gives us complete freedom to organize information into data structures that suit our needs best. Unsurprisingly, this requires *us* to take responsibility for engaging a robust data quality process, which may be both complex and time-consuming.

How do we know if a particular dataset is structured or unstructured up front? In this case, file extensions can definitely help us out. Feed-based data formats always have at least *some* structure to them, even if they contain chunks of "free text," like social media posts. So if you see the file extensions *.json*, *.xml*, *.rss*, or *.atom*, the data has at least some type of record-and-field structure, as we'll explore in "Feed-Based Data—Web-Driven Live Updates" on page 28. File-based data that ends in *.csv*, *.tsv*, *.txt*, *.xls(x)*, or *.ods* tends to follow a table-type, rows-and-columns structure, as we'll see in the next section. Truly unstructured data, meanwhile, is most likely to come to us as *.doc(x)* or *.pdf*.

Smart Searching for Specific Data Types

Since search engines are the first place most of us turn when we're looking for information, wouldn't it be great to be able to use the power of search engines to more efficiently find the data sources (and formats) we need?

While using keywords, sentences, or phrases is a typical way to begin an online search, tweaking those habits just a little can make all the difference when it comes to turning up useful data formats. By mixing in one or more *search operators*, you can tell your search engine to return results from only specific websites or domain types (like *.gov*), or even results with specific file extensions. For example:

`*Search terms or keywords*` `filetype: .csv`
: You can replace `.csv` with any file extension you like, including `.tsv`, `.txt`, `.pdf`, or even `.jpg`, `.mp3`, etc. This will return files with the specified extension that also match your search terms or keywords.

`*Search terms or keywords*` `site: oreilly.com`
: This search will return only results matching your search terms or keywords from within the site *oreilly.com*. This is particularly handy if you are looking for data created or published by a particular organization. Note that you can also use this to search within an entire *top-level domain* like *.gov* or *.co.uk*.

`*Search terms or keywords*` `inurl: https`
: A handy way to locate only secure websites.

`*Search terms or keywords*` `-` `*other search terms or keywords*`
: While this won't help you find specific files, using the hyphen (`-`) can be a great way to focus your search for information when you specifically want to exclude results that would be commonly associated with your main search term. To see this in action, compare the results of the search `steve jobs` with `steve jobs -apple` on your favorite search engine.

Of course, a search engine is just one way to find data; for more ideas about locating the data you need, check out Appendix C.

Now that we've got a good handle on the different types of data sources that we're likely to encounter—and even some sense of how to locate them—let's get wrangling!

Working with Structured Data

Since the early days of digital computing, the *table* has been one of the most common ways to structure data. Even today, many of the most common and easy-to-wrangle data formats are little more than tables or collections of tables. In fact, we already worked with one very common table-type data format in Chapter 2: the *.csv* or comma-separated value format.

File-Based, Table-Type Data—Take It to Delimit

In general, all of the table-type data formats you'll typically encounter are examples of what are known as *delimited* files: each data record is on its own line or row, and the boundaries between fields or columns of data values are indicated—or *delimited*—by a specific text character. Often, an indication of *which* text character is being used as the *delimiter* in a file is incorporated into the dataset's file extension. For example, the *.csv* file extension stands for *comma-separated value*, because these files use a comma character (`,`) as a delimiter; the *.tsv* file extension stands for *tab-separated value*, because the data columns are separated by a tab. A list of file extensions commonly associated with delimited data follows:

.csv
: *Comma-separated value* files are among the most common form of table-type structured data files you'll encounter. Almost any software system that handles tabular data (such as government or corporate data systems, spreadsheet programs, and even specialized commercial data programs) can output data as a *.csv*, and, as we saw in Chapter 2, there are handy libraries for easily working with this data type in Python.

.tsv
: *Tab-separated value* files have been around for a long time, but the descriptive *.tsv* extension has only become common relatively recently. While data providers don't often explain why they choose one delimiter over another, tab-delimited files may be more common for datasets whose values need to include commas, such as postal addresses.

.txt
: Structured data files with this extension are often *.tsv* files in disguise; older data systems often labeled tab-separated data with the *.txt* extension. As you'll see in the worked examples that follow, it's a good idea to open and review *any* data file you want to wrangle with a basic text program (or a code editor like Atom) before you write any code, since looking at the contents of the file is the only surefire way to know what delimiters you're working with.

.xls(x)
: This is the file extension of spreadsheets produced with Microsoft Excel. Because these files can contain multiple "sheets" in addition to formulas, formatting, and other features that simple delimited files cannot replicate, they need more memory to store the same amount of data. They also have other limitations (like

only being able to handle a certain number of rows) that can have implications for your dataset's integrity.

.ods
: *Open-document spreadsheet* files are the default extension for spreadsheets produced by a number of open source software suites like LibreOffice and OpenOffice and have limitations and features similar to those of *.xls(x)* files.

Before we dive into how to work with each of these file types in Python, it's worth spending just a little time thinking about when we might *want* to work with table-type data and where to find it when we do.

When to work with table-type data

Most of the time, we don't get much of a choice about the format of our source data. In fact, much of the reason we need to do data wrangling in the first place is because the data we have doesn't quite meet our needs. That said, it's still valuable to know what data format you would *prefer* to be able to work with so that you can use that to inform your initial search for data.

In "Structured Versus Unstructured Data" on page 3, we talked about the benefits and limitations of structured data, and we now know that table-type data is one of the oldest and most common forms of machine-readable data. This history means, in part, that over the years many forms of source data have been crammed into tables, even though they may *not* necessarily be well suited to table-like representations. Still, this format can be especially useful for answering questions about trends and patterns over time. In our Citi Bike exercise from Chapter 2, for example, we examined how many "Customers" versus "Subscribers" had taken Citi Bike rides over the course of a single month. If we wanted to, we could perform the same calculation for *every* available month of Citi Bike rides in order to understand any patterns in this ratio over time.

Of course, table-type data is generally not a great format for real-time data, or data where not every observation contains the same possible values. These kinds of data are often better suited to the feed-based data formats that we discuss in "Feed-Based Data—Web-Driven Live Updates" on page 28.

Where to find table-type data

Since the vast majority of machine-readable data is still in table-type data formats, it is among the easiest data formats to locate. Spreadsheets are common in every discipline, and a large number of government and commercial information systems rely on software that organizes data in this way. Almost any time you request data from an expert or organization, a table-type format is what you are likely to get. This is also true of almost every open-data portal and data-sharing site you'll find online. As we covered in "Smart Searching for Specific Data Types" on page 6, you can even find table-type data (and other specific file formats) via search engines, if you know how to look.

Wrangling Table-Type Data with Python

To help illustrate how simple it is to work with table-type data in Python, we'll walk through examples of how to read in data from all of the file types mentioned in this section—plus a few others, just for good measure. While in later chapters we'll look at how to do more with cleaning, transformation, and data quality assessments, our focus for the time being will simply be on accessing the data within each type of data file and interacting with it using Python.

Reading data from CSVs

In case you didn't follow along in Chapter 2, here's a refresher on how to read data from a *.csv* file, using a sample from the Citi Bike dataset (Example 4-1). As always, I've included a description of what the program is doing—as well as links to any source files—in the comments at the top of my script. Since we've worked with this data format before, for now we'll just worry about printing out the first few rows of data to see what they look like.

Example 4-1. csv_parsing.py

```
# a simple example of reading data from a .csv file with Python
# using the "csv" library.
# the source data was sampled from the Citi Bike system data:
# https://drive.google.com/file/d/17b461NhSjf_akFWvjgNXQfqgh9iFxCu_/
# which can be found here:
# https://s3.amazonaws.com/tripdata/index.html

# import the `csv` library ❶
import csv

# open the `202009CitibikeTripdataExample.csv` file in read ("r") mode
# this file should be in the same folder as our Python script or notebook
source_file = open("202009CitibikeTripdataExample.csv","r") ❷

# pass our `source_file` as an ingredient to the `csv` library's
# DictReader "recipe".
# store the result in a variable called `citibike_reader`
citibike_reader = csv.DictReader(source_file)

# the DictReader method has added some useful information to our data,
# like a `fieldnames` property that lets us access all the values
# in the first or "header" row
print(citibike_reader.fieldnames) ❸

# let's just print out the first 5 rows
```

```
for i in range(0,5): ❹
    print (next(citibike_reader))
```

❶ This is our workhorse library when it comes to dealing with table-type data.

❷ `open()` is a built-in function that takes a filename and a "mode" as parameters. In this example, the target file (`202009CitibikeTripdataExample.csv`) should be in the same folder as our Python script or notebook. Values for the "mode" can be `r` for "read" or `w` for "write."

❸ By printing out the `citibike_reader.fieldnames` values, we can see that the exact label for the "User Type" column is `usertype`.

❹ The `range()` function gives us a way to execute some piece of code a specific number of times, starting with the value of the first argument and ending just *before* the value of the second argument. For example, the code indented below this line will be executed five times, going through the `i` values of `0`, `1`, `2`, `3`, and `4`. For more on the `range()` function, see "Adding Iterators: The range Function" on page 10.

The output from running this should look something like:

```
['tripduration', 'starttime', 'StartDate', 'stoptime', 'start station id',
'start station name', 'start station latitude', 'start station longitude', 'end
station id', 'end station name', 'end station latitude', 'end station
longitude', 'bikeid', 'usertype', 'birth year', 'gender']
{'tripduration': '4225', 'starttime': '2020-09-01 00:00:01.0430', 'StartDate':
'2020-09-01', 'stoptime': '2020-09-01 01:10:26.6350', 'start station id':
'3508', 'start station name': 'St Nicholas Ave & Manhattan Ave', 'start station
latitude': '40.809725', 'start station longitude': '-73.953149', 'end station
id': '116', 'end station name': 'W 17 St & 8 Ave', 'end station latitude': '40.
74177603', 'end station longitude': '-74.00149746', 'bikeid': '44317',
'usertype': 'Customer', 'birth year': '1979', 'gender': '1'}
 ...
{'tripduration': '1193', 'starttime': '2020-09-01 00:00:12.2020', 'StartDate':
'2020-09-01', 'stoptime': '2020-09-01 00:20:05.5470', 'start station id':
'3081', 'start station name': 'Graham Ave & Grand St', 'start station
latitude': '40.711863', 'start station longitude': '-73.944024', 'end station
id': '3048', 'end station name': 'Putnam Ave & Nostrand Ave', 'end station
latitude': '40.68402', 'end station longitude': '-73.94977', 'bikeid': '26396',
'usertype': 'Customer', 'birth year': '1969', 'gender': '0'}
```

Adding Iterators: The range Function

Unlike many other programming languages, Python's `for` loop is designed to run through *all* values in a list or a dataset by default. While this can be handy for processing entire datasets quickly, it's not so helpful when we just want to quickly review a handful of rows.

