Learn to Code with Fantasy Football

v0.9.0

Contents

Prerequisites: Tooling

Files Included with this Book

This book is heavy on examples, most of which use small, "toy" datasets. You should be running and exploring the examples as you work through the book.

The first step is grabbing these files. They're available at:

https://github.com/nathanbraun/ltcwff-files/releases

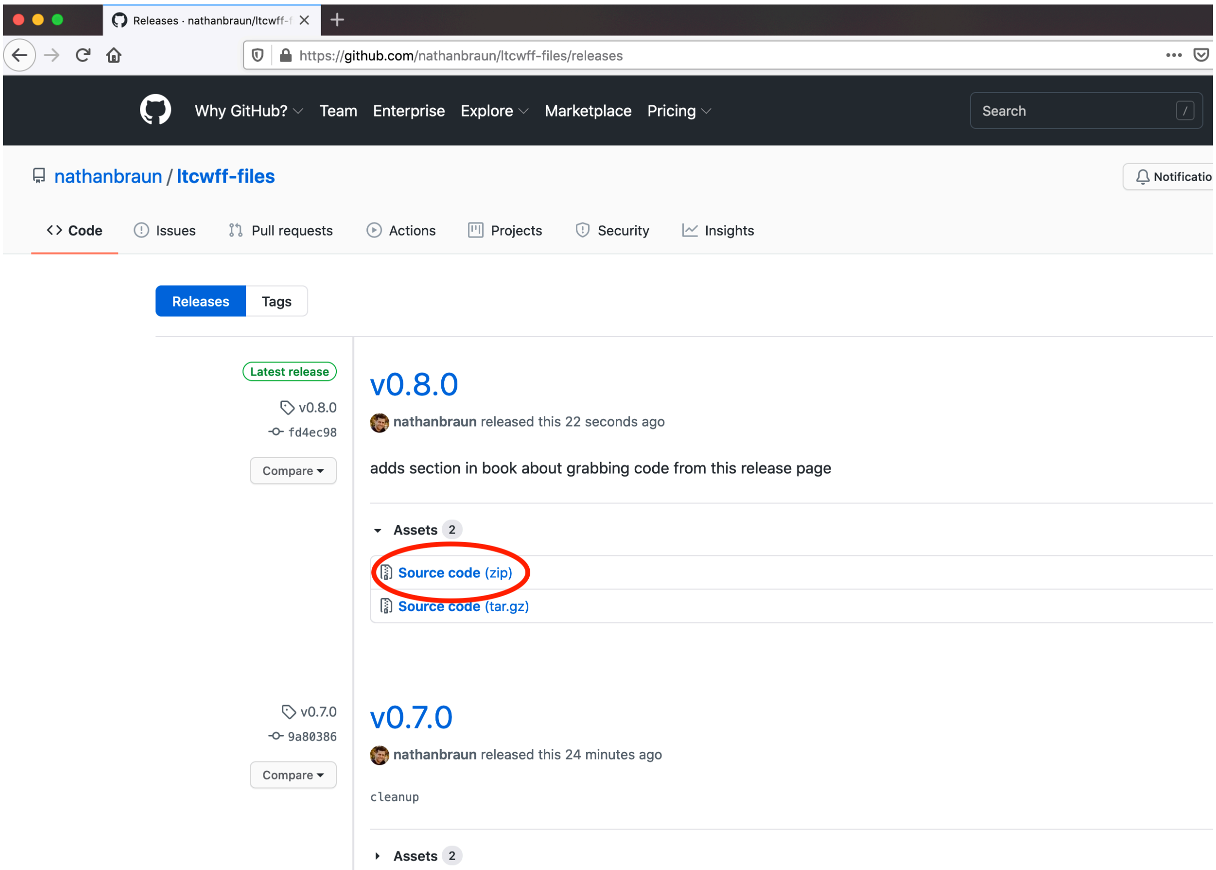


Figure 0.1: LTCWFF Files on GitHub

If you're not familiar with Git or GitHub, no problem. Just click the `Source code` link under the latest release to download the files. This will download a file called `ltcwff-files-vX.X.X.zip`, where X.X.X is the latest version number (v0.8.0 in the screenshot above).

When you unzip these (note in the book I've dropped the version number and renamed the directory just `ltcwff-files`, which you can do too) you'll see four sub-directories: `code`, `data`, `anki`, `solutions-to-excercises`.

You don't have to do anything with these right now except know where you put them. For example, on my mac, I have them in my home directory:

`/Users/nathanbraun/ltcwff-files`

If I were using Windows, it might look like this:

`C:\Users\nathanbraun\ltcwff-files`

Set these aside for now and we'll pick them up in chapter 2.

Python

In this book, we will be working with Python, a free, open source programming language.

This book is hands on, and you'll need the ability to run Python 3 code and install packages. If you can do that and have a setup that works for you, great. If you do not, the easiest way to get one is from Anaconda.

1. Go to: https://www.anaconda.com/products/individual
2. Scroll (way) down and click on the button under Anaconda Installers to download the 3.x version (3.8 at time of this writing) for your operating system.

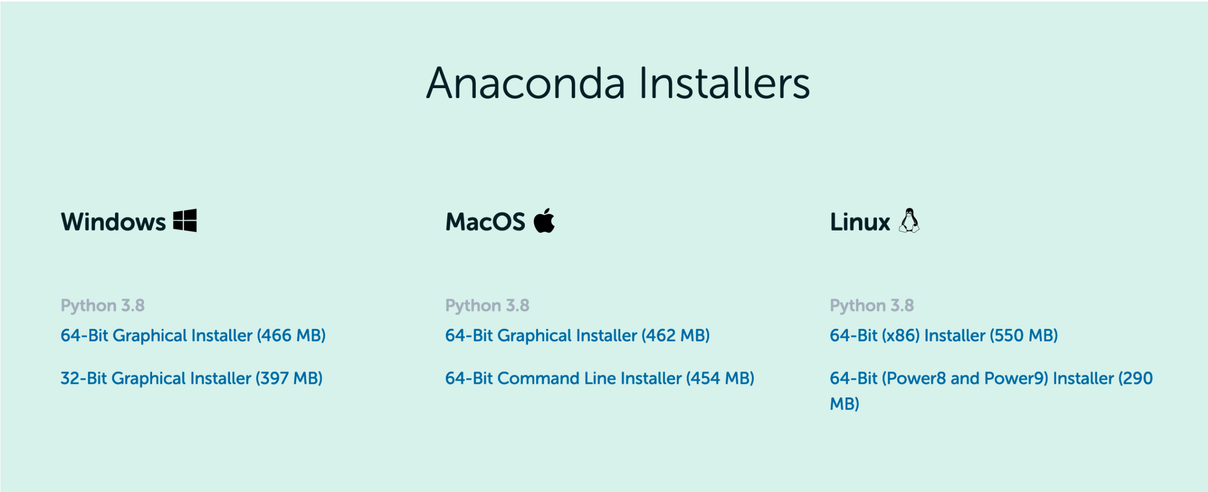


Figure 0.2: Python 3.x on the Anaconda site

3. Then install it[1]. It might ask whether you want to install it for everyone on your computer or just you. Installing it for just yourself is fine.
4. Once you have Anaconda installed, open up Anaconda Navigator and launch Spyder.
5. Then, in Spyder, go to View -> Window layouts and click on Horizontal split. Make sure pane selected on the right side is 'IPython console'.

Now you should be ready to code. Your editor is on left, and your Python console is on the right. Let's touch on each of these briefly.

[1]One thing about Anaconda is that it takes up a lot of disk space. This shouldn't be a big deal. Most computers have much more hard disk space than they need and using it will not slow down your computer. Once you are more familiar with Python, you may want to explore other, more minimalistic ways of installing it.

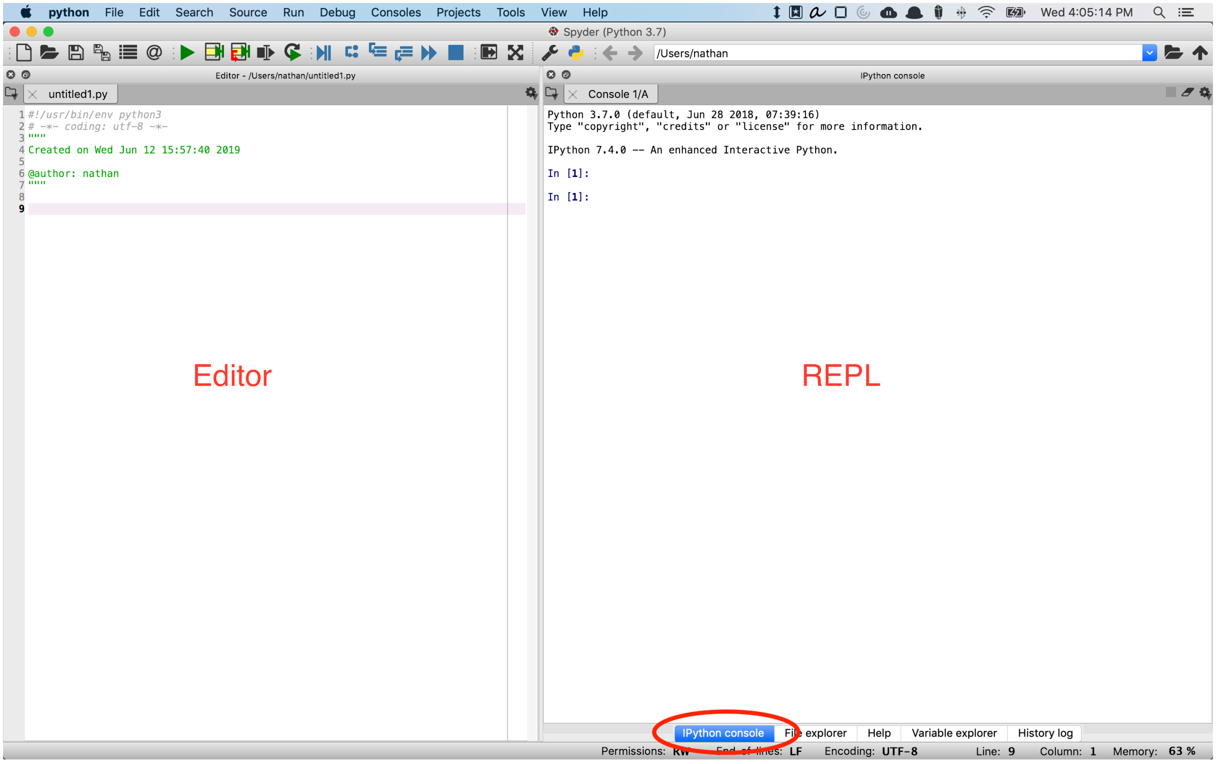


Figure 0.3: Editor and REPL in Spyder

Editor

This book assumes you have some familiarity working in a spreadsheet program like Excel, but not necessarily any familiarity with code.

What are the differences?

A spreadsheet lets you manipulate a table of data as you look at. You can point, click, resize columns, change cells, etc. The coder term for this style of interaction is "what you see is what you get" (WYSIWYG).

In contrast, Python code is a set of instructions for working with data. You tell your program what to do, and Python does (aka *executes* or *runs*) it.

It is possible to tell Python what to do one instruction at a time, but usually programmers write multiple instructions out at once. These instructions are called "programs" or "code", and (for Python, each language has its own file extension) are just plain text files with the extension .py.

When you tell Python to run some program, it will look at the file and run each line, starting at the top.

Your *editor* is the text editing program you use to write and edit these files. If you wanted, you could write all your Python programs in Notepad, but most people don't. An editor like Spyder will do nice things like highlight special Python related keywords and alert you if something doesn't look like proper code.

Console (REPL)

Your editor is the place to type code. The place where you actually run code is in what Spyder calls the IPython console. The IPython console is an example of what programmers call a read-eval(uate)-print-loop, or **REPL**.

A REPL does exactly what the name says, takes in ("reads") some code, evaluates it, and prints the result. Then it automatically "loops" back to the beginning and is ready for new code.

Try typing 1+1 into it. You should see:

```
In [1]: 1 + 1
Out[1]: 2
```

The REPL "reads" `1 + 1`, evaluates it (it equals `2`), and prints it. The REPL is then ready for new input.

A REPL keeps track of what you have done previously. For example if you type:

```
In [2]: x = 1
```

And then later:

```
In [3]: x + 1
Out[3]: 2
```

the REPL prints out 2. But if you quit and restart Spyder and try typing `x + 1` again it will complain that it doesn't know what `x` is.

```
In [1]: x + 1
...
NameError: name 'x' is not defined
```

By Spyder "complaining" I mean that Python gives you an **error**. An error — also sometimes called an **exception** — means something is wrong with your code. In this case, you tried to use `x` without telling Python what `x` was.

Get used to exceptions, because you'll run into them a lot. If you are working interactively in a REPL and do something against the rules of Python it will alert you (in red) that something went wrong, ignore whatever you were trying to do, and loop back to await further instructions like normal.

Try:

```
In [2]: x = 1

In [3]: x = 9/0
...

ZeroDivisionError: division by zero
```

Since dividing by 0 is against the laws of math[2], Python won't let you do it and will throw (or *raise*) an error. No big deal — your computer didn't crash and your data is still there. If you type `x` in the REPL again you will see it's still 1.

We'll mostly be using Python interactively like this, but know Python behaves a bit differently if you have an error in a file you are trying to run all at once. In that case Python will stop and quit, but — because Python executes code from top to bottom — everything above the line with your error will have run like normal.

[2] See https://www.math.toronto.edu/mathnet/questionCorner/nineoverzero.html

Using Spyder and Keyboard Shortcuts

When writing programs (or following along with the examples in this book) you will spend a lot of your time in the editor. You will also often want to send (run) code — sometimes the entire file, usually just certain sections — to the REPL. You also should go over to the REPL to examine certain variables or try out certain code.

At a minimum, I recommend getting comfortable with the following keyboard shortcuts in Spyder:

Pressing **F9** in the editor will send whatever code you have highlighted to the REPL. If you don't have anything highlighted, it will send the current line.

F5 will send the entire file to the REPL.

You should get good at navigating back and forth between the editor and the REPL. On Windows:

- **control + shift + e** moves you to the editor (e.g. if you're in the REPL).
- **control + shift + i** moves you to the REPL (e.g. if you're in the editor).

On a Mac, it's command instead of control:

- **command + shift + e** (move to editor).
- **command + shift + i** (move to REPL).

Anki

Remembering What You Learn

A problem with reading technical books is remembering everything you read. To help with that, this book comes with more than 300 flashcards covering the material. These cards are designed for **Anki**, a (mostly) free, open source *spaced repetition* flashcard program.

> "The single biggest change that Anki brings about is that it means memory is no longer a haphazard event, to be left to chance. Rather, it guarantees I will remember something, with minimal effort. That is, Anki makes memory a choice." — Michael Nielsen

With normal flashcards, you have to decide when and how often to review them. When you use Anki, it decides this for you.

Anki is definitely optional. Feel free to dive in now and set it up later. But it may be something to consider, particularly if your learning is going to be spread out over a long time or you won't have a chance to use Python on a regular basis.

See Appendix B for more on Anki, installing it, and using the flashcards that come with this book.

1. Introduction

The Purpose of Data Analysis

The purpose of data analysis is to get interesting or useful insights.

- I want to win my fantasy football game, who do I start this week?
- I'm an NFL GM, which QB should I draft?
- I'm a mad scientist, how many yards would Priest Holmes have run behind Dallas's 2017 offensive line?

Data analysis is one (hopefully) accurate and consistent way to get these insights.

Of course, that requires *data*.

What is Data?

At a very high level, data is a *collection of structured information*.

You might have data about anything, but let's take a football game, say Week 12, 2018 - Chiefs vs Rams. What would a collection of structured information about it look like?

Let's start with **collection**, or "a bunch of stuff." What is a football game a collection of? How about *plays*? This isn't the only acceptable answer — a collection of players, teams, drives, or quarters would fit — but it'll work. A football game is a collection of plays. OK.

Now **information** — what information might we have about each play in this collection? Maybe: down, distance, what team has the ball, whether the play was a run or pass, how many yards it went for, or who made the tackle.

Finally, it's **structured** as a big rectangle with columns and rows. A *row* is a single item in our collection (a play in this example). A *column* is one piece of information (down, distance, etc).

This is an efficient, organized way of presenting information. When we want to know, "who had the first carry in the second half and how many yards did it go for?", we can find the right row and columns, and say "Oh, Kareem Hunt for 3 yards".

```
off  def  qtr      time       type  yards     rusher
 KC   LA    3  14:55:00       pass     27        NaN
 KC   LA    3  14:40:00        run      3     K.Hunt
 KC   LA    3  14:01:00        run      6  P.Mahomes
 KC   LA    3  13:38:00       pass    -16        NaN
 LA   KC    3  13:27:00       pass      0        NaN
 LA   KC    3  13:22:00       pass      0        NaN
```

It's common to refer to rows as **observations** and columns as **variables**, particularly when using the data for more advanced forms of analysis, like modeling. Other names for this rectangle-like format include tabular data or flat file (because all this info about Chiefs-Rams is *flattened* out into one big table).

A spreadsheet program like Microsoft Excel is one way to store data, but it's proprietary and may not always be available. Spreadsheets also often contain extra, non-data material like annotations, highlighting or plots.

A simpler, more common way to store data is in a plain text file, where each row is a line and columns are separated by commas. So you could open up our play-by-play data in a basic text editor like Notepad and see:

```
off,def,qtr,time,type,yards,rusher
KC,LA,3,14:55:00,pass,27,
KC,LA,3,14:40:00,run,3,K.Hunt
KC,LA,3,14:01:00,run,6,P.Mahomes
KC,LA,3,13:38:00,pass,-16,
LA,KC,3,13:27:00,pass,0,
LA,KC,3,13:22:00,pass,0,
```

Data stored like this, with a character (usually a comma, sometimes a tab) in between columns is called *delimited* data. Comma delimited files are called **comma separated values** and usually have a csv file extension.

This is just how the data is stored on your computer. No one expects you to open these files in Notepad and work with all those commas directly. In Excel (or other spreadsheet program) you can open and write csv files and they will be in the familiar spreadsheet format. That's one of the main benefits of using csvs — most programs can read them.

Example Datasets

This book is heavy on examples, and comes with a few small csv files that we will practice on. Instructions for getting these files are in the prerequisites section.

Play-By-Play Data

The first dataset is play-by-play data from two games. The first is what ESPN's Bill Barnwell called the greatest regular season game ever played — the Rams 54-51 victory over the Chiefs in Week 12, 2018. The second is the Patriots 43-40 victory over those same Chiefs. This game was another classic, including 30 points in the 4th quarter alone.

This play-by-play data includes both pre-snap, situational information about each play (game, quarter, time left, yardline, down, yards to go, team with the ball) and what actually happened (play type — run, pass, field goal, punt — yards gained, QB name, receiver name, etc).

The dataset includes all regular downed plays — no extra points, kickoffs, or plays nullified by penalties. It's in the file `play_data_sample.csv`.

Player/Game Data

The second dataset this book comes with is a random sample of player-game totals from 2017. It's in the file `player_game_2017_sample.csv`. The first few rows (and some of the columns, they don't all fit here) look like this:

```
 player_name  week  carries  ...  rec_yards  receptions  targets
     T.Brady     1      0.0  ...        0.0         0.0      0.0
     A.Smith     1      2.0  ...        0.0         0.0      0.0
  D.Amendola     1      0.0  ...      100.0         6.0      7.0
  R.Burkhead     1      3.0  ...        8.0         1.0      3.0
     T.Kelce     1      1.0  ...       40.0         5.0      7.0
```

Remember: *Collection*. *Information*. *Structure*.

This data is a *collection* of player-game combinations. Each row represents one player's statistics for one game (Amendola/Week 1). If we had 100 players, and they each played 16 games, then our dataset would be `100*16=1600` rows long.

The columns (variables) are *information*. In the third row, each column tells us something about how Amendola did Week 1, 2017. The `targets` column shows us he had 7 targets, the `receptions` column indicates he caught 6 of them, and the `rec_yards` column says those catches went for 100 yards.

If we want to look at another player-game (Amendola/Week 2 or Gronk/Week 8), we look at a different row.

Notice how our columns can be different types of information, like text (`player_name`) or numbers (`rec_yards`) or semi-hybrid, technically-numbers but we would never do any math with them (`gameid`).

One thing to keep in mind: just because our data is at some level (player/game in this case), doesn't mean *every* column in the data has to be at that level.

Though you can't see it in the snippet above, in this dataset there is a column called `season`. It's always `2017`. Does this matter? No. We're just asking: "for this particular player/game result, what season was it?" It just happens that for this data the answer is the same for every row.

ADP Data

The third dataset is the 2017 pre-season average draft position (ADP) data from www.fantasyfootballcalculator.com. It's in the file adp_2017.csv. It is at the *player* level and looks like this:

```
             name team   adp  ...  high  low  times_drafted
     David Johnson  ARI   1.3  ...     1    4            310
       LeVeon Bell  PIT   2.3  ...     1    6            303
     Antonio Brown  PIT   3.7  ...     1    7            338
       Julio Jones  ATL   5.7  ...     1   15            131
   Ezekiel Elliott  DAL   6.2  ...     1   17            180
```

Later in the book you will learn how to build your own web scraper to get this or data from any other year or scoring system.

I encourage you to open all of these datasets up and explore them in your favorite spreadsheet program.

Now that we know what data is, let's move to the other end of the spectrum and talk about why data is ultimately valuable, which is because it provides insights.

What is Analysis?

How many footballs are in the following picture?

Figure 0.1: Few footballs

Pretty easy question right? What about this one?

Figure 0.2: Many footballs

Researchers have found that humans automatically know how many objects they're seeing, as long as there are no more than three or four. Any more than that, and counting is required.

If you open up the play-by-play data this book comes with, you'll notice it's 304 rows and 42 columns.

From that, do you think you would be able to glance at it and immediately tell me who the "best" player was? Worst? Most consistent or explosive? Of course not.

Raw data is the numerical equivalent of a pile of footballs. It's a collection of facts, way more than the human brain can reliably and accurately make sense of and meaningless without some work.

Data analysis is the process of transforming this raw data to something smaller and more useful you can fit in your head.

Types of Data Analysis

Broadly, it is useful to think of two types of analysis, both of which involve reducing a pile of data into a few, more manageable number of insights.

1. The first type of statistical analysis is calculating single number type summary statistics. Examples would include the mean (average), median, mode, quarterback rating (QBR) and wins over replacement player (WORP).
2. The second type of analysis is building *models* to understand relationships between data.

Summary Statistics

Summary statistics can be complex (QBR, WORP) or more basic (yards per catch or games missed due to injury), but all of them involve going from raw data to some more useful number.

Often, the goal of these single number summary statistics is to better understand things that happened previously.

Stats vary in ambition. Some, like QBR, try to be all encompassing, while others get at a particular facet of a player's performance. For example, we might measure "explosiveness" by looking at a player's longest carry, or "steadiness" by looking at the percentage of carries that don't lose yards. These are summary stats.

A key skill in data analysis is knowing how to look at data multiple ways via different summary statistics, keeping in mind their strengths and weaknesses. Doing this well can give you an edge.

For example, in the 2003 book *Moneyball*, Michael Lewis writes about how the Oakland A's were one of the first baseball teams to realize that batting average — which most teams relied on to evaluate a hitter's ability at the time — did not take into account a player's ability to draw walks.

By using a different statistic — on base percentage — that *did* take walks into account and signing players with high on base percentage relative to their batting average, the A's were able to get good players at a discount. As a result, they had a lot of success for the amount of money they spent[1].

In practice, calculating summary statistics requires creativity, clear thinking and the ability to manipulate data via code.

[1] It didn't take long for other teams to catch on. Now, on base percentage is a standard metric and the discount on players with high OBP relative to BA has largely disappeared.

Modeling

The other type of analysis is **modeling**. A model describes a mathematical *relationship* between variables in your data, specifically the relationship between one or more *input variables* and one *output variable*.

output variable = model(*input variables*)

This is called "modeling *output variable* as a function of *input variables*".

How do we find these relationships and actually "do" modeling in practice?

When working with flat, rectangular data, *variable* is just another word for *column*. In practice, modeling is making a dataset where the columns are your input variables and one output variable, then passing this data (with information about which columns are which) to your modeling program.

> In practice, modeling is making a dataset where the columns are your input variables and one output variable, then passing this data (with information about which columns are which) to your modeling program.

That's why most data scientists and modelers spend most of their time collecting and manipulating data. Getting all your inputs and output together in a dataset that your modeling program can accept is most of the work.

Later in the book we will get into the details and learn how to actually use these programs, but for now let's get into motivation.

Why Model?

Though all models describe some relationship, *why* you might want to analyze a relationship depends on the situation. Sometimes, it's because models help make sense of things that have already happened.

For example, modeling rushing yards as a function of the player, offensive line skill and game flow (e.g. down and distance or score), would be one way to figure out — by separating talent from other factors outside of the running back's control — which running back is the most "skilled".