This is where a special type of variable called an *iterator* comes in. Like any variable, you can name an iterator anything you like, though `i` (for *iterator*!) is traditional. As you can see from the preceding example, one place where Python *iterators* typically appear is within the `range` function—another example of a *control flow* function that, like `for` loops and `if` statements, has special, built-in properties.

For example, the `range` function includes an *iterator* variable that lets us write a slightly different kind of `for` loop—one that goes through a certain number of rows, rather than all of them. So rather than taking the form of:

```
for item in complete_list_of_items:
```

it lets us write a `for` loop that starts at a particular point in our list and continues for a certain number of items:

```
for item_position in range (starting_position, >number_of_places_to_move):
```

In Example 4-1, we chose to print the first several rows of the file:

```
for i in range(0,5):
   print (next(citibike_reader))
```

One thing to note is that when the `range` iterates over the values specified in the parentheses, it *includes* the first number but *excludes* the second one. This means that in order to print five rows of data, we need to provide an initial value of `0`, because lists in Python are what's known as *zero-indexed*—they start "counting" positions at `0` rather than `1`.

Reading data from TSV and TXT files

Despite its name, the Python *csv* library is basically a one-stop shop for wrangling table-type data in Python, thanks to the `DictReader` function's `delimiter` option. Unless you tell it differently, `DictReader` assumes that the comma character (`,`) is the separator it should look for. Overriding that assumption is easy, however: you can simply specify a different character when you call the function. In Example 4-2, we specify the tab character (`\t`), but we could easily substitute any delimiter we prefer (or that appears in a particular source file).

Example 4-2. tsv_parsing.py

```
# a simple example of reading data from a .tsv file with Python, using
# the `csv` library. The source data was downloaded as a .tsv file
# from Jed Shugerman's Google Sheet on prosecutor politicians: ❶
# https://docs.google.com/spreadsheets/d/1E6Z-jZWbrKmit_4lG36oyQ658Ta6Mh25HCOBaz7YVrA
```

```python
# import the `csv` library
import csv

# open the `ShugermanProsecutorPoliticians-SupremeCourtJustices.tsv` file
# in read ("r") mode.
# this file should be in the same folder as our Python script or notebook
tsv_source_file = open("ShugermanProsecutorPoliticians-SupremeCourtJustices.tsv","r")

# pass our `tsv_source_file` as an ingredient to the csv library's
# DictReader "recipe."
# store the result in a variable called `politicians_reader`
politicians_reader = csv.DictReader(tsv_source_file, delimiter='\t')

# the DictReader method has added some useful information to our data,
# like a `fieldnames` property that lets us access all the values
# in the first or "header" row
print(politicians_reader.fieldnames)

# we'll use the `next()` function to print just the first row of data
print (next(politicians_reader))
```

❶ This dataset was listed in Jeremy Singer-Vine's (@jsvine) "Data Is Plural" newsletter (*https://data-is-plural.com*).

This should result in output that looks something like:

```
['', 'Justice', 'Term Start/End', 'Party', 'State', 'Pres Appt', 'Other Offices
Held', 'Relevant Prosecutorial Background']
{'': '40', 'Justice': 'William Strong', 'Term Start/End': '1870-1880', 'Party':
'D/R', 'State': 'PA', 'Pres Appt': 'Grant', 'Other Offices Held': 'US House,
Supr Court of PA, elect comm for elec of 1876', 'Relevant Prosecutorial
Background': 'lawyer'}
```

What's in a File Extension?

While having computers take care of certain things for us "automagically" can often be convenient, one thing that learning to wrangle data and program in Python will hopefully make clear is that we have much more influence over how our computers behave than it might first appear.

A perfect example of this is file extensions. Throughout the course of this chapter, I've highlighted how file extensions can give us clues about the format of a dataset and even help us search for them more efficiently. Of course, computers *also* use file extensions to make inferences about the contents of a particular file, typically relying on them to select the appropriate program for opening it. This is why if you've ever *changed* a file extension—whether intentionally or by accident—you've probably seen a warning message to the effect of "Are you sure you want to change this? The file might not work properly if you do." While no doubt well-intentioned, those types of warning messages make it seem like you can actually break or corrupt your files by accidentally changing the file extension.

In fact, nothing could be further from the truth. Changing the extension of a file (for example, from *.tsv* to *.txt* or vice versa) does absolutely *nothing* to change its contents. All it does is change what your computer assumes should be done with it.

Fortunately, Python tools like the ones we're using don't make those sorts of assumptions. When we're working with table-type data, as long as the delimiter we specify matches what's actually used in the file, the extension on the data file doesn't matter either way. In fact, the *.txt* file we'll use in Example 4-3 was created simply by saving a copy of the *.tsv* file from Example 4-2 and changing the extension!

Though the *.tsv* file extension has become relatively common nowadays, many files generated by older databases that are *actually* tab-separated may reach you with a *.txt* file extension. Fortunately, as described in the preceding sidebar, this changes nothing about how we handle the file as long as we specify the correct delimiter—as you can see in Example 4-3.

Example 4-3. txt_parsing.py

```
# a simple example of reading data from a .tsv file with Python, using
# the `csv` library. The source data was downloaded as a .tsv file
# from Jed Shugerman's Google Sheet on prosecutor politicians:
# https://docs.google.com/spreadsheets/d/1E6Z-jZWbrKmit_4lG36oyQ658Ta6Mh25HCOBaz7YVrA
# the original .tsv file was renamed with a file extension of .txt

# import the `csv` library
import csv

# open the `ShugermanProsecutorPoliticians-SupremeCourtJustices.txt` file
# in read ("r") mode.
# this file should be in the same folder as our Python script or notebook
txt_source_file = open("ShugermanProsecutorPoliticians-SupremeCourtJustices.txt","r")

# pass our txt_source_file as an ingredient to the csv library's DictReader
# "recipe" and store the result in a variable called `politicians_reader`
# add the "delimiter" parameter and specify the tab character, "\t"
politicians_reader = csv.DictReader(txt_source_file, delimiter='\t') ❶

# the DictReader function has added useful information to our data,
# like a label that shows us all the values in the first or "header" row
print(politicians_reader.fieldnames)

# we'll use the `next()` function to print just the first row of data
print (next(politicians_reader))
```

❶ As discussed in Chapter 1, whitespace characters have to be *escaped* when we're using them in code. Here, we're using the escaped character for a `tab`, which is `\t`. Another common whitespace character code is `\n` for `newline` (or `\r` for `return`, depending on your device).

If everything has gone well, the output from this script should look exactly the same as that from Example 4-2.

One question you may be asking yourself at this point is "How do I know what delimiter my file has?" While there are programmatic ways to help detect this, the simple answer is: Look! Anytime you begin working with (or thinking about working with) a new dataset, start by opening it up in the most basic text program your device has to offer (any code editor will also be a reliable choice). Especially if the file is large, using the simplest program possible will let your device devote maximum memory and processing power to actually reading the data—reducing the likelihood that the program will hang or your device will crash (closing other programs and excess browser tabs will help, too)!

Though I'll talk about some ways to inspect small parts of *really* large files later on in the book, now is the time to start practicing the skills that are essential to assessing data quality—all of which require reviewing your data and making judgments about it. So while there *are* ways to "automate away" tasks like identifying the correct delimiter for your data, eyeballing it in a text editor will often be not just faster and more intuitive, but it will help you get more familiar with other important aspects of the data at the same time.

It's All Just Text

One reason why opening *.csv*, *.tsv*, and many other data formats in a text editor is so helpful is that *most* of the data formats we will (or want to) deal with are, at the most basic level, just text. In exactly the same way that written English is organized into sentences and paragraphs through the (somewhat) standardized use of periods, spaces, capital letters, and newlines, what distinguishes one data format from another at a practical level is also just the punctuation used to organize it. As we've seen, basic table-type data is separated into fields or columns through the use of *delimiters*, and into records or rows by using newlines. Feed-type data, which we'll look at in the next section, is a bit more flexible (and involved) but ultimately follows relatively simple punctuation and structure rules of its own.

Of course, there are plenty of nontext data formats out there, which are usually the output of specialized, *proprietary* programs that are designed to make data wrangling (and analysis and visualization) possible *without* writing much, if any, code. While these programs can make very specific data tasks faster or more approachable, the trade-off is that they are often expensive, challenging to learn, and sometimes inflexible. As we'll see in "XLSX, ODS, and All the Rest" on page 17 and beyond, getting data *out* of these proprietary formats can also be difficult, unreliable, or even impossible. So while Python can still help us wrangle some of the most common proprietary data formats, in some cases using alternate software (or enlisting someone else's help) is our best option.

Real-World Data Wrangling: Understanding Unemployment

The underlying dataset that we'll use to explore some of our trickier table-type data formats is unemployment data about the United States. Why? In one way or another, unemployment affects most of us, and in recent decades the US has experienced some particularly high unemployment rates. Unemployment numbers for the US are released monthly by the Bureau of Labor Statistics (BLS), and while they are often reported by general-interest news sources, they are usually treated as a sort of abstract indicator of how "the economy" is doing. What the numbers really represent is rarely discussed in-depth.

When I first joined the *Wall Street Journal* in 2007, building an interactive dashboard for exploring monthly economic indicator data—including unemployment—was my first major project. One of the more interesting things I learned in the process is that there isn't "an" unemployment rate calculated each month, there are *several* (six, to be exact). The one that usually gets reported by news sources is the so-called "U3" unemployment rate, which the BLS describes as:

> Total unemployed, as a percent of the civilian labor force (official unemployment rate).

On its surface, this seems like a straightforward definition of unemployment: of all the people who reasonably *could* be working, what percentage are not?

Yet the real story is a bit more complex. What does it mean to be "employed" or be counted as part of the "labor force"? A look at different unemployment numbers makes more clear what the "U3" number does *not* take into account. The "U6" unemployment rate is defined as:

> Total unemployed, plus all persons marginally attached to the labor force, plus total employed part time for economic reasons, as a percent of the civilian labor force plus all persons marginally attached to the labor force.

When we read the accompanying note, this longer definition starts to take shape:[5]

> NOTE: Persons marginally attached to the labor force are those who currently are neither working nor looking for work but indicate that they want and are available for a job and have looked for work sometime in the past 12 months. Discouraged

5 From the US Bureau of Labor Statistics.

> workers, a subset of the marginally attached, have given a job-market related reason for not currently looking for work. Persons employed part time for economic reasons are those who want and are available for full-time work but have had to settle for a part-time schedule. Updated population controls are introduced annually with the release of January data.

In other words, if you *want* a job (and have looked for one in the past year) but haven't looked for one very recently—or if you have a part-time job but *want* a full-time job—then you don't officially count as "unemployed" in the U3 definition. This means that the economic reality of Americans working multiple jobs (who are more likely to be women and have more children)[6], and potentially of "gig" workers (recently estimated as up to 30% of the American workforce),[7] are not necessarily reflected in the U3 number. Unsurprisingly, the U6 rate is typically several percentage points higher each month than the U3 rate.

To see how these rates compare over time, we can download them from the website of the St. Louis Federal Reserve, which provides thousands of economic datasets for download in a range of formats, including table-type *.xls(x)* files and, as we'll see later in Example 4-12, feed-type formats as well.

You can download the data for these exercises from the Federal Reserve Economic Database (FRED) website. It shows the current U6 unemployment rate since the measure was first created in the early 1990s.

To add the U3 rate to this graph, at the top right choose Edit graph → ADD LINE. In the search field, type **`UNRATE`** and then select "Unemployment Rate" when it populates below the search bar. Finally, click Add series. Close this side window using the X at the top right, and then select Download, being sure to select the first option, Excel.[8] This will be an *.xls* file, which we'll handle last because although still widely available, this is a relatively outdated file format (it was replaced by *.xlsx* as the default format for Microsoft Excel spreadsheets in 2007).

To get the additional file formats we need, just open the file you downloaded with a spreadsheet program like Google Sheets and choose "Save As," then select *.xlsx*, then repeat the process choosing *.ods*. You should now have the following three files, all containing the same information: *fredgraph.xlsx*, *fredgraph.ods*, and *fredgraph.xls*.[9]

6 "Multiple Jobholders" by Stéphane Auray, David L. Fuller, and Guillaume Vandenbroucke, posted December 21, 2018, *https://research.stlouisfed.org/publications/economic-synopses/2018/12/21/multiple-jobholders*.

7 See "New Recommendations on Improving Data on Contingent and Alternative Work Arrangements," *https://blogs.bls.gov/blog/tag/contingent-workers*; "The Value of Flexible Work: Evidence from Uber Drivers" by M. Keith Chen et al., *Nber Working Paper Series* No. 23296, *https://nber.org/system/files/working_papers/w23296/w23296.pdf*.

8 You can also find instructions for this on the FRED website.

9 You can also download copies of these files directly from my Google Drive.

If you opened the original *fredgraph.xls* file, you probably noticed that it contains more than just the unemployment data; it also contains some header information about where the data came from and the definitions of U3 and U6 unemployment, for example. While doing *analysis* on the unemployment rates these files contain would require separating this metadata from the table-type data further down, remember that our goal for the moment is simply to convert all of our various files to a *.csv* format. We'll tackle the data cleaning process that would involve removing this metadata in Chapter 7.

XLSX, ODS, and All the Rest

For the most part, it's preferable to avoid processing data saved as *.xlsx*, *.ods*, and most other nontext table-type data formats directly, if possible. If you're just at the stage of exploring datasets, I suggest you review these files simply by opening them with your preferred spreadsheet program and saving them as a *.csv* or *.tsv* file format before accessing them in Python. Not only will this make them easier to work with, it will give you a chance to actually look at the contents of your data file and get a sense of what it contains.

Resaving and reviewing *.xls(x)* and similar data formats as a *.csv* or equivalent text-based file format will both reduce the file size *and* give you a better sense of what the "real" data looks like. Because of the formatting options in spreadsheet programs, sometimes what you see onscreen is substantially different from the raw values that are stored in the actual file. For example, values that appear as percentages in a spreadsheet program (e.g., 10%) might actually be decimals (.1). This can lead to problems if you try to base aspects of your Python processing or analysis on what you saw in the spreadsheet as opposed to a text-based data format like *.csv*.

Still, there will definitely be situations where you need to access *.xls(x)* and similar file types with Python directly.[10] For example, if there's an *.xls* dataset you need to wrangle on a regular basis (say, every month), resaving the file manually each time would become unnecessarily time-consuming.

Fortunately, that active Python community we talked about in Chapter 1 has created libraries that can handle an impressive range of data formats with ease. To get a thorough feel for how these libraries work with more complex source data (and data formats), the following code examples read in the specified file format and then create a *new .csv* file that contains the same data.

10 As of this writing, LibreOffice can handle the same number of rows as Microsoft Excel (2^{20}), but far fewer columns. While Google Sheets can handle *more* columns than Excel, it can only handle about 40,000 rows.

To make use of these libraries, however, you'll first need to install them on your device by running the following commands one by one in a terminal window:[11]

```
pip install openpyxl
pip install pyexcel-ods
pip install xlrd==2.0.1
```

In the following code examples, we'll be using the *openpyxl* library to access (or *parse*) *.xlsx* files, the *pyexcel-ods* library for dealing with *.ods* files, and the *xlrd* library for reading from *.xls* files (for more on finding and selecting Python libraries, see Appendix A).

To better illustrate the idiosyncrasies of these different file formats, we're going to do something similar to what we did in Example 4-3: we'll take sample data that is being provided as an *.xls* file and create *.xlsx* and *.ods* files containing *the exact same data* by resaving that source file in the other formats using a spreadsheet program. Along the way, I think you'll start to get a sense of how these nontext formats make the process of data wrangling more (and, I would argue, unnecessarily) complicated.

We'll start by working through an *.xlsx* file in *\ref* (Example 4-4), using a version of the unemployment data downloaded from FRED. This example illustrates one of the first major differences between dealing with text-based table-type data files and nontext formats: because the nontext formats support multiple "sheets," we needed to include a `for` loop at the top of our script, *within* which we put the code for creating our individual output files (one for each sheet).

Example 4-4. xlsx_parsing.py

```python
# an example of reading data from an .xlsx file with Python, using the "openpyxl"
# library. First, you'll need to pip install the openpyxl library:
# https://pypi.org/project/openpyxl/
# the source data can be composed and downloaded from:
# https://fred.stlouisfed.org/series/U6RATE

# specify the "chapter" you want to import from the "openpyxl" library
# in this case, "load_workbook"
from openpyxl import load_workbook

# import the `csv` library, to create our output file
import csv

# pass our filename as an ingredient to the `openpyxl` library's
# `load_workbook()` "recipe"
# store the result in a variable called `source_workbook`
source_workbook = load_workbook(filename = 'fredgraph.xlsx')
```

11 As of this writing, all of these libraries are already available and ready to use in Google Colab.

```
# an .xlsx workbook can have multiple sheets
# print their names here for reference
print(source_workbook.sheetnames) ❶

# loop through the worksheets in `source_workbook`
for sheet_num, sheet_name in enumerate(source_workbook.sheetnames): ❷

    # create a variable that points to the current worksheet by
    # passing the current value of `sheet_name` to `source_workbook`
    current_sheet = source_workbook[sheet_name]

    # print `sheet_name`, just to see what it is
    print(sheet_name)

    # create an output file called "xlsx_"+sheet_name
    output_file = open("xlsx_"+sheet_name+".csv","w") ❸

    # use this csv library's "writer" recipe to easily write rows of data
    # to `output_file`, instead of reading data *from* it
    output_writer = csv.writer(output_file)

    # loop through every row in our sheet
    for row in current_sheet.iter_rows(): ❹

        # we'll create an empty list where we'll put the actual
        # values of the cells in each row
        row_cells = [] ❺

        # for every cell (or column) in each row....
        for cell in row:

            # let's print what's in here, just to see how the code sees it
            print(cell, cell.value)

            # add the values to the end of our list with the `append()` method
            row_cells.append(cell.value)

        # write our newly (re)constructed data row to the output file
        output_writer.writerow(row_cells) ❻

    # officially close the `.csv` file we just wrote all that data to
    output_file.close()
```

❶ Like the *csv* library's `DictReader()` function, `openpyxl`'s `load_workbook()` function adds properties to our source data, in this case, one that shows us the names of all the data sheets in our workbook.

❷ Even though our example workbook only includes one worksheet, we might have more in the future. We'll use the `enumerate()` function so we can access both an iterator *and* the sheet name. This will help us create one *.csv* file per worksheet.

❸ Each sheet in our `source_workbook` will need its own, uniquely named output *.csv* file. To generate these, we'll "open" a new file with the name `"xlsx_"+sheet_name+".csv"` and make it *writable* by passing `w` as the "mode" argument (up until now, we've used the `r` mode to *read* data from *.csvs*).

❹ The function `iter_rows()` is specific to the *openpyxl* library. Here, it converts the rows of `source_workbook` into a list that can be *iterated*, or looped, over.

❺ The *openpyxl* library treats each data cell as a Python `tuple` data type. If we try to just print the rows of `current_sheet` directly, we'll get sort of unhelpful cell locations, rather than the data values they contain. To address this, we'll make *another* loop inside this one to go through every cell in every row one at a time and add the actual data values to `row_cells`.

❻ Notice that this code is left-aligned with the `for cell in row` code in the example. This means that it is *outside* that loop and so will only be run *after* all the cells in a given row have been appended to our list.

This script also begins to demonstrate the way that, just as two chefs may have different ways of preparing the same dish, library creators may make different choices about how to (re)structure each source file type—with corresponding implications for our code. The creators of the *openpyxl* library, for example, chose to store each data cell's location label (e.g., `A6`) and the value it contains in a Python `tuple`. That design decision is why we need a second `for` loop to go through each row of data—because we actually have to access the data cell by cell in order to build the Python list that will become a single row in our output *.csv* file. Likewise, if you use a spreadsheet program to open the *xlsx_FRED Graph.csv* created by the script in Example 4-4, you'll see that the original *.xls* file shows the values in the `observation_date` column in a YYYY-MM-DD format, but our output file shows those values in a YYYY-MM-DD HH:MM:SS format. This is because the creator(s) of *openpyxl* decided that it would automatically convert any "date-like" data strings into the Python `datetime` datatype. Obviously, none of these choices are right or wrong; we simply need to account for them in writing our code so that we don't distort or misinterpret the source data.

Now that we've wrangled the *.xlsx* version of our data file, let's see what happens when we parse it as an *.ods*, as shown in Example 4-5.

Example 4-5. ods_parsing.py

```
# an example of reading data from an .ods file with Python, using the
# "pyexcel_ods" library. First, you'll need to pip install the library:
# https://pypi.org/project/pyexcel-ods/

# specify the "chapter" of the "pyexcel_ods" library you want to import,
# in this case, `get_data`
from pyexcel_ods import get_data

# import the `csv` library, to create our output file
import csv

# pass our filename as an ingredient to the `pyexcel_ods` library's
# `get_data()` "recipe"
# store the result in a variable called `source_workbook`
source_workbook = get_data("fredgraph.ods")

# an `.ods` workbook can have multiple sheets
for sheet_name, sheet_data in source_workbook.items(): ❶

    # print `sheet_name`, just to see what it is
    print(sheet_name)

    # create "ods_"+sheet_name+".csv" as an output file for the current sheet
    output_file = open("ods_"+sheet_name+".csv","w")

    # use this csv library's "writer" recipe to easily write rows of data
    # to `output_file`, instead of reading data *from* it
    output_writer = csv.writer(output_file)

    # now, we need to loop through every row in our sheet
    for row in sheet_data: ❷

        # use the `writerow` recipe to write each `row`
        # directly to our output file
        output_writer.writerow(row) ❸

    # officially close the `.csv` file we just wrote all that data to
    output_file.close()
```

❶ The *pyexcel_ods* library converts our source data into Python's `OrderedDict` data type. The associated `items()` method then lets us access each sheet's name and data as a key/value pair that we can loop through. In this case, `sheet_name` is the "key" and the entire worksheet's data is the "value."