Then as an analyst for an NFL team assigned to scout free agent running backs, I can report back to my GM on who my model thinks is truly the best, the one who will run for the most yards behind our offensive line.

Models that Predict the Future

Often, we want to use a model to predict what will happen in the future, say, next season's fantasy points or this week's daily fantasy ownership percentage.

Again, modeling is about relationships. For prediction-type models that relationship is between data we have *now* and events that will happen in the *future*.

But if something is in the future, how can we relate it to the present? The answer is by starting with the past.

For example, I'm writing this in early 2021, which means I have 2020 data on: ADP; weather; and actual fantasy points scored. And I could build a model:

player's points for some week in 2020 = model(*player's 2020 ADP*, *weather for that week in 2020*)

Training (or **fitting**) this model is the process of using that known/existing/already happened data to find a relationship between the input variables (*ADP*, *weather*) and the output variable (*fantasy points scored*). Once I establish that relationship, I can feed it new inputs — an ADP of 2.7, rainy with 20 mph winds — transform it using my relationship, and get back an output — 18.7 points.

The inputs I feed my model might be from past events that have already happened. This is often done to evaluate model performance. For example, I could put in Todd Gurley's 2020 ADP and the weather for Week 1, 2020, and see what the model says. Hopefully it's close to how he actually did[2].

Alternatively, I can feed my model data from *right now* in order to predict things that *haven't happened yet*. For example — again, I'm writing this early in 2021 — I could put in Gurley's 2021 ADP, take a guess at the weather and get back projected points for Week 1.

High Level Data Analysis Process

Now that we've covered both the inputs (data) and final outputs (analytical insights), let's take a very high level look at what's in between.

Everything in this book will fall somewhere in one of the following steps:

1. Collecting Data

Whether you scrape a website, connect to a public API, download some spreadsheets, or enter it yourself, you can't do data analysis without data. The first step is getting ahold of some.

[2] The actual values for many models are picked so that this difference — called the *residual* — is as small as possible across all observations.

This book covers how to scrape a website and get data by connecting to an API. It also suggests a few ready-made datasets.

2. Storing Data

Once you have data, you have to put it somewhere. This could be in several spreadsheet or text files in a folder on your desktop, sheets in an Excel file, or a database.

This book covers the basics and benefits of storing data in a SQL database.

3. Loading Data

Once you have your data stored, you need to be able to retrieve the parts you want. This can be easy if it's in a spreadsheet, but if it's in a database then you need to know some SQL — pronounced "sequel" and short for Structured Query Language — to get it out.

This book covers basic SQL and loading data with Python.

4. Manipulating Data

Talk to any data scientist, and they'll tell you they spend most of their time preparing and manipulating their data. Football data is no exception. Sometimes called *munging*, this means getting your raw data in the right format for analysis.

There are many tools available for this step. Examples include Excel, R, Python, Stata, SPSS, Tableau, SQL, and Hadoop. In this book you'll learn how to do it in Python, particularly using the library Pandas.

The boundaries between this step and the ones before and after it can be a little fuzzy. For example, though we won't do it in this book, it is possible to do some basic manipulation in SQL. In other words, loading (3) and manipulating (4) data can be done with the same tools. Similarly Pandas — the primary tool we'll use for data manipulation (4) — also includes basic functionality for analysis (5) and input-output capabilities (3).

Don't get too hung up on this. The point isn't to say, "this technology is *always* associated with this part of the analysis process". Instead, it's a way to keep the big picture in mind as you are working through the book and your own analysis.

5. Analyzing Data for Insights

This step is the model, summary stat or plot that takes you from formatted data to insight.

This book covers a few different analysis methods, including summary stats, a few modeling techniques, and data visualization.

We will do these in Python using the scikit-learn, statsmodels, and matplotlib libraries, which cover machine learning, statistical modeling and data visualization respectively.

Connecting the High Level Analysis Process to the Rest of the Book

Again, everything in this book falls into one of the five sections above. Throughout, I will tie back what you are learning to this section so you can keep sight of the big picture.

This is the forest. If you ever find yourself banging your head against a tree — either confused or wondering *why* we're talking about something — refer back here and think about where it fits in.

Some sections above may be more applicable to you than others. Perhaps you are comfortable analyzing data in Excel, and just want to learn how to get data via scraping a website or connecting to an API. Feel free to focus on whatever sections are most useful to you.

End of Chapter Exercises

1.1

Name the granularity for the following, hypothetical datasets:

a)

```
    game_id  qtr  posteam  score  yards  passes  turnovers
2018101412    1       KC    3.0     66     9.0        1.0
2018101412    1       NE   10.0    133     9.0        0.0
2018101412    2       KC    9.0    144    14.0        1.0
2018101412    2       NE   24.0     57     7.0        0.0
2018101412    3       KC   19.0    155     8.0        0.0
```

b)

```
     gameid player_name  rush_yards  receptions  pass_yards
2017100105    D.Murray        31.0         2.0         0.0
2017090700     T.Brady         0.0         0.0       267.0
2017111201      R.Cobb         8.0         3.0         0.0
2017092408     M.Forte        25.0         0.0         0.0
2017091701      C.Clay         0.0         3.0         0.0
```

c)

```
  player_name  ngames  rush_yards  receptions  pass_yards  season
    A.Collins      15       976.0        23.0         0.0    2017
     A.Cooper      14         4.0        47.0         0.0    2017
      A.Derby      11         0.0        21.0         0.0    2017
   A.Robinson      14         0.0        19.0         0.0    2017
    B.Bortles      16       326.0         0.0      3716.0    2017
```

d)

```
             pass_tds
week               1  2  3  4  5  6  7  8  9  10 11 12 13 14 15 16 17
player_name
C.Newton             2  0  0  3  3  1  1  1  0  4  0  0  2  1  4  0  1
T.Taylor             2  0  2  1  1  0  1  1  3  0  1  1  0  0  1  1  1
T.Brady              0  3  5  2  1  2  2  1  0  3  3  4  0  1  1  3  2
M.Ryan               1  1  3  1  0  1  1  2  2  2  2  1  0  1  0  1  2
B.Bortles            1  1  4  1  0  1  1  0  1  1  1  0  2  2  3  3  0
```

e)

```
          adp_mean  adp_std  adp_min  adp_25%  adp_50%  adp_75%  adp_max
position
WR           75.52    47.05      3.7    36.55     70.0  116.450    162.9
RB           78.25    50.45      1.3    33.25     76.6  121.550    160.7
TE           92.90    43.44     18.1    57.60     83.6  132.600    152.7
QB           96.22    39.58     23.4    74.20    100.3  126.500    162.4
DEF         138.92    21.16    105.5   123.90    138.1  161.500    168.2
PK          160.42     9.68    145.0   154.20    161.8  168.275    172.7
```

1.2

You're an analyst for a team in need of some playmakers. Your GM says he wants someone who is "explosive" with "big play potential". He's tasked you with evaluating the crop of FA WRs.

What are some simple summary stats you might look at?

1.3

I want to build a model that uses weather data (wind speed, temperature at kickoff) to predict a game's combined over-under. What are my:

a) Input variables.

b) Output variable.

c) What level of granularity is this model at?

d) What's the main limitation with this model?

1.4

List where each of the following techniques and technologies fall in the high-level pipeline.

a) getting data to the right level of granularity for your model
b) experimenting with different models
c) dealing with missing data
d) SQL
e) scraping a website
f) plotting your data
g) getting data from an API
h) pandas
i) taking the mean of your data
j) combining multiple data sources

2. Python

Introduction to Python Programming

This section is an introduction to basic Python programming.

Much of the functionality in Python comes from third party **libraries** (or **packages**), specially designed for specific tasks.

For example: the **Pandas** library lets us manipulate tabular data. And the library **BeautifulSoup** is the Python standard for scraping data from websites.

We'll write code that makes heavy use of both later in the book. But, even when using third party packages, you will also be using a core set of Python features and functionality. These features — called the **standard library** — are built-in to Python.

This section of the book covers the parts of the standard library that are most important. All the Python code we write in this book is built upon the concepts covered in this chapter. Since we'll be using Python for nearly everything, this section touches all parts of the high level, five-step data analysis process.

How to Read This Chapter

This chapter — like the rest of the book — is heavy on examples. All the examples in this chapter are included in the Python file `02_python.py`. Ideally, you would have this file open in your Spyder editor and be running the examples (highlight the line(s) you want and press F9 to send it to the REPL/console) as we go through them in the book.

If you do that, I've included what you'll see in the REPL here. That is:

```
In [1]: 1 + 1
Out[1]: 2
```

Where the line starting with `In[1]` is what you send, and `Out[1]` is what the REPL prints out. These are lines `[1]` for me because this was the first thing I entered in a new REPL session. Don't worry if the numbers you see in `In[ ]` and `Out[ ]` don't match exactly what's in this chapter. In fact, they probably won't, because as you run the examples you should be exploring and experimenting. That's what the REPL is for.

Nor should you worry about messing anything up: if you need a fresh start, you can type `reset` into the REPL and it will clear out everything you've run previously. You can also type `clear` to clear all the printed output.

Sometimes, examples build on each other (remember, the REPL keeps track of what you've run previously), so if something isn't working, it might be relying on something you haven't run yet.

Let's get started.

Important Parts of the Python Standard Library

Comments

As you look at `02_python.py` you might notice a lot of lines beginning with `#`. These are **comments**. When reading your code, the computer will ignore everything from `#` to the end of the line.

Comments exist in all programming languages. They are a way to explain to anyone reading your code (including your future self) more about what's going on and what you were trying to do when you wrote it.

The problem with comments is it's easy for them to become out of date. This often happens when you change your code and forget to update the comment.

An incorrect or misleading comment is worse than no comment. For that reason, most beginning programmers probably comment too often, especially because Python's **syntax** (the language related rules for writing programs) is usually pretty clear.

For example, this would be an unnecessary comment:

```
# print the result of 1 + 1
print(1 + 1)
```

Because it's not adding anything that isn't obvious by just looking at the code. It's better to use descriptive names, let your code speak for itself, and save comments for particularly tricky portions of code.

Variables

Variables are a fundamental concept in any programming language.

At their core, variables are just named pieces of information. This information can be anything from a single number to an entire dataset — the point is that they let you store and recall things easily.

The rules for naming variables differ by programming language. In Python, they can be any upper or lowercase letter, number or _ (underscore), but they can't start with a number.

Note: previously we talked about how, in the language of modeling and tabular data, *variable* is another word for *column*. That's different than what we're talking about here.

A variable in a dataset or model is a column; a variable in your code is named piece of information. You should usually be able to tell by the context which one you're dealing with. Unfortunately, imprecise language comes with the territory when learning new subjects, but I'll do my best to warn you about any similar pitfalls.

While you can name your variables whatever you want (provided it follows the rules), the **convention** in Python for most variables is all lowercase letters, with words separated by underscores.

Conventions are things that, while not strictly required, programmers include to make it easier to read each other's code. They vary by language. So, while in Python I might have a variable `pts_per_passing_td`, a JavaScript programmer would write `ptsPerPassingTD` instead.

Assigning data to variables

You **assign** a piece of data to a variable with an equals sign, like this:

```
In [6]: pts_per_passing_td = 4
```

Another, less common, word for assignment is **binding**, as in `pts_per_passing_td` is bound to the number 4.

Now, whenever you use `pts_per_passing_td` in your code, the program automatically substitutes it with `4` instead.

```
In [8]: pts_per_passing_td
Out[8]: 4

In [9]: 3*pts_per_passing_td
Out[9]: 12
```

One of the benefits of developing with a REPL is that you can type in a variable, and the REPL will evaluate (i.e. determine what it is) and print it. That's what the code above is doing. But note while `pts_per_passing_td` is `4`, the assignment statement itself, `pts_per_passing_td = 4`, doesn't evaluate to anything, so the REPL doesn't print anything out.

You can update and override variables too. Going into the code below, `pts_per_passing_td` has a value of 4 (from the code we just ran above). So the right hand side, `pts_per_passing_td - 3` is evaluated first (4 - 3 = 1), and *then* the result gets (re)assigned to `pts_per_passing_td`, overwriting the 4 it held previously.

```
In [12]: pts_per_passing_td = pts_per_passing_td - 3

In [13]: pts_per_passing_td
Out[13]: 1
```

Types

Like Excel, Python includes concepts for both numbers and text. Technically, Python distinguishes between two types of numbers: integers (whole numbers) and floats (numbers that may have decimal points), but the difference isn't important for us right now.

```
over_under = 48  # int
wind_speed = 22.8  # float
```

Text, called a **string** in Python, is wrapped in either single (`'`) or double (`"`) quotes. I usually just use single quotes, unless the text I want to write has a single quote in it (like in Le'Veon), in which case trying to use `'Le'Veon Bell'` would give an error.

```
starting_qb = 'Tom Brady'
starting_rb = "Le'Veon Bell"
```

You can check the type of any variable with the type function.

```
In [20]: type(starting_qb)
Out[20]: str

In [21]: type(over_under)
Out[21]: int
```

Keep in mind the difference between strings (quotes) and variables (no quotes). A variable is a named of a piece of information. A string (or a number) *is* the information.

One common thing to do with strings is to insert variables inside of them. The easiest way to do that is via **f-strings**.

```
In [4]: team_name = f'{starting_qb}, {starting_rb}, & co.'

In [5]: team_name
Out[5]: "Tom Brady, Le'Veon Bell, & co."
```

Note the `f` immediately preceding the quotation mark. Adding that tells Python you want to use variables inside your string, which you wrap in curly brackets.

f-strings are new as of Python 3.8, so if they're not working for you make sure that's at least the version you're using.

Strings also have useful **methods** you can use to do things to them. You invoke methods with a `.` and parenthesis. For example, to make a string uppercase you can do:

```
In [6]: 'he could go all the way'.upper()
Out[6]: 'HE COULD GO ALL THE WAY'
```

Note the parenthesis. That's because sometimes these take additional data, for example the `replace` method.

```
In [7]: 'Chad Johnson'.replace('Johnson', 'Ochocinco')
Out[7]: 'Chad Ochocinco'
```

There are a bunch of these string methods, most of which you won't use that often. Going through them all right now would bog down progress on more important things. But occasionally you *will* need one of these string methods. How should we handle this?

The problem is we're dealing with a comprehensiveness-clarity trade off. And, since anything short of Python in a Nutshell: A Desktop Quick Reference (which is 772 pages) is going to necessarily fall short on comprehensiveness, we'll do something better.

Rather than teaching you all 44 of Python's string methods, I am going to teach you how to quickly see which are available, what they do, and how to use them.

Though we're nominally talking about string methods here, this advice applies to any of the programming topics we'll cover in this book.

Interlude: How to Figure Things Out in Python

> "A simple rule I taught my nine year-old today: if you can't figure something out, figure out how to figure it out." — Paul Graham

The first tool you can use to figure out your options is the REPL. In particular, the REPL's **tab completion** functionality. Type in a string like `'tom brady'` then `.` and hit tab. You'll see all the options available to you (this is only the first page, you'll see more if you keep pressing tab).

```
'tom brady'.
    capitalize()   encode()       format()
    isalpha()      isidentifier() isspace()
    ljust()        casefold()     endswith()
    format_map()   isascii()      islower()
```

Note: tab completion on a string directly like this doesn't always work in Spyder. If it's not working for you, assign `'tom brady'` to a variable and tab complete on that. Like this[1]:

```
In [14]: foo = 'tom brady'
Out[14]: foo.
            capitalize()   encode()       format()
            isalpha()      isidentifier() isspace()
            ljust()        casefold()     endswith()
            format_map()   isascii()      islower()
```

Then, when you find something you're interested in, enter it in the REPL with a question mark after it, like `'tom brady'.capitalize?` (or `foo.capitalize?` if that doesn't work).

You'll see:

```
Signature: str.capitalize(self, /)
Docstring:
Return a capitalized version of the string.

More specifically, make the first character have upper case and
the rest lower case.
```

So, in this case, it sounds like `capitalize` will make the first letter uppercase and the rest of the string lowercase. Let's try it:

```
In [15]: 'tom brady'.capitalize()
Out[15]: 'Tom brady'
```

Great. Many of the items you'll be working with in the REPL have methods, and tab completion is a great way to explore what's available.

The second strategy is more general. Maybe you want to do something that you know is string related but aren't necessarily sure where to begin or what it'd be called.

For example, maybe you've scraped some data that looks like:

```
In [8]: '  tom brady'
```

[1] The upside of this Spyder autocomplete issue is you can learn about the programming convention "foo". When dealing with a throwaway variable that doesn't matter, many programmers will name it `foo`. Second and third variables that don't matter are `bar` and `baz`. Apparently this dates back to the 1950's.

But you want it to be like this, i.e. without the spaces before "tom":

```
In [9]: 'tom brady'
```

Here's what you should do — and I'm not trying to be glib here — Google: "python string get rid of leading white space".

When you do that, you'll see the first result is from stackoverflow and says:

> "The lstrip() method will remove leading whitespaces, newline and tab characters on a string beginning."

A quick test confirms that's what we want.

```
In [99]: '  tom brady'.lstrip()
Out[99]: 'tom brady'
```

Stackoverflow

Python — particularly the data libraries we'll be using — became popular during the golden age of stackoverflow.com, a programming question and answer site that specializes in answers to small, self-contained technical problems.

How it works: people ask questions related to programming, and other, more experienced programmers answer. The rest of the community votes, both on questions ("that's a very good question, I was wondering how to do that too") as well as answers ("this solved my problem perfectly"). In that way, common problems and the best solutions rise to the top over time. Add in Google's search algorithm, and you usually have a way to figure out exactly how to do most anything you'll want to do in a few minutes.

You don't have to ask questions yourself or vote or even make a stackoverflow account to get the benefits. In fact, most people probably don't. But enough people do, especially when it comes to Python, that it's a great resource.

If you're used to working like this, this advice may seem obvious. Like I said, I don't mean to be glib. Instead, it's intended for anyone who might mistakenly believe "real" coders don't Google things.

As programmer-blogger Umer Mansoor writes,

> Software developers, especially those who are new to the field, often ask this question… Do experienced programmers use Google frequently?

> The resounding answer is YES, experienced (and good) programmers use Google… a lot. In fact, one might argue they use it more than the beginners. [that] doesn't make them bad programmers or imply that they cannot code without Google. In fact, truth is quite the opposite: Google is an essential part of their software development toolkit and they know when and how to use it.

> A big reason to use Google is that it is hard to remember all those minor details and nuances especially when you are programming in multiple languages… As Einstein said: 'Never memorize something that you can look up.'

Now you know how to figure things out in Python. Back to the basics.

Bools

There are other data types besides strings and numbers. One of the most important ones is **bool** (for boolean). Boolean's — which exist in every language — are for binary, yes or no, true or false data. While a string can have almost an unlimited number of different values, and an integer can be any whole number, bools in Python only have two possible values: `True` or `False`.

Similar to variable names, bool values lack quotes. So `"True"` is a string, not a bool. For that reason, it's also a good idea to avoid using True or False as variable names.

A Python expression (any number, text or bool) is a bool when it's yes or no type data. For example:

```
# some numbers to use in our examples
In [23]: team1_pts = 110

In [24]: team2_pts = 120

# these are all bools:
In [25]: team1_won = team1_pts > team2_pts

In [26]: team2_won = team1_pts < team2_pts

In [27]: teams_tied = team1_pts == team2_pts

In [28]: teams_did_not_tie = team1_pts != team2_pts

In [29]: type(team1_won)
Out[29]: bool

In [30]: teams_did_not_tie
Out[30]: True
```

Notice the == by `teams_tied`. That tests for equality. It's the double equals sign because — as we learned above — Python uses the single = to assign to a variable. This would give an error:

```
In [31]: teams_tied = (team1_pts = team2_pts)
  File IPython Input, line 1
    teams_tied = (team1_pts = team2_pts)
                            ^
SyntaxError: invalid syntax
```

So `team1_pts == team2_pts` will be `True` if those numbers are the same, `False` if not.

The reverse is `!=`, which means *not equal*. The expression `team1_pts != team2_pts` is `True` if the values are different, `False` if they're the same.

You can manipulate bools — i.e. chain them together or negate them — using the keywords `and`, `or`, `not` and parenthesis.

```
In [2]: shootout = (team1_pts > 150) and (team2_pts > 150)

In [3]: at_least_one_good_team = (team1_pts > 150) or (team2_pts > 150)

In [4]: you_guys_are_bad = not ((team1_pts > 100) or (team2_pts > 100))

In [5]: meh = not (shootout or at_least_one_good_team or you_guys_are_bad)
```

if statements

Bools are used frequently; one place is with if statements. The following code assigns a string to a variable `message` depending on what happened.

```
In [17]: if team1_won:
    ...:     message = "Nice job team 1!"
    ...: elif team2_won:
    ...:     message = "Way to go team 2!!"
    ...: else:
    ...:     message = "must have tied!"

In [18]: message
Out[18]: 'Way to go team 2!!'
```

Notice how in the code I'm saying `if team1_won`, not `if team1_won == True`. While the latter would technically work, it's a good way to show anyone looking at your code that you don't really understand bools. `team1_won` is `True`, it's a bool. `team1_won == True` is also `True`, and it's still a bool. Similarly, don't write `team1_won == False`, write `not team1_won`.

Container Types

Strings, integers, floats, and bools are called **primitives**; they're the basic building block types.

There are other **container** types that can hold other values. Two important container types are **lists** and **dicts**. Sometimes containers are also called **collections**.

Lists

Lists are built with square brackets and are basically a simple way to hold other, ordered pieces of data.

```
In [1]: my_roster_list = ['tom brady', 'adrian peterson', 'antonio brown']
```

Every spot in a list has a number associated with it. The first spot is 0. You can get sections (called **slices**) of your list by separating numbers with a colon. Both single numbers and slices are called inside square brackets, i.e. `[]`.

A single integer inside a bracket returns one element of your list, while a slice returns a smaller list. Note a slice returns *up to* the last number, so `[0:2]` returns the `0` and `1` items, but not item `2`.

```
In [2]: my_roster_list[0]
Out[2]: 'tom brady'

In [3]: my_roster_list[0:2]
Out[3]: ['tom brady', 'adrian peterson']
```

Passing a negative number gives you the end of the list. To get the last two items you could do:

```
In [4]: my_roster_list[-2:]
Out[4]: ['adrian peterson', 'antonio brown']
```

Also note how when you leave off the number after the colon the slice will automatically use the end of the list.

Lists can hold anything, including other lists. Lists that hold other lists are often called *nested* lists.

Dicts

A **dict** is short for dictionary. You can think about it like an actual dictionary if you want. Real dictionaries have words and definitions, Python dicts have **keys** and **values**.

Dicts are basically a way to hold data and give each piece a name. They're written with curly brackets, like this:

```
In [5]: my_roster_dict = {'qb': 'tom brady',
    ..:                   'rb1': 'adrian peterson',
    ..:                   'wr1': 'antonio brown'}
```

You can access items in a dict like this:

```
In [6]: my_roster_dict['qb']
Out[6]: 'tom brady'
```

And add new things to dicts like this:

```
In [7]: my_roster_dict['k'] = 'mason crosby'
```

Notice how keys are strings (they're surrounded in quotes). They can also be numbers or even bools. They cannot be a variable that has not already been created. You could do this:

```
In [8]: pos = 'qb'

In [9]: my_roster_dict[pos]
Out[9]: 'tom brady'
```

Because when you run it Python is just replacing `pos` with `'qb'`.

But you will get an error if `pos` is undefined. You also get an error if you try to use a key that's not present in the dict (note: *assigning* something to a key that isn't there yet — like we did with '`mason crosby`' above — is OK).

While dictionary *keys* are usually strings, dictionary *values* can be anything, including lists or other dicts.

Unpacking

Now that we've seen an example of container types, we can mention **unpacking**. Unpacking is a way to assign multiple variables at once, like this:

```
In [1]: qb, rb = ['tom brady', 'todd gurley']
```

That does the exact same thing as assigning these separately on their own line.

```
In [2]: qb = 'tom brady'

In [3]: rb = 'todd gurley'
```

One pitfall when unpacking values is that the number of whatever you're assigning to has to match the number of values available in your container. This would give you an error:

```
In [4]: qb, rb = ['tom brady', 'todd gurley', 'julio jones']
ValueError: too many values to unpack (expected 2)
```

Unpacking isn't used that frequently. Shorter code isn't always necessarily better, and it's probably clearer to someone reading your code if you assign qb and rb on separate lines.

However, some built-in parts of Python (including material below) use unpacking, so we needed to touch on it briefly.

Loops

Loops are a way to "do something" for every item in a collection.

For example, maybe I have a list of lowercase player names and I want to go through them and change them all to proper name formatting using the title string method, which capitalizes the first letter of every word in a string.