❷ Here, `sheet_data` is already a list, so we can just loop through that list with a basic `for` loop.

❸ This library converts each row in a worksheet to a list, which is why we can pass these directly to the `writerow()` method.

In the case of the *pyexcel_ods* library, the contents of our output *.csv* file *much* more closely resembles what we see visually when we open the original *fredgraph.xls* via a spreadsheet program like Google Sheets—the `observation_date` field, for example, is in a simple YYYY-MM-DD format. Moreover, the library creator(s) decided to treat the values in each row as a list, allowing us to write each record directly to our output file without creating any additional loops or lists.

Finally, let's see what happens when we use the *xlrd* library to parse the original *.xls* file directly in Example 4-6.

Example 4-6. xls_parsing.py

```
# a simple example of reading data from a .xls file with Python
# using the "xrld" library. First, pip install the xlrd library:
# https://pypi.org/project/xlrd/2.0.1/

# import the "xlrd" library
import xlrd

# import the `csv` library, to create our output file
import csv

# pass our filename as an ingredient to the `xlrd` library's
# `open_workbook()` "recipe"
# store the result in a variable called `source_workbook`
source_workbook = xlrd.open_workbook("fredgraph.xls") ❶

# an `.xls` workbook can have multiple sheets
for sheet_name in source_workbook.sheet_names():

    # create a variable that points to the current worksheet by
    # passing the current value of `sheet_name` to the `sheet_by_name` recipe
    current_sheet = source_workbook.sheet_by_name(sheet_name)

    # print `sheet_name`, just to see what it is
    print(sheet_name)
    # create "xls_"+sheet_name+".csv" as an output file for the current sheet
    output_file = open("xls_"+sheet_name+".csv","w")

    # use the `csv` library's "writer" recipe to easily write rows of data
    # to `output_file`, instead of reading data *from* it
    output_writer = csv.writer(output_file)

    # now, we need to loop through every row in our sheet
    for row_num, row in enumerate(current_sheet.get_rows()): ❷

        # each row is already a list, but we need to use the `row_value()`
        # method to access them
        # then we can use the `writerow` recipe to write them
        # directly to our output file
        output_writer.writerow(current_sheet.row_values(row_num)) ❸

    # officially close the `.csv` file we just wrote all that data to
    output_file.close()
```

❶ Notice that this structure is similar to the one we use when working with the *csv* library.

❷ The function `get_rows()` is specific to the *xlrd* library; it converts the rows of our current worksheet into a list that can be looped over.[12]

❸ There will be some funkiness within the "dates" written to our output file.[13] We'll look at how to fix up the dates in Chapter 7.

One thing we'll see in this output file is some *serious* weirdness in the values recorded in the `observation_date` field, reflecting the fact that, as the *xlrd* library's creators put it:[14]

> Dates in Excel spreadsheets: In reality, there are no such things. What you have are floating point numbers and pious hope.

As a result, getting a useful, human-readable date out of an *.xls* file requires some significant cleanup, which we'll address in Chapter 7.

As these exercises have hopefully demonstrated, with some clever libraries and a few tweaks to our basic code configuration, it's possible to wrangle data from a wide range of table-type data formats with Python quickly and easily. At the same time, I hope that these examples have also illustrated why working with text-based and/or open

12 For more about `get_rows()`, see the *xlrd* documentation.

13 See the *xlrd* documentation for more on this issue.

14 From Stephen John Machin and Chris Withers, "Dates in Excel Spreadsheets".

source formats is almost always preferable,[15] because they often require less "cleaning" and transformation to get them into a clear, usable state.

Finally, Fixed-Width

Though I didn't mention it at the top of this section, one of the very oldest versions of table-type data is what's known as "fixed-width." As the name implies, each data column in a fixed-width table contains a specific, predefined number of characters—and *always* that number of characters. This means that the meaningful data in fixed-width files are often padded with extra characters, such as spaces or zeroes.

Though very uncommon in contemporary data systems, you are still likely to encounter fixed-width formats if you're working with government data sources whose infrastructure may be decades old.[16] For example, the US National Oceanic and Atmospheric Administration (NOAA), whose origins date back to the early 19th century, offers a wide range of detailed, up-to-date weather information online for free through its Global Historical Climatology Network, much of which is published in a fixed-width format. For example, information about the stations' unique identifier, locations, and what network(s) they are a part of is stored in the *ghcnd-stations.txt* file. To interpret any actual weather data readings (many of which are *also* released as fixed-width files), you'll need to cross-reference the station data with the weather data.

Even more than other table-type data files, working with fixed-width data can be especially tricky if you don't have access to the metadata that describes how the file and its fields are organized. With delimited files, it's often possible to eyeball the file in a text editor and identify the delimiter used with a reasonable level of confidence. At worst, you can simply try parsing the file using different delimiters and see which yields the best results. With fixed-width files—especially large ones—if there's no data for a particular field in the sample of the data you inspect, it's easy to end up inadvertently lumping together multiple data fields.

15 If you open the output files from the three preceding code examples in a text editor, you'll notice that the open source *.ods* format is the simplest and cleanest.

16 As in, for example, Pennsylvania or Colorado.

Tab-Separated Versus Fixed-Width

As mentioned in "File-Based, Table-Type Data—Take It to Delimit" on page 7, it's still not uncommon to come across tab-separated files that have a file extension of *.txt*—which is the same one used for fixed-width files. Since both file formats *also* rely on whitespace (spaces or tabs) to separate fields, how can you be sure which one you're working with?

This is yet another situation where opening up your data file and looking at it in a text or code editor will save you some headaches, because there are clear visual differences between these two file formats. Start by looking at the right side of the document: tab-separated files will be "ragged-right" (the data records will have different line lengths), while fixed-width files will be "justified" (all the records will end at the same point).

For example, here's how a few lines of our *.tsv* data from Example 4-2 look in Atom:

```
42      Ward Hunt       1873-1882       R       NY      Grant
43      Morrison Waite  1874-1888       R       OH      Grant
44      John Marshall Harlan    1877-1911       R       KT      Hayes
```

And here's how a few lines of the `ghcnd-stations.txt` file look:

```
AEM00041217  24.4330   54.6510   26.8    ABU DHABI INTL                      41217
AEM00041218  24.2620   55.6090  264.9    AL AIN INTL                         41218
AF000040930  35.3170   69.0170 3366.0    NORTH-SALANG                GSN     40930
```

As you can see, not only is the fixed-width file right justified but *so are all the numbers*. This is another clue that what you're looking at is actually a fixed-width file, rather than a tab-delimited one.

Fortunately, metadata about the *ghcnd-stations.txt* file that we're using as our data source *is* included in the *readme.txt* file in the same folder on the NOAA site.

Looking through that *readme.txt* file, we find the heading `IV. FORMAT OF "ghcnd-stations.txt"`, which contains the following table:

```
------------------------------
Variable   Columns   Type
------------------------------
ID            1-11   Character
LATITUDE     13-20   Real
LONGITUDE    22-30   Real
ELEVATION    32-37   Real
STATE        39-40   Character
NAME         42-71   Character
GSN FLAG     73-75   Character
HCN/CRN FLAG 77-79   Character
```

```
    WMO ID       81-85   Character
    ------------------------------
```

This is followed by a detailed description of what each field contains or means, including information like units. Thanks to this robust *data dictionary*, we now know not just how the *ghcnd-stations.txt* file is organized but also how to interpret the information it contains. As we'll see in Chapter 6, finding (or building) a data dictionary is an essential part of assessing or improving the quality of our data. At the moment, however, we can just focus on transforming this fixed-width file into a *.csv*, as detailed in Example 4-7.

Example 4-7. fixed_width_parsing.py

```python
# an example of reading data from a fixed-width file with Python.
# the source file for this example comes from NOAA and can be accessed here:
# https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/ghcnd-stations.txt
# the metadata for the file can be found here:
# https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/readme.txt

# import the `csv` library, to create our output file
import csv

filename = "ghcnd-stations"

# reading from a basic text file doesn't require any special libraries
# so we'll just open the file in read format ("r") as usual
source_file = open(filename+".txt", "r")

# the built-in "readlines()" method does just what you'd think:
# it reads in a text file and converts it to a list of lines
stations_list = source_file.readlines()

# create an output file for our transformed data
output_file = open(filename+".csv","w")

# use the `csv` library's "writer" recipe to easily write rows of data
# to `output_file`, instead of reading data *from* it
output_writer = csv.writer(output_file)

# create the header list
headers = ["ID","LATITUDE","LONGITUDE","ELEVATION","STATE","NAME","GSN_FLAG",
           "HCNCRN_FLAG","WMO_ID"] ❶

# write our headers to the output file
output_writer.writerow(headers)

# loop through each line of our file (multiple "sheets" are not possible)
for line in stations_list:

    # create an empty list, to which we'll append each set of characters that
    # makes up a given "column" of data
    new_row = []

    # ID: positions 1-11
    new_row.append(line[0:11]) ❷

    # LATITUDE: positions 13-20
    new_row.append(line[12:20])

    # LONGITUDE: positions 22-30
    new_row.append(line[21:30])

    # ELEVATION: positions 32-37
    new_row.append(line[31:37])

    # STATE: positions 39-40
    new_row.append(line[38:40])

    # NAME: positions 42-71
    new_row.append(line[41:71])

    # GSN_FLAG: positions 73-75
    new_row.append(line[72:75])

    # HCNCRN_FLAG: positions 77-79
    new_row.append(line[76:79])

    # WMO_ID: positions 81-85
    new_row.append(line[80:85])

    # now all that's left is to use the
    # `writerow` function to write new_row to our output file
    output_writer.writerow(new_row)

# officially close the `.csv` file we just wrote all that data to
output_file.close()
```

❶ Since we don't have anything *within* the file that we can draw on for column headers, we have to "hard code" them based on the information in the *readme.txt* file. Note that I've eliminated special characters and used underscores in place of spaces to minimize hassles when cleaning and analyzing this data later on.

❷ Python actually views lines of text as just lists of characters, so we can just tell it to give us the characters between two numbered index positions. Like the `range()` function, the character at the first position is included, but the second number is not. Also recall that Python starts counting lists of items at zero (often called *zero-indexing*). This means that for each entry, the first number will be one *less* than whatever the metadata says, but the righthand number will be the same.