One way to do that is with a **for** loop:

```
1 my_roster_list = ['tom brady', 'adrian peterson', 'antonio brown']
2
3 my_roster_list_upper = ['', '', '']
4 i = 0
5 for player in my_roster_list:
6     my_roster_list_upper[i] = player.title()
7     i = i + 1
```

What's happening here is lines 6-7 are run multiple times, once for every item in the list. The first time player has the value 'tom brady', the second 'adrian peterson', etc. We're also using a variable i to keep track of our position in our list. The last line in the body of each loop is to increment i by one, so that we'll be working with the correct spot the next time we go through it.

```
In [9]: my_roster_list_upper
Out[9]: ['Tom Brady', 'Adrian Peterson', 'Antonio Brown']
```

The programming term for "going over each element in some collection" is **iterating**. Collections that allow you to iterate over them are called **iterables**.

Dicts are also iterables. The default behavior when iterating over dicts is you get access to the keys only. So:

```
In [58]: for x in my_roster_dict:
    ...:     print(f"position: {x}")

position: wr1
position: qb
position: rb1
```

But what if we want access to the values too? One thing we could do is write `my_roster_dict[x]`, like this:

```
In [62]: for x in my_roster_dict:
    ...:     print(f"position: {x}")
    ...:     print(f"player: {my_roster_dict[x]}")

position: wr1
player: antonio brown
position: qb
player: tom brady
position: rb1
player: adrian peterson
position: k
player: mason crosby
```

But Python has a shortcut that makes things easier: we can add `.items()` to our dict to get access to the value.

```
In [65]: for x, y in my_roster_dict.items():
    ...:     print(f"position: {x}")
    ...:     print(f"player: {y}")

position: wr1
player: antonio brown
position: qb
player: tom brady
position: rb1
player: adrian peterson
```

Notice the `for x, y`… part of the loop. Adding `.items()` unpacks the key and value into our two loop variables (we choose `x` and `y`).

Loops are occasionally useful. And they're definitely better than copying and pasting a bunch of code over and over and making some minor change.

But in many instances, there's a better option: **comprehensions**.

Comprehensions

Comprehensions are a way to modify lists or dicts with not a lot of code. They're like loops condensed onto one line.

List Comprehensions

When you want to go from one list to another different list you should be thinking comprehension. Our first **for** loop example, where we wanted to take our list of lowercase players and make a list where they're all properly formatted, is a great candidate.

The list comprehension way of doing that would be:

```
In [1]: my_roster_list
Out[1]: ['tom brady', 'adrian peterson', 'antonio brown']

In [2]: my_roster_list_proper = [x.title() for x in my_roster_list]

In [3]: my_roster_list_proper
Out[3]: ['Tom Brady', 'Adrian Peterson', 'Antonio Brown']
```

All list comprehensions take the form [*a* for *b* in *c*] where *c* is the list you're iterating over, and *b* is the variable you're using in *a* to specify exactly what you want to do to each item.

In the above example *a* is `x.title()`, *b* is `x`, and *c* is `my_roster_list`.

Note, it's common to use `x` for your comprehension variable, but — like loops — you can use whatever you want. So this:

```
In [4]: my_roster_list_proper_alt = [y.title() for y in my_roster_list]
```

does exactly the same thing as the version using `x` did.

Comprehensions can be tricky at first, but they're not that bad once you get the hang of them. They're useful and we'll see them again though, so if the explanation above is fuzzy, read it again and look at the example until it makes sense.

A List Comprehension is a List

A comprehension evaluates to a regular Python list. That's a fancy way of saying the result of a comprehension *is* a list.

```
In [5]: type([x.title() for x in my_roster_list])
Out[5]: list
```

And we can slice it and do everything else we could do to a normal list:

```
In [6]: [x.title() for x in my_roster_list][:2]
Out[6]: ['Tom Brady', 'Adrian Peterson']
```

More Comprehensions

Let's do another, more complicated, comprehension:

```
In [7]: my_roster_last_names = [full_name.split(' ')[1]
            for full_name in my_roster_list]

In [7]: my_roster_last_names
Out[7]: ['brady', 'peterson', 'brown']
```

Remember, all list comprehensions take the form [*a* for *b* in *c*]. The last two are easy: `c` is just `my_roster_list` and `b` is `full_name`.

That leaves `a`, which is `full_name.split('')[1]`.

Sometimes its helpful to prototype this part in the REPL with an actual item from your list.

```
In [8]: full_name = 'tom brady'

In [9]: full_name.split(' ')
Out[9]: ['tom', 'brady']

In [10]: full_name.split(' ')[1]
Out[10]: 'brady'
```

We can see `split` is a string method that returns a list of substrings. After calling it we can pick out each player's last name in spot `1` of our new list.

The programming term for how we've been using comprehensions so far — "doing something" to each item in a collection — is **mapping**. As in, I *mapped* `title` to each element of `my_roster_list`.

We can also use comprehensions to **filter** a collection to include only certain items. To do this we add *if some criteria that evaluates to a boolean* at the end.

```
In [11]: my_roster_a_only = [
    ...:     x for x in my_roster_list if x.startswith('a')]

In [12]: my_roster_a_only
Out[12]: ['adrian peterson', 'antonio brown']
```

Updating our notation, a comprehension technically has the form [*a* for *b* in *c* if *d*], where *if d* is optional.

Above, *d* is `x.startswith('a')`. The `startswith` string method takes a string and returns a bool indicating whether the original string starts with it or not. Again, it's helpful to test it out with actual items from our list.

```
In [13]: 'adrian peterson'.startswith('a')
Out[13]: True

In [14]: 'tom brady'.startswith('a')
Out[14]: False

In [15]: 'tom brady'.startswith('tom br')
Out[15]: True
```

Interestingly, in this comprehension the *a* in our [*a* for *b* in *c* if *d*] notation is just `x`. That means we're doing *nothing* to the value itself (we're taking `x` and returning `x`); the whole purpose of this comprehension is to filter `my_roster_list` to only include items that start with `'a'`.

You can easily extend this to map and filter in the same comprehension:

```
In [16]: my_roster_a_only_title = [
    ...:     x.title() for x in my_roster_list if x.startswith('a')]

In [16]: my_roster_a_only_title
Out[16]: ['Adrian Peterson', 'Antonio Brown']
```

Dict Comprehensions

Dict comprehensions work similarly to list comprehensions. Except now, the whole thing is wrapped in `{}` instead of `[]`.

And — like with our **for** loop over a dict, we can use `.items()` to get access to the key and value.

```
In [1]: pts_per_player = {
    'tom brady': 20.7, 'adrian peterson': 10.1, 'antonio brown': 18.5}

In [2]: pts_x2_per_upper_player = {
            name.upper(): pts*2 for name, pts in pts_per_player.items()}

In [3]: pts_x2_per_upper_player
Out[3]: {'ADRIAN PETERSON': 20.2, 'ANTONIO BROWN': 37.0,
         'TOM BRADY': 41.4}
```

Comprehensions make it easy to go from a list to a dict or vice versa. For example, say we want to total up all the points in our dict `pts_per_player`.

Well, one way to add up numbers in Python is to pass a list of them to the `sum()` function.

```
In [4]: sum([1, 2, 3])
Out[4]: 6
```

If we want to get the total number points in our pts_per_player dict, we make a list of just the points using a list comprehension, then pass it to sum like:

```
In [5]: sum([pts for _, pts in pts_per_player.items()])
Out[5]: 49.3
```

This is still a *list* comprehension even though we're starting with a dict (pts_per_player). When in doubt, check the surrounding punctuation. It's brackets here, which means list.

Also note the `for _, pts in ...` part of the code. The only way to get access to a value of a dict (i.e., the points here) is to use `.items()`, which also gives us access to the key (the player name in this case). But since we don't actually need the key for summing points, the Python convention is to name that variable `_`. This lets people reading our code know we're not using it.

Functions

In the last section we saw `sum()`, which is a Python built-in that takes in a list of numbers and totals them up.

`sum()` is an example of a **function**. Functions are code that take inputs (the function's **arguments**) and return outputs. Python includes several built-in functions. Another common one is `len`, which finds the length of a list.

```
In [80]: len(['tom brady', 'adrian peterson', 'antonio brown'])
Out[80]: 3
```

Using the function — i.e. giving it some inputs and having it return its output — is also known as **calling** or **applying** the function.

Once we've called a function, we can use it just like any other value. There's no difference between `len(['tom brady', 'adrian peterson', 'antonio brown'])` and `3`. We could define variables with it:

```
In [81]: pts_per_fg = len(
            ['tom brady', 'adrian peterson', 'antonio brown'])

In [82]: pts_per_fg
Out[82]: 3
```

Or use it in math.

```
In [83]: 4 + len(['tom brady', 'adrian peterson', 'antonio brown'])
Out[83]: 7
```

Or whatever. Once it's called, it's the value the function returned, that's it.

Defining Your Own Functions

It is very common to define your own functions.

```
def rec_pts(yds, rec, tds):
    """
    multi line strings in python are between three double quotes

    it's not required, but the convention is to put what the fn does in
       one of these multi line strings (called "docstring") right away in
       function

    this function takes number of receiving: yards, receptions and
       touchdowns and returns fantasy points scored (ppr scoring)
    """
    return yds*0.1 + rec*1 + tds*6
```

After defining a function (i.e. highlighting it and sending it to the REPL) you can call it like this:

```
In [1]: rec_pts(110, 6, 1)
Out[1]: 23.0
```

Note the arguments `yds`, `rec` and `tds`. These work just like normal variables, except they are only available inside your function. The programming term for where you have access to a variable is **scope**.

So if after defining `rec_pts` function, you try to type:

```
In [2]: print(`yds`)
NameError: name 'yds' is not defined
```

You'll get an error. `yds` only exists inside the `rec_pts` function.

You could put the print statement *inside* the function:

```
def rec_pts_noisy(yds, rec, tds):
    """
    this function takes number of receiving: yards, receptions and
       touchdowns and returns fantasy points scored (ppr scoring)

    it also prints out yds
    """
    print(yds)
    return yds*0.1 + rec*1 + tds*6
```

And then when we call it:

```
In [2]: rec_pts_noisy(110, 6, 1)
110
Out[2]: 23.0
```

Note the `110` in the REPL. Along with returning a bool, `rec_pts_noisy` prints the value of `yds`. This is a **side effect** of calling the function. A side effect is anything your function does besides returning a value.

Avoid Side Effects

Printing variable values isn't a big deal (it can be helpful if your function isn't working like you expect), but apart from that you should avoid side effects in your functions. You should especially avoid modifying arguments or other outside data.

For example, say we need a function `is_player_on_team` that takes roster and player name, and returns a boolean indicating whether the player is on the team.

One (bad) way to implement this function:

```
def is_player_on_team(player, team):
    """
    take a player string and team list and check whether the player is on
        team

    do this by adding the player to the team, then returning True if the
        player shows up 2 or more times
    """
    team.append(player)
    return team.count(player) >= 2
```

There are two problems. First, it's needlessly complicated (a much easier way to check whether an item is in a list is with `player in team`). Second, and more importantly, it introduces side effects.

Let's try running it:

```
In [2]: my_roster_list = ['tom brady', 'adrian peterson', 'antonio brown']

In [3]: is_player_on_team('gronk', my_roster_list)
Out[3]: False
```

So far so good. Gronk is indeed not on our roster, and the function returned `False`. Seems to be working. Except now look at `my_roster_list`:

```
In [4]: my_roster_list
Out[4]: ['tom brady', 'adrian peterson', 'antonio brown', 'gronk']
```

Now gronk *is* on our roster. Calling `is_player_on_team` modified `my_roster_list`. This function has the *side effect* of adding whichever player we're looking at to roster. Now if we call it again —

```
In [6]: is_player_on_team('gronk', my_roster_list)
Out[6]: True
```

not only do we get the "wrong" answer (technically he is on our team, but we didn't mean to put him there), our function added him *again*.

```
In [7]: my_roster_list
Out[7]: ['tom brady', 'adrian peterson', 'antonio brown', 'gronk',
         'gronk']
```

Bottom line: avoid side effects in your functions. Your function should return what it needs to without permanently modifying arguments or other outside data.

Default Values in Functions

Back to our `rec_pts` function.

```
def rec_pts(rec, yds, tds):
    """
    takes number of recieving: yards, receptions and touchdowns and
        returns fantasy points scored (ppr scoring)
    """
    return yds*0.1 + rec*1 + tds*6
```

Here's a question: what happens if we leave out any of the arguments when calling it? Let's try it:

```
In [1]: rec_pts(4, 54)
...
TypeError: rec_pts() missing 1 required positional argument: 'tds'
```

We can avoid this error by including **default** values. Let's give any missing arguments a default value of `0`.

```
def rec_pts_wdefault(rec=0, yds=0, tds=0):
    """
    takes number of receiving: yards, receptions and touchdowns and
        returns fantasy points scored (ppr scoring)
    """
    return yds*0.1 + rec*1 + tds*6
```

Now the function call works:

```
In [2]: rec_pts_wdefault(4, 54)
Out[2]: 9.4

In [3]: rec_pts_wdefault()
Out[3]: 0.0
```

Let's make our function a bit more flexible. We'll default to PPR scoring, but allow the user to enter other scoring systems too.

```
def rec_pts2(rec=0, yds=0, tds=0, ppr=1):
    """
    takes number of receiving: yards, receptions and touchdowns AND points
        per reception and returns fantasy points scored
    """
    return yds*0.1 + rec*ppr + tds*6
```

So what's our 4 receptions for 54 yard line in half PPR? How about:

```
In [4]: rec_pts2(4, 54, 0.5)
Out[4]: 12.4
```

Wait that's not right. It should be `7.4` (2 points for the receptions, another `5.4` for the yards). What's going on?

The issue is how we called `rec_pts2`. It takes up to four arguments (`rec`, `yds`, `tds` and `ppr`), but we only passed three values. When we do that, Python assigns them left to right, using the default values for whatever is left over. Arguments passed this way are known as **positional** arguments.

So here, Python figured we wanted `rec`, `yds`, and `tds` to get values of `4`, `54`, and `0.5` respectively. That left `ppr` its default of `1`.

Our function is *actually* returning:

```
In [5]: 54*0.1 + 4*1 + 0.5*6
Out[5]: 12.4
```

The solution is either to let Python know we have 0 touchdowns:

```
In [6]: rec_pts2(4, 54, 0, 0.5)
Out[6]: 7.4
```

or let Python know the `0.5` is meant for the `ppr` argument, like this:

```
In [7]: rec_pts2(4, 54, ppr=0.5)
Out[7]: 7.4
```

Here, `ppr=0.5` is called a **keyword** argument. We're explicitly telling our function that `ppr` gets the value of `0.5`. The first two arguments — the 4 (`rec`) and 54 (`yds`) are positional arguments.

Again, we didn't actually have to tell our function that 4 and 54 were meant for `rec` and `yds`, Python assumed that's what wanted because that's the order they show up in the function definition.

```
def rec_pts2(rec=0, yds=0, ...)  # rec is first, then yds
  ...
```

Positional and Keyword Argument Summary

Without keywords, Python will match up your arguments left to right based on the function definition.

If you want to skip arguments — using the default for some values but changing others — or don't want to worry about passing arguments in the correct order, you need to use keyword arguments.

Finally, any keyword arguments need to come *after* positional arguments. You can't do this:

```
In [38]: rec_pts2(ppr=0.5, 4, 54)
  File "<ipython-input-38-740b86c05f2d>", line 1
    rec_pts2(ppr=0.5, 4, 54)
                     ^
SyntaxError: positional argument follows keyword argument
```

One thing this last rule implies is it's a good idea to put your most "important" arguments first, leaving your optional arguments for the end of the function definition.

For example, later we'll learn about the `read_csv` function in Pandas, whose job is to load your csv data into Python. The first argument to `read_csv` is a string with the path to your file, and that's the only argument you'll use 95% of the time. But it also has more than 40 optional keyword arguments, everything from `skip_blank_lines` (defaults to `True`) to `parse_dates` (defaults to `False`).

What this means is usually you can just use the function like this:

```
data = read_csv('my_data_file.csv')
```

And on the rare occasions when you do need to tweak some option, change the specific settings you want using keyword arguments:

```
data = read_csv('my_data_file.csv', skip_blank_lines=False,
                  parse_dates=True)
```

Functions That Take Other Functions

A cool feature of Python is that functions can take other functions as arguments.

```
def do_to_list(working_list, working_fn, desc):
    """
    this function takes a list, a function that works on a list, and a
       description

    it applies the function to the list, then returns the result along
       with description as a string
    """

    value = working_fn(working_list)

    return f'{desc} {value}'
```

Now let's also make a function to use this on.

```
def last_elem_in_list(working_list):
    """
    returns the last element of a list.
    """
    return working_list[-1]
```

And try it out:

```
In [1]: positions = ['QB', 'RB', 'WR', 'TE', 'K', 'DST']

In [2]: do_to_list(positions, last_elem_in_list, "last element in your
    list:")
Out[2]: 'last element in your list: DST'

In [3]: do_to_list([1, 2, 4, 8], last_elem_in_list, "last element in your
    list:")
Out[3]: 'last element in your list: 8'
```

The function `do_to_list` can work on built in functions too.

```
In [4]: do_to_list(positions, len, "length of your list:")
Out[4]: 'length of your list: 6'
```

You can also create functions on the fly without names, usually for purposes of passing to other, flexible functions.

```
In [5]: do_to_list([2, 3, 7, 1.3, 5], lambda x: 3*x[0],
     ...:      "first element in your list times 3 is:")
Out[5]: 'first element in your list times 3 is: 6'
```

These are called **anonymous** or **lambda** functions.

Libraries are Functions and Types

There is much more to basic Python than this, but this is enough of a foundation to learn the other **libraries** we'll be using.

Libraries are just a collection of user defined functions and types [2] that other people have written using Python [3] and other libraries. That's why it's critical to understand the concepts in this section. Libraries *are* Python, with lists, dicts, bools, functions and all the rest.

os Library and path

Some libraries come built-in to Python. One example we'll use is the `os` (for operating system) library. To use it, we have to import it, like this:

```
In [1]: import os
```

That lets us use all the functions written in the `os` library. For example, we can call `cpu_count` to see the number of computer cores we currently have available.

```
In [2]: os.cpu_count()
Out[2]: 12
```

Libraries like `os` can contain sub-libraries too. The sub-library we'll use from `os` is `path`, which is useful for working with filenames. One of the main function is `join`, which takes a directory (or multiple directories) and a filename and puts them together in a string. Like this:

```
In [1]: from os import path

In [2]: DATA_DIR = '/Users/nathan/ltcwff-files/data'

In [3]: path.join(DATA_DIR, 'adp_2017.csv')
Out[3]: '/Users/nathan/ltcwff-files/data/adp_2017.csv'

In [4]: os.path.join(DATA_DIR, 'adp_2017.csv')  # alt way of calling
Out[4]: '/Users/nathan/ltcwff-files/data/adp_2017.csv'
```

[2] While we covered defining your own functions, we did *not* cover defining your own types — sometimes called *classes* — in Python. While being able to work with and write your own classes is sometimes helpful, it's definitely not required for everyday data analysis. I hardly ever use them myself.

[3] Technically sometimes they use other programming languages too. Parts of the data analysis library Pandas, for example, are written in the programming language C for performance reasons. But we don't have to worry about that.

With `join`, you don't have to worry about trailing slashes or operating system differences or anything like that. You can just replace `DATA_DIR` with the directory that holds the csv files that came with this book and you'll be set.

End of Chapter Exercises

2.1

Which of the following are valid Python variable names?

a) `_throwaway_data`
b) `pts_per_passing_td`
c) `2nd_rb_name`
d) `puntReturnsForTds`
e) `rb1_name`
f) `flex spot name`
g) `@home_or_away`
h) `'pts_per_rec_yd'`

2.2

What is the value of weekly_points at the end of the following code?

```
weekly_points = 100
weekly_points = weekly_points + 28
weekly_points = weekly_points + 5
```

2.3

Write a function named `for_the_td` that takes in the name of two players (e.g. `'Dak'`, `'Zeke'`) and returns a string of the form: `'Dak to Zeke for the td!'`

2.4

Without looking it up, what do you think the string method `islower` does? What type of value does it return? Write some code to test your guess.

2.5

Write a function `is_leveon` that takes in a player name and returns a `bool` indicating whether the player's name is "Le'Veon Bell" — regardless of case or whether the user included the `'`.

2.6

Write a function `commentary` that takes in a number (e.g. 120 or 90) and returns a string `'120 is a good score'` if the number is >= 100 or `"90's not that good"` otherwise.

2.7

Say we have a list:

```
giants_roster = ['Daniel Jones', 'Saquon Barkley', 'Evan Engram', 'OBJ']
```

List at least three ways you can to print the list without `'OBJ'`. Use at least one list comprehension.

2.8

Say we have a dict:

```
league_settings = {'number_of_teams': 12, 'ppr': True}
```

a) How would you change `'number_of_teams'` to 10?

b) Write a function `toggle_ppr` that takes a dict like `league_settings`, turns `'ppr'` to the opposite of whatever it is, and returns the updated settings dict.

2.9

Assuming we've defined our same dict:

```
league_settings = {'number_of_teams': 12, 'ppr': True}
```

Go through each line and say whether it'll work without error:

a) `league_settings['has_a_flex']`
b) `league_settings[number_of_teams]`
c) `league_settings['year founded'] = 2002`

2.10

Say we're working with the list:

```
my_roster_list = ['tom brady', 'adrian peterson', 'antonio brown']
```

a) Write a loop that goes through and prints the last name of every player in `my_roster_list`.
b) Write a comprehension that uses `my_roster_list` to make a dict where the keys are the player names and the values are the length's of the strings.

2.11

Say we're working with the dict:

```
my_roster_dict = {
    'qb': 'tom brady', 'rb1': 'adrian peterson', 'wr1': 'davante adams', '
       wr2':
    'john brown'}
```

a) Write a comprehension that turns 'my_roster_dict1 into a list of just the positions.
b) Write a comprehension that turns `my_roster_dict` into a list of just players who's last names start with `'a'` or `'b'`.

2.12

a) Write a function `mapper` that takes a list and a function, applies the function to every item in the list and returns it.
b) Assuming 0.1 points per rushing yard, use `mapper` with an anonymous function to get a list of pts from rushing yds

```
list_of_rushing_yds = [1, 110, 60, 4, 0, 0, 0]
```

3. Pandas

Introduction to Pandas

In the last chapter we talked about basic, built-in Python.

In this chapter we'll talk about **Pandas**, which is the most important Python library for working with data. It's an external library, but don't underestimate it. It's really the only game in town for what it does.

And what it does is important. Remember the five steps to doing data analysis: (1) collecting, (2) storing, (3) loading, (4) manipulating, and (5) analyzing data. Pandas is the primary tool for (4), which is where data scientists spend most of their time.

But we'll use it in other sections too. It has input-output capabilities for (2) storing and (3) loading data, and works well with key (5) analysis libraries.

Types and Functions

In chapter one, we how learned data is a collection of structured information; each row is an observation and each column some attribute.

Pandas gives you types and functions for working with this tabular data. The most important is a **DataFrame**, which is a container type like a list or dict and holds a single data table. One column of a DataFrame is its own type, called a **Series**, which you'll also sometimes use.

At a very high level, you can think about Pandas as a Python library that gives you access to these two types and functions that operate on them.

This sounds simple, but Pandas is powerful, and there are many ways to "operate" on data. As a result, this is the longest and most information-dense chapter in the book. Don't let that scare you, it's all learnable. To make it easier, let's map out what we'll cover and the approach we'll take.

First, we'll learn how to load data from a csv file into a DataFrame. We'll learn basics like how to access specific columns and print out the first five rows. We'll go over a fundamental feature of DataFrames called indexes, and wrap up with outputting DataFrames as csv files.

With those basics covered, we'll learn about *things you can do with DataFrames*. This list is long and — rapid fire one after the other — might get overwhelming. But everything you do with DataFrames falls into one of the following categories:

1. Modifying or creating new columns of data.
2. Using built-in Pandas functions that operate on DataFrames (or Series) and provide you with ready-made statistics or other useful information.
3. *Filtering* observations, i.e. selecting only certain rows from your data.
4. Changing the *granularity* of the data within a DataFrame.
5. Combining two or more DataFrames via Pandas's `merge` or `concat` functions.

That's it. Most of your time spent as a Python fantasy data analyst will be working with Pandas. Most of your time in Pandas will be working with DataFrames. Most of your time working with DataFrames will fall into one of these five categories.

How to Read This Chapter

This chapter — like the rest of the book — is heavy on examples. All the examples in this chapter are included in a series of Python files. Ideally, you would have the file open in your Spyder editor and be running the examples (highlight the line(s) you want and press F9 to send it to the REPL/console) as we go through them in the book.

Let's get started.

Part 1. DataFrame Basics

Importing Pandas

Note the examples for this section are in the file `03_00_basics.py`. The book picks up from the top of the file.