If you run the script in Example 4-7 and open your output *.csv* file in a spreadsheet program, you'll notice that the values in some of the columns are not formatted consistently. For example, in the `ELEVATION` column, the numbers with decimals are left justified, but those without decimals are right justified. What's going on?

Once again, opening the file in a text editor is enlightening. Although the file we've created is *technically* comma separated, the values we put into each of our newly "delimited" columns still contain the extra spaces that existed in the original file. As a result, our new file still looks pretty "fixed-width."

In other words—just as we saw in the case of Excel "dates"—converting our file to a *.csv* does not "automagically" generate sensible data types in our output file. Determining what data type each field should have—and cleaning them up so that they behave appropriately—is part of the data cleaning process that we'll address in Chapter 7.

Feed-Based Data—Web-Driven Live Updates

The structure of table-type data formats is well suited to a world where most "data" has already been filtered, revised, and processed into a relatively well-organized collection of numbers, dates, and short strings. With the rise of the internet, however, came the need to transmit large quantities of the type of "free" text found in, for example, news stories and social media feeds. Because this type of data content typically includes characters like commas, periods, and quotation marks that affect its semantic meaning, fitting it into a traditional delimited format will be problematic at best. What's more, the horizontal bias of delimited formats (which involves lots of left-right scrolling) runs counter to the vertical-scrolling conventions of the web. Feed-based data formats have been designed to address both of these limitations.

At a high level, there are two main types of feed-based data formats: XML and JSON. Both are text-based formats that allow the data provider to define their own unique data structure, making them extremely flexible and, consequently, useful for the wide variety of content found on internet-connected websites and platforms. Whether they're located online or you save a copy locally, you'll recognize these formats, in part, by their coordinating *.xml* and *.json* file extensions:

.xml
: Extensible Markup Language encompasses a broad range of file formats, including *.rss*, *.atom*, and even *.html*. As the most generic type of markup language, XML is extremely flexible and was perhaps the original data format for web-based data feeds.

.json
: JavaScript Object Notation files are somewhat more recent than XML files but serve a similar purpose. In general, JSON files are less descriptive (and therefore

shorter and more concise) than XML files. This means that they can encode an almost identical amount of data as an XML file while taking up less space, which is especially important for speed on the mobile web. Equally important is the fact that JSON files are essentially large `object` data types within the JavaScript programming language—which is the language that underpins many, if not most, websites and mobile apps. This means that parsing JSON-formatted data is very easy for any site or program that uses JavaScript, especially when compared with XML. Fortunately, JavaScript `object` data types are very similar to Python `dict` data types, which also makes working with JSON in Python very straightforward.

Before we dive into how to work with each of these file types in Python, let's review when we might *want* feed-type data and where to find it when we do.

When to work with feed-type data

In a sense, feed-type data is to the 21st century what table-type data was to the 20th: the sheer volume of feed-type data generated, stored, and exchanged on the web every day is probably millions of times greater than that of all of the table-type data in the world put together—in large part because feed-type data is what powers social media sites, news apps, and everything in between.

From a data wrangling perspective, you'll generally want feed-type data when the phenomenon you're exploring is time sensitive and updated on a frequent and/or unpredictable basis. Typically, this type of data is generated in response to a human or natural process, such as (once again) posting to social media, publishing a news story, or recording an earthquake.

Both file-based, table-type data and web-based, feed-type data can contain historical information, but as we discussed at the start of this chapter, the former usually reflects the data as it stood at a fixed point in time. The latter, by contrast, is typically organized in a "reverse-chronological" (most recent first) order, with the first entry being whatever data record was most recently created at the time you accessed the data, rather than a predetermined publication date.

Where to find feed-type data

Feed-type data is found almost exclusively on the web, often at special URLs known as application programming interface (API) *endpoints*. We'll get into the details of working with APIs in Chapter 5, but for now all you need to know is that API endpoints are really just data-only web pages: you can view many of them using a regular web browser, but all you'll see is the data itself. Some API endpoints will even return different data depending on the information *you* send to them, and this is part of what makes working with feed-type data so flexible: by changing just a few words or values in your code, you can access a totally different dataset!

Finding APIs that offer feed-type data doesn't require too much in the way of special search strategies because usually the sites and services that have APIs *want* you to find them. Why? Simply put, when someone writes code that makes use of an API, it (usually) returns some benefit to the company that provides it—even if that benefit is just more public exposure. In the early days of Twitter, for example, many web developers wrote programs using the Twitter API—both making the platform more useful *and* saving the company the expense and effort of figuring out what users wanted and then building it. By making so much of their platform data available for free (at first), the API gave rise to several companies that Twitter would eventually purchase—though many more would also be put out of business when either the API or its terms of service changed.[17] This highlights one of the particular issues that can arise when working with any type of data, but especially the feed-type data made available by for-profit companies: both the data and your right to access it can change at any time, without warning. So while feed-type data sources are indeed valuable, they are also ephemeral in more ways than one.

Wrangling Feed-Type Data with Python

As with table-type data, wrangling feed-type data in Python is made possible by a combination of helpful libraries and the fact that formats like JSON already resemble existing data types in the Python programming language. Moreover, we'll see in the following sections that XML and JSON are often functionally interchangeable for our purposes (though many APIs will only offer data in one format or the other).

XML: One markup to rule them all

Markup languages are among the oldest forms of standardized document formats in computing, designed with the goal of creating text-based documents that can be easily read by both humans and machines. XML became an increasingly important part of internet infrastructure in the 1990s as the variety of devices accessing and displaying web-based information made the separation of content (e.g., text and images) from formatting (e.g., page layout) more of a necessity. Unlike an HTML document—in which content and formatting are fully commingled—an XML document says pretty much nothing about how its information should be displayed. Instead, its tags and attributes act as *metadata* about what kind of information it contains, along with the data itself.

To get a feel for what XML looks like, take a look at Example 4-8.

17 See Vassili van der Mersch's post, "Twitter's 10 Year Struggle with Developer Relations" from Nordic APIs.

Example 4-8. A sample XML document

```
<?xml version="1.0" encoding="UTF-8"?>
<mainDoc>
   <!--This is a comment-->
   <elements>
       <element1>This is some text in the document.</element1>
       <element2>This is some other data in the document.</element2>
       <element3 someAttribute="aValue" />
   </elements>
   <someElement anAttribute="anotherValue">More content</someElement>
</mainDoc>
```

There are a couple of things going here. The very first line is called the *document type* (or `doc-type`) declaration; it's letting us know that the rest of the document should be interpreted as XML (as opposed to any of the other web or markup languages, some of which we'll review later in this chapter).

Starting with the line:

```
<mainDoc>
```

we are into the substance of the document itself. Part of what makes XML so flexible is that it only contains two real grammatical structures, both of which are included in Example 4-8:

tags
: Tags can be either paired (like `element1`, `element2`, `someElement`, or even `mainDoc`) or self-closed (like `element3`). The name of a tag is always enclosed by *carets* (`<>`). In the case of a closing tag, the opening caret is immediately followed by a forward slash (`/`). A matched pair of tags, or a self-closed tag, are also described as XML *elements*.

attributes
: Attributes can exist only inside of tags (like `anAttribute`). Attributes are a type of *key/value pair* in which the attribute name (or *key*) is immediately followed by an equals sign (`=`), followed by the *value* surrounded by double quotation marks (`""`).

An XML element is whatever is contained between an opening tag and its matching closing tag (e.g., `<elements>` and `</elements>`). As such, a given XML element may contain many tags, each of which may also contain other tags. Any tags may also have any number of attributes (including none). A self-closed tag is also considered an element.

The only other meaningful rule for structuring XML documents is that when tags appear inside other tags, *the most recently opened tag must be closed first*. In other words, while this is a legitimate XML structure:

```
<outerElement>
   <!-- Notice that that the `innerElement1` is closed
   before the `innerElement2` tag is opened -->
   <innerElement1>Some content</innerElement1>
   <innerElement2>More content</innerElement2>
</outerElement>
```

this is not:

```
<outerElement>
   <!-- NOPE! The `innerElement2` tag was opened
   before the `innerElement1` tag was closed -->
   <innerElement1>Some content<innerElement2>More content</innerElement1>
   </innerElement2>
</outerElement>
```

This principle of *last opened, first closed* is also described as *nesting*, similar to the "nested" `for...in` loops from Figure 2-3.[18] Nesting is especially important in XML documents because it governs one of the primary mechanisms that we use to read or *parse* XML (and other markup language) documents with code. In an XML document, the first element after the `doc-type` declaration is known as the *root* element. If the XML document has been formatted, the root element will always be left justified, and any element that is nested directly *within* that element will be indented one level to the right and is referred to as a *child* element. In Example 4-8, then, `<mainDoc>` would be considered the *root* element, and `<elements>` would be its child. Likewise, `<mainDoc>` is the *parent* element of `<elements>` (Example 4-9).

Example 4-9. An annotated XML document

```
 <?xml version="1.0" encoding="UTF-8"?>
 <mainDoc>
    <!--`mainDoc` is the *root* element, and `elements` is its *child*-->
    <elements>
        <!-- `elements` is the *parent* of `element1`, `element2`, and
        `element3`, which are *siblings* of one another -->
        <element1>This is text data in the document.</element1>
        <element2>This is some other data in the document.</element2>
        <element3 someAttribute="aValue" />
    </elements>
    <!-- `someElement` is also a *child* of `mainDoc`,
    and a *sibling* of `elements` -->
    <someElement anAttribute="anotherValue">More content</someElement>
</mainDoc>
```

18 Unlike Python code, XML documents do *not* have to be properly indented in order to work, though it certainly makes them more readable!

Given this trend for genealogical jargon, you might be wondering: if `<elements>` is the parent of `<element3>`, and `<mainDoc>` is the parent of `<elements>`, does that make `<mainDoc>` the *grandparent* of `<element3>`? The answer is: yes, but no. While `<mainDoc>` *is* the "parent" of the "parent" of `<element3>`, the term "grandparent" is never used in describing an XML structure—that could get complicated fast! Instead, we simply describe the relationship as exactly that: `<mainDoc>` is the *parent* of the *parent* of `<element3>`.

Fortunately, there is no such complexity associated with XML attributes: they are simply key/value pairs, and they can *only* exist within XML tags, like so:

```
<element3 someAttribute="aValue" />
```

Note that there is no space on either side of the equals sign, just as there is no space between the carets and slashes of an element tag.

Like writing in English (or in Python), the question of when to use tags versus attributes for a particular piece of information is largely a matter of preference and style. Both Examples 4-10 and 4-11, for example, contain the same information about this book, but each is structured slightly differently.

Example 4-10. Sample XML book data—more attributes

```
<aBook>
    <bookURL url="https://www.oreilly.com/library/view/practical-python-data/
    9781492091493"/>
    <bookAbstract>
    There are awesome discoveries to be made and valuable stories to be
    told in datasets--and this book will help you uncover them.
    </bookAbstract>
    <pubDate date="2022-02-01" />
</aBook>
```

Example 4-11. Sample XML book data—more elements

```
<aBook>
    <bookURL>
        https://www.oreilly.com/library/view/practical-python-data/9781492091493
    </bookURL>
    <bookAbstract>
        There are awesome discoveries to be made and valuable stories to be
        told in datasets--and this book will help you uncover them.
    </bookAbstract>
    <pubDate>2022-02-01</pubDate>
</aBook>
```

This degree of flexibility means XML is highly adaptable to a wide variety of data sources and formatting preferences. At the same time, it can easily create a situation where *every* new data source requires writing custom code. Obviously, this would be a pretty inefficient system, especially if many people and organizations were publishing pretty similar types of data.

It's not surprising, then, that there are a large number of XML *specifications* that define additional rules for formatting XML documents that are intended to hold particular types of data. I'm highlighting a few notable examples here, as these are formats you may come across in the course of your data wrangling work. Despite their various format names and file extensions, however, we can parse them all using the same method that we'll look at shortly in Example 4-12:

RSS
: Really Simple Syndication is an XML specification first introduced in the late 1990s for news information. The *.atom* XML format is also widely used for these purposes.

KML
: Keyhole Markup Language is an internationally accepted standard for encoding both two-dimensional and three-dimensional geographic data and is compatible with tools like Google Earth.

SVG
: Scalable Vector Graphics is a commonly used format for graphics on the web, thanks to its ability to scale drawings without loss of quality. Many common graphics programs can output *.svg* files, which can then be included in web pages and other documents that will look good on a wide variety of screen sizes and devices.

EPUB
: Electronic publication format (*.epub*) is the widely accepted open standard for digital book publishing.

As you can see from the preceding list, some common XML formats clearly indicate their relationship to XML; many others do not.[19]

Now that we have a high-level sense of how XML files work, let's see what it takes to parse one with Python. Although Python has some built-in tools for parsing XML, we'll be using a library called *lxml*, which is particularly good at quickly parsing large XML files. Even though our example files that follow are quite small, know that we could use basically the same code even if our data files got considerably larger.

19 Fun fact: the second *x* in the *.xlsx* format actually refers to XML!

To begin with, we'll be using an XML version of the same "U6" unemployment data that I've already downloaded from the FRED website using its API.[20] After downloading a copy of this file from Google Drive, you can use the script in Example 4-12 to convert the source XML to a *.csv*. Start with the `pip install`:

```
pip install lxml
```

Example 4-12. xml_parsing.py

```
# an example of reading data from an .xml file with Python, using the "lxml"
# library.
# first, you'll need to pip install the lxml library:
# https://pypi.org/project/lxml/
# a helpful tutorial can be found here: https://lxml.de/tutorial.html
# the data used here is an instance of
# https://api.stlouisfed.org/fred/series/observations?series_id=U6RATE& \
# api_key=YOUR_API_KEY_HERE


# specify the "chapter" of the `lxml` library you want to import,
# in this case, `etree`, which stands for "ElementTree"
from lxml import etree

# import the `csv` library, to create our output file
import csv

# choose a filename
filename = "U6_FRED_data" ❶

# open our data file in read format, using "rb" as the "mode"
xml_source_file = open(filename+".xml","rb") ❷

# pass our xml_source_file as an ingredient to the `lxml` library's
# `etree.parse()` method and store the result in a variable called `xml_doc`
xml_doc = etree.parse(xml_source_file)

# start by getting the current xml document's "root" element
document_root = xml_doc.getroot() ❸

# let's print it out to see what it looks like
print(etree.tostring(document_root)) ❹

# confirm that `document_root` is a well-formed XML element
if etree.iselement(document_root):

    # create our output file, naming it "xml_"+filename+".csv
    output_file = open("xml_"+filename+".csv","w")
```

20 Again, we'll walk through using APIs like this one step by step in Chapter 5, but using this document lets us see how different data formats influence our interactions with the data.

```
# use the `csv` library's "writer" recipe to easily write rows of data
# to `output_file`, instead of reading data *from* it
output_writer = csv.writer(output_file)

# grab the first element of our xml document (using `document_root[0]`)
# and write its attribute keys as column headers to our output file
output_writer.writerow(document_root[0].attrib.keys()) ❺

# now, we need to loop through every element in our XML file
  for child in document_root: ❻

    # now we'll use the `.values()` method to get each element's values
    # as a list and then use that directly with the `writerow` recipe
    output_writer.writerow(child.attrib.values())

# officially close the `.csv` file we just wrote all that data to
output_file.close()
```

❶ In this instance, there's nothing within the data file (like a sheet name) that we can pull as a filename, so we'll just make our own and use it to both load our source data and label our output file.

❷ I lied! The values we've been using for the "mode" of the `open()` function assume we want to interpret the source file as *text*. But because the *lxml* library expects byte data rather than text, we'll use `rb` ("read bytes") as the "mode."

❸ There is a lot of malformed XML out there! In order to make sure that what looks like good XML actually *is*, we'll retrieve the current XML document's "root" element and make sure that it works.

❹ Because our XML is currently stored as byte data, we need to use the `etree.tostring()` method in order to view it as one.

❺ Thanks to the *lxml*, each XML element (or "node") in our document has a property called `attrib`, whose data type is a Python dictionary (`dict`). Using the `.keys()` method returns all of our XML element's attribute keys as a list. Since all of the elements in our source file are identical, we can use the keys of the first one to create a "header" row for our output file.

❻ The *lxml* library converts XML elements to lists, so we can use a simple `for...in` loop to go through the elements in our document.

As it happens, the XML version of our unemployment data is structured very simply: it's just a list of elements, and *all* the values we want to access are stored as attributes.

As a result, we were able to pull the attribute values out of each element as a list and write them directly to our *.csv* file with only one line of code.

Of course, there are many times when we'll want to pull data from more complex XML formats, especially those like RSS or Atom. To see what it takes to handle something slightly more complex, in Example 4-13 we'll parse the BBC's RSS feed of science and environment stories, which you can download a copy of from my Google Drive.

Example 4-13. rss_parsing.py

```
# an example of reading data from an .xml file with Python, using the "lxml"
# library.
# first, you'll need to pip install the lxml library:
# https://pypi.org/project/lxml/
# the data used here is an instance of
# http://feeds.bbci.co.uk/news/science_and_environment/rss.xml

# specify the "chapter" of the `lxml` library you want to import,
# in this case, `etree`, which stands for "ElementTree"
from lxml import etree

# import the `csv` library, to create our output file
import csv

# choose a filename, for simplicity
filename = "BBC News - Science & Environment XML Feed"

# open our data file in read format, using "rb" as the "mode"
xml_source_file = open(filename+".xml","rb")

# pass our xml_source_file as an ingredient to the `lxml` library's
# `etree.parse()` method and store the result in a variable called `xml_doc`
xml_doc = etree.parse(xml_source_file)

# start by getting the current xml document's "root" element
document_root = xml_doc.getroot()

# if the document_root is a well-formed XML element
if etree.iselement(document_root):

    # create our output file, naming it "rss_"+filename+".csv"
    output_file = open("rss_"+filename+".csv","w")

    # use the `csv` library's "writer" recipe to easily write rows of data
    # to `output_file`, instead of reading data *from* it
    output_writer = csv.writer(output_file)

    # document_root[0] is the "channel" element
    main_channel = document_root[0]
```

```
# the `find()` method returns *only* the first instance of the element name
article_example = main_channel.find('item') ❶

# create an empty list in which to store our future column headers
tag_list = []

for child in article_example.iterdescendants(): ❷

    # add each tag to our would-be header list
    tag_list.append(child.tag) ❸

    # if the current tag has any attributes
    if child.attrib: ❹

        # loop through the attribute keys in the tag
        for attribute_name in child.attrib.keys(): ❺

            # append the attribute name to our `tag_list` column headers
            tag_list.append(attribute_name)

# write the contents of `tag_list` to our output file as column headers
output_writer.writerow(tag_list) ❻

# now we want to grab *every* <item> element in our file
# so we use the `findall()` method instead of `find()`
for item in main_channel.findall('item'):

    # empty list for holding our new row's content
    new_row = []

    # now we'll use our list of tags to get the contents of each element
    for tag in tag_list:

        # if there is anything in the element with a given tag name
        if item.findtext(tag):

            # append it to our new row
            new_row.append(item.findtext(tag))

        # otherwise, make sure it's the "isPermaLink" attribute
        elif tag == "isPermaLink":

            # grab its value from the <guid> element
            # and append it to our row
            new_row.append(item.find('guid').get("isPermaLink"))

    # write the new row to our output file!
    output_writer.writerow(new_row)

# officially close the `.csv` file we just wrote all that data to
output_file.close()
```

❶ As always, we'll want to balance what we handle programmatically and what we review visually. In looking at our data, it's clear that each article's information is stored in a separate `item` element. Since copying over the individual tag and attribute names would be time-consuming and error prone, however, we'll go through *one* `item` element and make a list of all the tags (and attributes) within it, which we'll then use as the column headers for our output *.csv* file.

❷ The `iterdescendants()` method is particular to the *lxml* library. It returns *only* the *descendants* of an XML element, while the more common `iter()` method would return *both* the element itself *and* its children or "descendants."

❸ Using `child.tag` will retrieve the text of the tagname of the child element. For example, for the `<pubDate>`` element it will return `pubDate`.

❹ Only one tag in our `<item>` element has an attribute, but we still want to include it in our output.

❺ The `keys()` method will give us a list of all the keys in the list of attributes that belong to the tag. Be sure to get its name as a string (instead of a one-item list).

❻ That whole `article_example` `for` loop was just to build `tag_list`—but it was worth it!

As you can see from Example 4-13, with the help of the *lxml* library, parsing even slightly more complex XML in Python is still reasonably straightforward.

While XML is still a popular data format for news feeds and a handful of other file types, there are a number of features that make it less than ideal for handling the high-volume data feeds of the modern web.

First, there is the simple issue of size. While XML files can be wonderfully descriptive—reducing the need for separate data dictionaries—the fact that most elements contain both an opening tag and a corresponding closing tag (e.g., `<item>` and `</item>`) also makes XML somewhat *verbose*: there is a lot of text in an XML document that *isn't* content. This isn't a big deal when your document has a few dozen or even a few thousand elements, but when you're trying to handle millions or billions of posts on the social web, all that redundant text can really slow things down.