The first step to working with Pandas is importing it. Open up `03_00_basics.py` in your editor, and lets take a look at a few things.

First, note the lines at very top:

```
from os import path
import pandas as pd

DATA_DIR = '/Users/nathanbraun/fantasymath/fantasybook/data'
```

These import the *libraries* (collections of functions and types that other people have written) we'll be using in this section.

It's customary to import all the libraries you'll need at the top of a file. We covered `path` in chapter 2. Though `path` is part of the standard library (i.e. no third party installation necessary), we still have to import it in order to use it.

Pandas is an external, third party library. Normally you have to install third party libraries — using a tool like **pip** — before you can import them, but if you're using the Anaconda Python bundle, it comes with Pandas installed.

After you've changed `DATA_DIR` to the location where you've stored the files that came with the book, you can run these in your REPL:

```
In [1]: from os import path

In [2]: import pandas as pd

In [3]: DATA_DIR = '/Users/nathan/fantasybook/data' # <- change this
```

Like all code — you have to send this to the REPL before you can use `pd` or `DATA_DIR` later in your programs. To reduce clutter, I'll usually leave this part out on future examples. But if you ever get an error like:

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last
    )
<ipython-input-4-6fecebd0febc> in <module>
----> 1 pd

NameError: name 'pd' is not defined
```

Remember you have to run `import pandas as pd` in the REPL before doing anything else.

Loading Data

When importing Pandas, the convention is to import it under the name `pd`. This lets us use any Pandas function by calling `pd.` (i.e. `pd` dot — type the period) and the name of our function.

One of the functions Pandas comes with is `read_csv`, which takes as its argument a string with the path to the csv file you want to load. It returns a DataFrame of data.

Let's try it:

```
In [4]: adp = pd.read_csv(path.join(DATA_DIR, 'adp_2017.csv'))

In [5]: type(adp)
Out[5]: pandas.core.frame.DataFrame
```

Congratulations, you've loaded your first DataFrame!

DataFrame Methods and Attributes

Like other Python types, DataFrames have methods you can call. For example, the method `head` prints the first five rows your data.

```
In [6]: adp.head()
Out[6]:
   adp  adp_formatted  bye  ...  stdev  team times_drafted
0  1.3           1.01   12  ...    0.6   ARI           310
1  2.3           1.02    7  ...    0.8   PIT           303
2  3.7           1.04    7  ...    1.0   PIT           338
3  5.7           1.06    9  ...    3.2   ATL           131
4  6.2           1.06    8  ...    2.8   DAL           180

[5 rows x 11 columns]
```

Note `head` hides some columns here (indicated by the `...`) because they don't fit on the screen.

We'll use `head` frequently in this chapter to quickly glance at DataFrames in our examples and show the results of what we're doing. This isn't just for the sake of the book; I use `head` all the time when I'm coding with Pandas in real life.

Methods vs Attributes

`head` is a *method* because you can pass it the number of rows to print (the default is 5). But DataFrames also have fixed *attributes* that you can access without passing any data in parenthesis.

For example, the columns are available in the attribute `columns`.

```
In [7]: adp.columns
Out[7]:
Index(['adp', 'adp_formatted', 'bye', 'high', 'low', 'name', 'player_id',
       'position', 'stdev', 'team', 'times_drafted'],
      dtype='object')
```

And the number of rows and columns are in `shape`.

```
In [8]: adp.shape
Out[8]: (184, 11)
```

Working with Subsets of Columns

A Single Column

Referring to a single column in a DataFrame is similar to returning a value from a dictionary, you put the name of the column (usually a string) in brackets.

```
In [9]: adp['name'].head()
Out[9]:
0      David Johnson
1        LeVeon Bell
2      Antonio Brown
3        Julio Jones
4    Ezekiel Elliott
```

Technically, a single column is a Series, not a DataFrame.

```
In [10]: type(adp['name'])
Out[10]: pandas.core.series.Series
```

The distinction isn't important right now, but eventually you'll run across functions that operate on Series instead of a DataFrames or vis versa. Calling the `to_frame` method will turn any Series into a one-column DataFrame.

```
In [11]: adp['name'].to_frame().head()
Out[11]:
              name
0    David Johnson
1      LeVeon Bell
2    Antonio Brown
3      Julio Jones
4  Ezekiel Elliott

In [12]: type(adp['name'].to_frame())
Out[12]: pandas.core.frame.DataFrame
```

Multiple Columns

To refer to multiple columns in a DataFrame, you pass it a list. The result — unlike the single column case — is another DataFrame.

```
In [13]: adp[['name', 'position', 'adp']].head()
Out[13]:
              name position  adp
0    David Johnson       RB  1.3
1      LeVeon Bell       RB  2.3
2    Antonio Brown       WR  3.7
3      Julio Jones       WR  5.7
4  Ezekiel Elliott       RB  6.2

In [14]: type(adp[['name', 'position', 'adp']])
Out[14]: pandas.core.frame.DataFrame
```

Notice the difference between `adp['name']` and `adp[['name', 'position', 'adp']]`. In the former we have `'name'`. It's completely replaced by `['name', 'position', 'adp']` in the latter. That is — since you're putting a list with your column names *inside* another pair brackets — when working with multiple columns there are two sets of brackets in all.

I guarantee at some point you will forget about this and accidentally do something like:

```
In [15]: adp['name', 'position', 'adp'].head()
...
KeyError: ('name', 'position', 'adp')
```

which will throw an error. No big deal, just remember: inside the brackets is a single, dict-like string to return one column, a list to return multiple columns.

Indexing

A key feature of Pandas is that every DataFrame (and Series) has an **index**. The main benefit of indexes is they keep everything aligned.

You can think of the index as a built-in column of row IDs. Pandas lets you specify which column to use as the index when loading your data. If you don't, the default is a series of numbers starting from 0 and going up to the number of rows.

The index is on the very left hand side of the screen when you look at output from `head`. We didn't specify any column to use as the index when calling `read_csv` above, so you can see it defaults to `0`, 1, 2, …

```
In [14]: adp[['name', 'position', 'adp']].head()
Out[14]:
              name position  adp
0    David Johnson       RB  1.3
1      LeVeon Bell       RB  2.3
2    Antonio Brown       WR  3.7
3      Julio Jones       WR  5.7
4  Ezekiel Elliott       RB  6.2
```

Indexes don't have to be numbers; they can be strings or dates, whatever. A lot of times they're more useful when they're meaningful to you.

Let's make our index the `player_id` column.

```
In [15]: adp.set_index('player_id').head()
Out[15]:
           adp  adp_formatted  ...  team  times_drafted
player_id                      ...
2297       1.3           1.01  ...   ARI            310
1983       2.3           1.02  ...   PIT            303
1886       3.7           1.04  ...   PIT            338
1796       5.7           1.06  ...   ATL            131
2343       6.2           1.06  ...   DAL            180
```

Copies and the Inplace Argument

Now that we've run `set_index`, our new index is the `player_id` column. Or is it? Try running `head` again:

```
In [16]: adp.head()
Out[16]:
   adp  adp_formatted  bye  ...  stdev  team times_drafted
0  1.3           1.01   12  ...    0.6   ARI           310
1  2.3           1.02    7  ...    0.8   PIT           303
2  3.7           1.04    7  ...    1.0   PIT           338
3  5.7           1.06    9  ...    3.2   ATL           131
4  6.2           1.06    8  ...    2.8   DAL           180
```

Our index is still `0`, `1` … `4` — what happened? The answer is that `set_index` returns a new, *copy* of the `adp` DataFrame with the index we set. When we called `adp.set_index('player_id')` above, we just displayed that newly indexed `adp` in the REPL. We didn't actually do anything to the existing, original `adp`.

To make it permanent, we can either set the `inplace` argument to `True`:

```
In [17]: adp.set_index('player_id', inplace=True)

In [18]: adp.head()  # now player_id is index
Out[18]:
           adp  adp_formatted  ...  team  times_drafted
player_id                      ...
2297       1.3           1.01  ...   ARI            310
1983       2.3           1.02  ...   PIT            303
1886       3.7           1.04  ...   PIT            338
1796       5.7           1.06  ...   ATL            131
2343       6.2           1.06  ...   DAL            180
```

Or we can overwrite adp with our newly, updated DataFrame:

```
# reload adp with default 0, 1, ... index
In [19]: adp = pd.read_csv(path.join(DATA_DIR, 'adp_2017.csv'))

In [20]: adp = adp.set_index('player_id')
```

Most DataFrame methods (including non-index related methods) behave like this, returning copies unless you explicitly include `inplace=True`. So if you're calling a method and it's behaving unexpectedly, this is one thing to watch out for.

The opposite of `set_index` is `reset_index`. It sets the index to `0`, `1`, `2`, … and turns the old index into a regular column.

```
In [21]: adp.reset_index().head()
Out[21]:
   player_id  adp  ...  team  times_drafted
0       2297  1.3  ...   ARI            310
1       1983  2.3  ...   PIT            303
2       1886  3.7  ...   PIT            338
3       1796  5.7  ...   ATL            131
4       2343  6.2  ...   DAL            180
```

Indexes Keep Things Aligned

The main benefit of indexes in Pandas is automatic alignment.

To illustrate this, let's make a mini, subset of our DataFrame with just the names and teams of the RBs. Don't worry about the `loc` syntax for now, just know that we're creating a smaller subset of our data that is just the running backs.

```
In [22]: adp_rbs = adp.loc[adp['position'] == 'RB',
                           ['name', 'position', 'team']]

In [23]: adp_rbs.head()
Out[23]:
                      name position team
player_id
2297         David Johnson       RB  ARI
1983           LeVeon Bell       RB  PIT
2343       Ezekiel Elliott       RB  DAL
2144       Devonta Freeman       RB  ATL
1645          LeSean McCoy       RB  BUF
```

Yep, all running backs. Now let's use another DataFrame method to sort them by name.

```
In [24]: adp_rbs.sort_values('name', inplace=True)

In [25]: adp_rbs.head()
Out[25]:
                      name position team
player_id
925        Adrian Peterson       RB  ARI
2439          Alvin Kamara       RB   NO
2293         Ameer Abdullah      RB  DET
1867          Bilal Powell       RB  NYJ
2071           CJ Anderson       RB  DEN
```

Now, what if we want to go back and add in the `times_drafted` column from our original, all positions DataFrame?

Adding a column works similarly to variable assignment in regular Python.

```
In [26]: adp_rbs['times_drafted'] = adp['times_drafted']

In [27]: adp_rbs.head()
Out[27]:
                      name position team  times_drafted
player_id
925        Adrian Peterson       RB  ARI            187
2439          Alvin Kamara       RB   NO            129
2293         Ameer Abdullah      RB  DET            246
1867          Bilal Powell       RB  NYJ            231
2071           CJ Anderson       RB  DEN            241
```

Viola. Even though we have a separate, smaller dataset with a different number of rows (only the RBs) in a different order (sorted alphabetically instead of by ADP), we were able to easily add in the correct `times_drafted` values from our old DataFrame.

We're able to do that because `adp`, `adp_rbs`, and the Series `adp['times_drafted']` all have the same index for the rows they have in common.

In a spreadsheet program you have to be aware about how your data was sorted and the number of rows before copying and pasting and moving columns around. The benefit of indexes in Pandas is you can just modify what you want without having to worry about it.

Outputting Data

The opposite of loading data is outputting it, and Pandas does that too.

While the input methods are in the top level Pandas namespace — i.e. you load csv files by calling `pd.read_csv` — the output methods are called on the DataFrame itself.

For example, to save our RB DataFrame:

```
In [28]: adp_rbs.to_csv(path.join(DATA_DIR, 'adp_rb.csv'))
```

By default, Pandas will include the index in the csv file. This is useful when the index is meaningful (like it is here), but if the index is just the default range of numbers you might not want to write it. In that case you would set `index=False`.