Second, while XML isn't exactly *difficult* to transform into other data formats, the process also isn't exactly seamless. The *lxml* library (among others) makes parsing XML with Python pretty simple, but doing the same task with web-focused languages like JavaScript is convoluted and onerous. Given JavaScript's prevalence on the web, it's not surprising that a feed-type data format that works seamlessly with JavaScript would be developed at some point. As we'll see in the next section, many of XML's limitations as a data format are addressed by the `object`-like nature of the *.json* format, which is at this point the most popular format for feed-type data on the internet.

JSON: Web data, the next generation

In principle, JSON is similar to XML in that it uses nesting to cluster related pieces of information into records and fields. JSON is also fairly human readable, though the fact that it doesn't support comments means that JSON feeds may require more robust data dictionaries than XML documents.

To get started, let's take a look at the small JSON document in Example 4-14.

Example 4-14. Sample JSON document

```
{
"author": "Susan E. McGregor",
"book": {
    "bookURL": "https://www.oreilly.com/library/view/practical-python-data/
        9781492091493/",
    "bookAbstract": "There are awesome discoveries to be made and valuable
        stories to be told in datasets--and this book will help you uncover
        them.",
    "pubDate": "2022-02-01"
},
"papers": [{
    "paperURL": "https://www.usenix.org/conference/usenixsecurity15/
        technical-sessions/presentation/mcgregor",
    "paperTitle": "Investigating the computer security practices and needs
        of journalists",
    "pubDate": "2015-08-12"
},
    {
    "paperURL": "https://www.aclweb.org/anthology/W18-5104.pdf",
    "paperTitle": "Predictive embeddings for hate speech detection on
        twitter",
    "pubDate": "2018-10-31"
}
    ]
}
```

Like XML, the grammatical "rules" of JSON are quite simple: there are only three distinct data structures in JSON documents, all of which appear in Example 4-14:

Key/value pairs
: Technically, everything within a JSON document is a key/value pair, with the *key* enclosed in quotes to the left of a colon (`:`) and the *value* being whatever appears to the right of the colon. Note that while keys must *always* be strings, *values* can be strings (as in `author`), objects (as in `book`), or lists (as in `papers`).

Objects

These are opened and closed using pairs of curly braces ({}). In Example 4-14, there are four objects total: the document itself (indicated by the left-justified curly braces), the book object, and the two unnamed objects in the papers list.

Lists

These are enclosed by square brackets ([]) and can only contain comma-separated objects.

While XML and JSON can be used to encode the same data, there are some notable differences in what each allows. For example, JSON files do not contain a doc-type specification, nor can they include comments. Also, while XML lists are somewhat implicit (any repeated element functions something like a list), in JSON, lists must be specified by square brackets ([]).

Finally, although JSON was designed with JavaScript in mind, you may have noticed that its structures are very similar to Python dict and list types. This is part of what makes parsing JSON very straightforward with Python as well as JavaScript (and a range of other languages).

To see just how straightforward this is, in Example 4-15 we'll parse the same data as we did in Example 4-12 but in the *.json* format also provided by the FRED API. You can download the file from this Google Drive link: *https://drive.google.com/file/d/1Mpb2f5qYgHnKcU1sTxTmhOPHfzIdeBsq/view?usp=sharing*.

Example 4-15. json_parsing.py

```
# a simple example of reading data from a .json file with Python,
# using the built-in "json" library. The data used here is an instance of
# https://api.stlouisfed.org/fred/series/observations?series_id=U6RATE& \
# file_type=json&api_key=YOUR_API_KEY_HERE

# import the `json` library, since that's our source file format
import json

# import the `csv` library, to create our output file
import csv

# choose a filename
filename = "U6_FRED_data"

# open the file in read format ("r") as usual
json_source_file = open(filename+".json","r")

# pass the `json_source_file` as an ingredient to the json library's `load()`
# method and store the result in a variable called `json_data`
json_data = json.load(json_source_file)
```

```
# create our output file, naming it "json_"+filename
output_file = open("json_"+filename+".csv","w")

# use the `csv` library's "writer" recipe to easily write rows of data
# to `output_file`, instead of reading data *from* it
output_writer = csv.writer(output_file)

# grab the first element (at position "0"), and use its keys as the column headers
output_writer.writerow(list(json_data["observations"][0].keys())) ❶

for obj in json_data["observations"]: ❷

    # we'll create an empty list where we'll put the actual values of each object
    obj_values = []

    # for every `key` (which will become a column), in each object
    for key, value in obj.items(): ❸

        # let's print what's in here, just to see how the code sees it
        print(key,value)

        # add the values to our list
        obj_values.append(value)

    # now we've got the whole row, write the data to our output file
    output_writer.writerow(obj_values)

# officially close the `.csv` file we just wrote all that data to
output_file.close()
```

❶ Because the *json* library interprets every object as a dictionary view object, we need to tell Python to convert it to a regular list using the `list()` function.

❷ In most cases, the simplest way to find the name (or "key") of the main JSON object in our document is just to look at it. Because JSON data is often rendered on a single line, however, we can get a better sense of its structure by pasting it into JSONLint. This lets us see that our target data is a list whose key is `observations`.

❸ Because of the way that the *json* library works, if we try to just write the rows directly, we'll get the values labeled with `dict`, rather than the data values themselves. So we need to make another loop that goes through every value in every `json` object one at a time and appends that value to our `obj_values` list.

Although JSON is not *quite* as human readable as XML, it has other advantages that we've touched on, like smaller file size and broader code compatibility. Likewise, while JSON is not as descriptive as XML, JSON data sources (often APIs) are usually reasonably well documented; this reduces the need to simply infer what a given key/value pair is describing. Like all work with data, however, the first step in wrangling JSON-formatted data is to understand its context as much as possible.

Wherefore Art Thou, Whitespace?

Unlike *.tsv* and *.txt* files—and the Python programming language itself—neither XML nor JSON is "whitespace dependent." As long as the carets, curly braces, and other punctuation marks are all in the right place, these data feed-type formats can have everything crushed up on a single line and still work just fine. For the sake of readability, the examples I've presented in this chapter have all been nicely formatted, but that's not how you'll usually encounter these data types, especially on the web. Though many web browsers *will* show XML in its properly indented format (for example, see *Los Angeles Times*' daily "sitemap"), most JSON data will be rendered as run-on lines of text (as with the Citi Bike real-time data feed).

Since effectively parsing either data format first requires understanding its overall structure, looking at a properly formatted version of any feed-type data file you're working with is a crucial first step. With well-structured XML, opening the file (or URL) in a web browser in usually enough.[21]

For smaller *.json* files, you can copy and paste (using keyboard shortcuts to "Select All" and "Copy" is easiest) the data straight from the source into an online formatting tool like JSONLint or JSON formatter. If the JSON file is especially large, or you don't have internet access, however, it's also possible to use Python in the terminal to create a new, formatted *.json* file from an unformatted source JSON file, using the following command:

```
cat ugly.json | python -mjson.tool > pretty.json
```

where `ugly.json` is your unformatted file. This will create the output file `pretty.json`, which you can then open in Atom or another text editor in order to see the structure of the document.

Working with Unstructured Data

As we discussed in "Structured Versus Unstructured Data" on page 3, the process of creating data depends on introducing some structure to information; otherwise we can't methodically analyze or derive meaning from it. Even though the latter often includes large segments of human-written "free" text, both table-type and feed-type data are relatively structured and, most importantly, machine readable.

21 If a stylesheet has been applied, as in the case of the BBC feed we used in Example 4-13, you can context+click the page and select "View Source" to see the "raw" XML.

When we deal with unstructured data, by contrast, our work always involves approximations: we cannot be certain that our programmatic wrangling efforts will return an accurate interpretation of the underlying information. This is because most unstructured data is a representation of content that is designed to be perceived and interpreted by humans. And, as we discussed in Chapter 2, while they can process large quantities of data much faster and with fewer errors than humans can, computers can still be tricked by unstructured data that would never fool a human, such as mistaking a slightly modified stop sign for a speed limit sign. Naturally, this means that when dealing with data that *isn't* machine readable, we always need to do extra proofing and verification—but Python can still help us wrangle such data into a more usable format.

Image-Based Text: Accessing Data in PDFs

The Portable Document Format (PDF) was created in the early 1990s as a mechanism for preserving the visual integrity of electronic documents—whether they were created in a text-editing program or captured from printed materials.[22] Preserving documents' visual appearance also meant that, *unlike* machine-readable formats (such as word-processing documents), it was difficult to alter or extract their contents—an important feature for creating everything from digital versions of contracts to formal letters.

In other words, wrangling the data in PDFs was, at first, somewhat difficult by design. Because accessing the data in printed documents is a shared problem, however, work in optical character recognition (OCR) actually began as early as the late *19th* century.[23] Even digital OCR tools have been widely available in software packages and online for decades, so while they are far from perfect, the data contained in this type of file is also not entirely out of reach.

When to work with text in PDFs

In general, working with PDFs is a last resort (much, as we'll see in Chapter 5, as web scraping should be). In general, if you can avoid relying on PDF information, you should. As noted previously, the process of extracting information from PDFs will generally yield an *approximation* of the document's contents, so proofing for accuracy is a nonnegotiable part of any *.pdf*-based data wrangling workflow. That said, there is an enormous quantity of information that is *only* available as images or PDFs of

22 See Adobe's About PDF page for more information.

23 George Nagy, "Disruptive Developments in Document Recognition," *Pattern Recognition Letters* 79 (2016): 106–112, *https://doi.org/10.1016/j.patrec.2015.11.024*. Available at *https://ecse.rpi.edu/~nagy/PDF_chrono/2016_PRL_Disruptive_asPublished.pdf*.

scanned documents, and Python is an efficient way to extract a reasonably accurate first version of such document text.

Where to find PDFs

If you're confident that the data you want can only be found in PDF format, then you can (and should) use the tips in "Smart Searching for Specific Data Types" on page 6 to locate this file type using an online search. More than likely, you will request information from a person or organization, and they will provide it as PDFs, leaving you to deal with the problem of how to extract the information you need. As a result, most of the time you will not need to go looking for PDFs—more often than not they will, unfortunately, find you.

Wrangling PDFs with Python

Because PDFs can be generated both from machine-readable text (such as word-processing documents) and from scanned images, it is sometimes possible to extract the document's "live" text programmatically with relatively few errors. While it seems straightforward, however, this method can still be unreliable because *.pdf* files can be generated with a wide range of encodings that can be difficult to detect accurately. So while this *can* be a high-accuracy method of extracting text from a *.pdf*, the likelihood of it working for any *given* file is low.

Because of this, I'm going to focus here on using OCR to recognize and extract the text in *.pdf* files. This will require two steps:

1. Convert the document pages into individual images.
2. Run OCR on the page images, extract the text, and write it to individual text files.

Unsurprisingly, we'll need to install quite a few more Python libraries in order to make this all possible. First, we'll install a couple of libraries for converting our *.pdf* pages to images. The first is a general-purpose library called `poppler` that is needed to make our Python-specific library `pdf2image` work. We'll be using `pdf2image` to (you guessed it!) convert our *.pdf* file to a series of images:

```
sudo apt install poppler-utils
```

Then:

```
pip install pdf2image
```

Next, we need to install the tools for performing the OCR process. The first one is a general library called *tesseract-ocr*, which uses machine learning to recognize the text in images; the second is a Python library that relies on *tesseract-ocr* called *pytesseract*:

```
sudo apt-get install tesseract-ocr
```

Then:

```
pip install pytesseract
```

Finally, we need a helper library for Python that can do the computer vision needed to bridge the gap between our page images and our OCR library:

```
pip install opencv-python
```

Phew! If that seems like a lot of extra libraries, keep in mind that what we're technically using here are is *machine learning*, one of those buzzy data science technologies that drives so much of the "artificial intelligence" out there. Fortunately for us, Tesseract in particular is relatively robust and inclusive: though it was originally developed by Hewlett-Packard as a proprietary system in the early 1980s, it was open sourced in 2005 and currently supports more than 100 languages—so feel free to try the solution in Example 4-16 out on non-English text as well!

Example 4-16. pdf_parsing.py

```python
# a basic example of reading data from a .pdf file with Python,
# using `pdf2image` to convert it to images, and then using the
# openCV and `tesseract` libraries to extract the text

# the source data was downloaded from:
# https://files.stlouisfed.org/files/htdocs/publications/page1-econ/2020/12/01/ \
# unemployment-insurance-a-tried-and-true-safety-net_SE.pdf

# the built-in `operating system` or `os` Python library will let us create
# a new folder in which to store our converted images and output text
import os

# we'll import the `convert_from_path` "chapter" of the `pdf2image` library
from pdf2image import convert_from_path

# the built-in `glob`library offers a handy way to loop through all the files
# in a folder that have a certain file extension, for example
import glob

# `cv2` is the actual library name for `openCV`
import cv2

# and of course, we need our Python library for interfacing
# with the tesseract OCR process
import pytesseract

# we'll use the pdf name to name both our generated images and text files
pdf_name = "SafetyNet"

# our source pdf is in the same folder as our Python script
pdf_source_file = pdf_name+".pdf"

# as long as a folder with the same name as the pdf does not already exist
if os.path.isdir(pdf_name) == False:

    # create a new folder with that name
    target_folder = os.mkdir(pdf_name)


# store all the pages of the PDF in a variable
pages = convert_from_path(pdf_source_file, 300) ❶


# loop through all the converted pages, enumerating them so that the page
# number can be used to label the resulting images
for page_num, page in enumerate(pages):

    # create unique filenames for each page image, combining the
    # folder name and the page number
    filename = os.path.join(pdf_name,"p"+str(page_num)+".png") ❷

    # save the image of the page in system
    page.save(filename, 'PNG')

# next, go through all the files in the folder that end in `.png`
for img_file in glob.glob(os.path.join(pdf_name, '*.png')): ❸

    # replace the slash in the image's filename with a dot
    temp_name = img_file.replace("/",".")

    # pull the unique page name (e.g. `p2`) from the `temp_name`
    text_filename = temp_name.split(".")[1] ❹

    # now! create a new, writable file, also in our target folder, that
    # has the same name as the image, but is a `.txt` file
    output_file = open(os.path.join(pdf_name,text_filename+".txt"), "w")

    # use the `cv2` library to interpret our image
    img = cv2.imread(img_file)

    # create a new variable to hold the results of using pytesseract's
    # `image_to_string()` function, which will do just that
    converted_text = pytesseract.image_to_string(img)

    # write our extracted text to our output file
    output_file.write(converted_text)

    # close the output file
    output_file.close()
```

❶ Here we pass the path to our source file (in this case, that is just the filename, because it is in the same folder as our script) and the desired dots per inch (DPI) resolution of the output images to the `convert_from_path()` function. While setting a lower DPI will be much faster, the poorer-quality images may yield significantly less accurate OCR results. 300 DPI is a standard "print" quality resolution.

❷ Here we use the *os* library's `.join` function to save the new files into our target folder. We also have to use the `str()` function to convert the page number into a string for use in the filename.

❸ Note that `*.png` can be translated to "any file ending in .png." The `glob()` function creates a list of all the filenames in the folder where our images are stored (which in this case has the value `pdf_name`).

❹ String manipulation is fiddly! To generate unique (but matching!) filenames for our OCR'd text files, we need to pull a unique page name out of `img_file` whose value starts with `SafetyNet/` and ends in `.png`. So we'll replace the forward slash with a period to get something like `SafetyNet.p1.png`, and then if we `split()` *that* on the period, we'll get a list like: `["SafetyNet", "p1", "png"]`. Finally, we can access the "page name" at position 1. We need to do all this because we can't be sure that `glob()` will, for example, pull `p1.png` from the image folder *first*, or that it will pull the images in order at all.

For the most part, running this script serves our purposes: with a few dozen lines of code, it converts a multipage PDF file first into images and then writes (most of) the contents to a series of new text files.

This all-in-one approach also has its limitations, however. Converting a PDF to images—or images to text—is the kind of task that we might need to do quite often but not always at the same time. In other words, it would probably be much more useful in the long run to have two *separate* scripts for solving this problem, and then to run them one after the other. In fact, with a little bit of tweaking, we could probably break up the preceding script in such a way that we could convert *any* PDF to images or *any* images to text without having to write *any* new code at all. Sounds pretty nifty, right?

This process of rethinking and reorganizing working code is known as *code refactoring*. In writing English, we would describe this as revising or editing, and the objective in both cases is the same: to make your work simpler, clearer, and more effective. And just like documentation, refactoring is actually another important way to scale your data wrangling work, because it makes *reusing* your code much more straightforward. We'll look at various strategies for code refactoring and script reuse in Chapter 8.

Accessing PDF Tables with Tabula

If you looked at the text files produced in the preceding section, you'll likely have noticed that there are a lot of "extras" in those files: page numbers and headers, line breaks, and other "cruft." There are also some key elements missing, like images and tables.

While our data work won't extend to analyzing images (that is a much more specialized area), it's not unusual to find tables inside PDFs that hold data we might want to work with. In fact, this problem is common enough in my home field of journalism that a group of investigative journalists designed and built a tool called Tabula specifically to deal with this problem.

Tabula isn't a Python library—it's actually a standalone piece of software. To try it out, download the installer for your system; if you're on a Chromebook or Linux machine, you'll need to download the *.zip* file and follow the directions in *README.txt*. Whatever system you're using, you'll probably need to install the Java programming library first, which you can do by running the following command in a terminal window:

```
sudo apt install default-jre
```

Like some of the other open source tools we'll discuss in later chapters (like OpenRefine, which I used to prepare some of the sample data in Chapter 2 and cover briefly in Chapter 11), Tabula does its work behind the scenes (though some of it is visible in the terminal window), and you interact with it in a web browser. This is a way to get access to a more traditional graphical interface while still leaving most of your computer's resources free to do the heavy-duty data work.

Conclusion

Hopefully, the coding examples in this chapter have started to give you an idea of the wide variety of data wrangling problems you can solve with relatively little Python code, thanks to a combination of carefully selected libraries and those few essential Python scripting concepts that were introduced in Chapter 2.

You may also have noticed that, with the exception of our PDF text, the output of *all* the exercises in this chapter was essentially a *.csv* file. This is not by accident. Not only are *.csv* files efficient and versatile, but it turns out that to do almost any basic statistical analyses or visualizations, we need table-type data to work with. That's not to say that it isn't *possible* to analyze nontable data; that, in fact, is what much of contemporary computer science research (like machine learning) is all about. However, because those systems are often both complex and opaque, they're not really suitable for the type of data wrangling work we're focused on here. As such, we'll spend our energy on the types of analyses that can help us understand, explain, and communicate new insights about the world.

Finally, while our work in this chapter focused on file-based data and pre-saved versions of feed-based data, in Chapter 5 we'll explore how we can use Python with APIs and web scraping to wrangle data out of online systems and, where necessary, right off of web pages themselves!

About the Author

Susan E. McGregor is a researcher at Columbia University's Data Science Institute, where she also cochairs its Center for Data, Media and Society. For over a decade, she has been refining her approach to teaching programming and data analysis to non-STEM learners at the professional, graduate, and undergraduate levels.

McGregor has been a full-time faculty member and researcher at Columbia University since 2011, when she joined Columbia Journalism School and the Tow Center for Digital Journalism. While there, she developed the school's first data journalism curriculum and served as a primary academic advisor for its dual-degree program in Journalism and Computer Science. Her academic research centers on security and privacy issues affecting journalists and media organizations, and is the subject of her first book, *Information Security Essentials: A Guide for Reporters, Editors, and Newsroom Leaders* (CUP).

Prior to her work at Columbia, McGregor spent several years as the Senior Programmer on the News Graphics team at the *Wall Street Journal*. She was named a 2010 Gerald Loeb Award winner for her work on WSJ's original "What They Know" series, and has spoken and published at a range of leading academic security and privacy conferences. Her work has received support from the National Science Foundation, the Knight Foundation, Google, and multiple schools and offices of Columbia University. McGregor is also interested in how the arts can help stimulate critical thinking and introduce new perspectives around technology issues. She holds a master's degree in Educational Communication and Technology from NYU and a bachelor's degree in Interactive Information Design from Harvard University.

Colophon

The animal on the cover of *Practical Python Data Wrangling and Data Quality* is a horseshoe whip snake (*Hemorrhois hippocrepis*).

Native to southwestern Europe and northern Africa, this snake can be found living in a variety of habitats including shrubby vegetation, rocky and sandy shores, pastureland, plantations, rural gardens, and some urban areas. Adults can grow to a total length of 5 feet (or 1.5 meters). The horseshoe whip snake has smooth scales and a yellowish/red body with a series of large black or dark brown spots edged with black running down its back. It gets its name from the light horseshoe-shaped mark on the neck and back of head.

The horseshoe whip snake climbs well and hunts birds, small reptiles, and small mammals from the tops of trees, roofs, or rocky cliffs. While it can be aggressive when handled and has a strong bite, this snake is not venomous or particularly dangerous to humans.

Thought to be highly adaptable, the current conversation status of the horseshoe whip snake is "Least Concern." Many of the animals on O'Reilly covers are endangered; all of them are important to the world.

The cover illustration is by Jose Marzan Jr., based on an antique line engraving from Lydekker's *Royal Natural History*. The cover fonts are Gilroy Semibold and Guardian Sans. The text font is Adobe Minion Pro; the heading font is Adobe Myriad Condensed; and the code font is Dalton Maag's Ubuntu Mono.