```
In [29]: adp_rbs.to_csv(path.join(DATA_DIR, 'adp_rb_no_index.csv'),
                        index=False)
```

Exercises

3.0.1

Load the ADP data into a DataFrame named `adp`. You'll use it for the rest of the problems in this section.

3.0.2

Use the `adp` DataFrame to create another DataFrame, `adp50`, that is the top 50 (by ADP) players.

3.0.3

Sort `adp` by name in descending order (so Zay Jones is on the first line). On another line, look at `adp` in the REPL and make sure it worked.

3.0.4

What is the type of `adp.sort_values('adp')`?

3.0.5

a) Make a new DataFrame, `adp_simple`, with just the columns `'name'`, `'position'`, `'adp'` in that order.

b) Rearrange `adp_simple` so the order is `'pos'`, `'name'`, `'adp'`.

c) Using the original `adp` DataFrame, add the `'team'` column to `adp_simple`.

d) Write a copy of `adp_simple` to your computer, `adp_simple.txt` that is `'|'` (pipe) delimited instead of `','` (comma) delimited.

Part 2. Things You Can Do With DataFrames

Introduction

Now that we understand DataFrames (Python container types for tabular data with indexes), and how to load and save them, let's get into what you can do with them.

In general, here's everything you can do with DataFrames:

1. Modify or create new columns of data.
2. Use built-in Pandas functions that operate on DataFrames (or Series) and provide you with ready-made statistics or other useful information.
3. *Filter* observations, i.e. select only certain rows from your data.
4. Change the *granularity* of the data within a DataFrame.
5. Combine two or more DataFrames via Pandas's `merge` or `concat` functions.

Let's dive in.

1. Modify or Create New Columns of Data

Note the examples for this section are in the file `03_01_columns.py`. The top of the file is importing libraries, setting DATA_DIR, and loading the player game data into a DataFrame named `pg`. The rest of this section picks up from there.

The first thing we'll learn is how to work with *columns* in DataFrames. We'll cover both modifying and creating new columns, because they're really variations on the same thing.

Creating and Modifying Columns

We've already seen how creating a new column works similarly to variable assignment in regular Python.

```
In [1]: pg['pts_pr_pass_td'] = 4

In [2]: pg[['gameid', 'player_id', 'pts_pr_pass_td']].head()
Out[2]:
       gameid   player_id  pts_pr_pass_td
0  2017090700  00-0019596               4
1  2017090700  00-0023436               4
2  2017090700  00-0026035               4
3  2017090700  00-0030288               4
4  2017090700  00-0030506               4
```

What if we want to modify pg['pts_pr_pass_td'] after creating it? It's no different than creating it originally.

```
In [3]: pg['pts_pr_pass_td'] = 6

In [4]: pg[['gameid', 'player_id', 'pts_pr_pass_td']].head()
Out[4]:
       gameid   player_id  pts_pr_pass_td
0  2017090700  00-0019596               6
1  2017090700  00-0023436               6
2  2017090700  00-0026035               6
3  2017090700  00-0030288               6
4  2017090700  00-0030506               6
```

So the distinction between modifying and creating columns is minor. Really this section is about working with columns in general.

To start, let's go over three of the main column types — number, string, and boolean — and how you might work with them.

Math and Number Columns

Doing math operations on columns is intuitive and probably works how you would expect:

```
In [5]: pg['rushing_pts'] = (
          pg['rush_yards']*0.1 +
          pg['rush_tds']*6 +
          pg['rush_fumbles']*-3)

In [6]: pg[['player_name', 'gameid', 'rushing_pts']].head()
Out[6]:
  player_name      gameid  rushing_pts
0     T.Brady  2017090700          0.0
1     A.Smith  2017090700          0.9
2  D.Amendola  2017090700          0.0
3  R.Burkhead  2017090700          1.5
4     T.Kelce  2017090700          0.4
```

This adds a new column rushing_pts to our pg DataFrame[1]. We can see Tom Brady and Alex Smith combined for less than 1 rushing fantasy point for the first week of the 2017 season. Sounds about right.

[1] If we wanted, we could also create a separate column (Series), unattached to pg, but with the same index like this `rushing_pts = (pg['rush_yards']*0.1 + pg['rush_tds']*6 + pg['rush_fumbles']*-3)`.

Other math operations work too, though for some functions we have to load new libraries. Numpy is a more raw, math oriented Python library that Pandas is built on. It's commonly imported as `np`.

Here we're taking the absolute value and natural log[2] of rushing yards:

```
In [7]: import numpy as np

In [8]: pg['distance_traveled'] = np.abs(pg['rush_yards'])

In [9]: pg['ln_rush_yds'] = np.log(pg['rush_yards'])
```

You can also assign scalar (single number) columns. In that case the value will be constant throughout the DataFrame.

```
In [10]: pg['points_per_fg'] = 3

In [11]: pg[['player_name', 'gameid', 'points_per_fg']].sample(5)
Out[11]:
     player_name      gameid  points_per_fg
149      T.Kelce  2017120308              3
336     L.Murray  2017120300              3
638     M.Breida  2017100109              3
90     A.Jeffery  2017091704              3
1014     T.Smith  2017102906              3
```

Note: I want to keep printing out results with `head`, but looking at the same first five rows is boring. Instead, let's pick 5 random rows using the `sample` method. If you're following along in Spyder, you'll see five different rows because `sample` returns a random sample every time.

String Columns

Data analysis work almost always involves columns of numbers, but it's common to work with string columns too.

Pandas let's you manipulate these by calling `str` on the relevant column.

[2] If you're not familiar with what the natural log means this is a good link: https://betterexplained.com/articles/demystifying-the-natural-logarithm-ln/

```
In [1]: pg['player_name'].str.upper().sample(5)
Out[1]:
53          R.BURKHEAD
511             K.COLE
264     B.ROETHLISBERGER
1134           K.ALLEN
366             G.TATE

In [2]: pg['player_name'].str.replace('.', ' ').sample(5)
Out[2]:
643     A Jeffery
1227    D Jackson
517        K Cole
74         K Hunt
1068     A Kamara
```

The plus sign (+) concatenates (sticks together) string columns.

```
In [3]: (pg['player_name'] + ', ' + pg['pos'] + ' - ' + pg['team']).sample
    (5)
Out[3]:
489          M.Lee, WR - JAX
1255         C.Sims, RB - TB
350     M.Stafford, QB - DET
129     R.Anderson, WR - NYJ
494          M.Lee, WR - JAX
```

If you want to chain these together (i.e. call multiple string functions in a row) you can, but you'll have to call `str` multiple times.

```
In [4]: pg['player_name'].str.replace('.', ' ').str.lower().sample(5)
Out[4]:
499          m lee
937     t williams
1249        c sims
53      r burkhead
1150      b fowler
Name: player_name, dtype: object
```

Boolean Columns

It's common to work with columns of booleans.

The following creates a column that is `True` if the row in question is a running back.

```
In [1]: pg['is_a_rb'] = (pg['pos'] == 'RB')

In [2]: pg[['player_name', 'is_a_rb']].sample(5)
Out[2]:
       player_name  is_a_rb
332    L.Fitzgerald    False
137          M.Ryan    False
681          F.Gore     True
548        D.Murray     True
1142       B.Fowler    False
```

We can combine logic operations too. Note the parenthesis, and | and & for `or` and `and` respectively.

```
In [3]: pg['is_a_rb_or_wr'] = (pg['pos'] == 'RB') | (pg['pos'] == 'WR')

In [3]: pg['good_rb_game'] = ((pg['pos'] == 'RB') &
                               (pg['rush_yards'] >= 100))
```

You can also negate (change `True` to `False` and vis versa) booleans using the tilda character (~).

```
In [4]: pg['is_not_a_rb_or_wr'] = ~(
                                   (pg['pos'] == 'RB') |
                                   (pg['pos'] == 'WR'))
```

Pandas also lets you work with multiple columns at once. Sometimes this is useful when working with boolean columns. For example, to check whether a player went for over 100 rushing or receiving yards you could do:

```
In [5]: (pg[['rush_yards', 'rec_yards']] > 100).sample(5)
Out[5]:
      rush_yards  rec_yards
1105       False      False
296         True      False
627        False      False
455        False      False
1165       False      False
```

This returns a DataFrame of all boolean values.

Applying Functions to Columns

Pandas has a lot of built in functions that modify columns, but sometimes you need to come up with your own.

For example, maybe you want to go through and *flag* (note: when you hear "flag" think *make a column of booleans*) skill position players. Rather than writing a long boolean expression with many | values, we might do something like:

```
In [1]:
def is_skill(pos):
  """
  Takes some string named pos ('QB', 'K', 'RT' etc) and checks
  whether it's a skill position (RB, WR, TE).
  """
  return pos in ['RB', 'WR', 'TE']

In [2]: pg['is_skill'] = pg['pos'].apply(is_skill)

In [3]: pg[['player_name', 'is_skill']].sample(5)
Out[3]:
     player_name pos  is_skill
1026   N.Agholor  WR      True
756   M.Trubisky  QB     False
384       L.Bell  RB      True
149      T.Kelce  TE      True
346       M.Sanu  WR      True
```

This takes our function and **applies** it to every row in our column of positions, one at a time.

Our function `is_skill` is pretty simple. It just takes one argument and does a quick check to see if it's in a list. This is where an unnamed, anonymous (or lambda) function would be useful.

```
In [4]: pg['is_skill_alternate'] = pg['pos'].apply(
                lambda x: x in ['RB', 'WR', 'TE'])
```

Dropping Columns

Dropping a column works like this:

```
In [5]: pg.drop('is_skill_alternate', axis=1, inplace=True)
```

Note the `inplace` and `axis` arguments. The `axis=1` is necessary because the default behavior of `drop` is to operate on rows. I.e., you pass it an *index* value, and it drops that row from the DataFrame. In my experience this is hardly ever what you want. It's much more common to have to pass `axis=1` so that it'll drop the name of the column you provide instead.

Renaming Columns

Technically, renaming a column is one way to modify it, so let's talk about that here.

There are two ways to rename columns in Pandas. First, you can assign new data to the `columns` attribute of your DataFrame.

Let's rename all of our columns in pg to be uppercase. Note the list comprehension.

```
In [1]: pg.columns = [x.upper() for x in pg.columns]

In [2]: pg.head()
Out[2]:
       GAMEID   PLAYER_ID  ...  GOOD_RB_GAME  IS_NOT_A_RB_OR_WR
0  2017090700  00-0019596  ...         False               True
1  2017090700  00-0023436  ...         False               True
2  2017090700  00-0026035  ...         False              False
3  2017090700  00-0030288  ...         False              False
4  2017090700  00-0030506  ...         False               True
```

Uppercase isn't the Pandas convention so let's change it back.

```
In [3]: pg.columns = [x.lower() for x in pg.columns]
```

Another way to rename columns is by calling the `rename` method and passing in a dictionary. Maybe we want to rename `interceptions` to just `ints`.

```
In [4]: pg.rename(columns={'interceptions': 'ints'}, inplace=True)
```

Missing Data in Columns

Missing values are common when working with data. Sometimes data is missing because we just don't have it. For instance, maybe we've set up an automatic web scraper to collect and store daily injury reports, but the website was temporarily down and we missed a day. That day might be represented as missing in our data.

Other times we might want to intentionally treat data as missing. For example, in our play-by-play data we have a column *yards after catch*. What should its value be on running plays?

It could be zero, but then if we tried to calculate average yards after the catch, it'd be misleadingly low. We also wouldn't be able to distinguish between running plays and plays where the receiver got tackled right away. Missing is better.

Missing values in Pandas have the value `np.nan`. Remember, `np` is the numpy library that much of Pandas is built upon; `nan` stands for "not a number".

Pandas comes with functions that work with and modify missing values, including `isnull` and `notnull`. These return a column of booleans indicating whether the column is or is not missing respectively.

Continuing with `03_01_columns.py`, right below where we've loaded `pbp` into the REPL:

```
In [1]: pbp['yards_after_catch'].isnull().head()
Out[1]:
0    False
1     True
2     True
3     True
4     True

In [2]: pbp['yards_after_catch'].notnull().head()
Out[2]:
0     True
1    False
2    False
3    False
4    False
```

You can also use `fillna` to replace all missing values with a value of your choosing.

```
In [3]: pbp['yards_after_catch'].fillna(-99).head()
Out[3]:
0      3.0
1    -99.0
2    -99.0
3    -99.0
4    -99.0
```

Changing Column Types

Another common way to modify columns is to change between data types, going from a column of strings to a column of numbers, or vis versa.

For example, maybe we want to add a "month" column to our player-game data and notice we can get it from the `gameid` column.

```
In [1]: pg['gameid'].head()
Out[1]:
0    2017090700
1    2017091705
2    2017092407
3    2017100107
4    2017100500
```

In normal Python, if we wanted to get the year, month and day out of a string like `'2017090700'` we would just do:

```
In [2]: gameid = '2017090700'

In [3]: year = gameid[0:4]
In [4]: month = gameid[4:6]
In [5]: day = gameid[6:8]

In [6]: year
Out[6]: '2017'

In [7]: month
Out[7]: '09'

In [8]: day
Out[8]: '07'
```

So let's try some of our string methods on the `gameid` column.

```
In [9]: pg['month'] = pg['gameid'].str[4:6]

AttributeError: Can only use .str accessor with string values,
which use np.object_ dtype in pandas
```

It looks like `gameid` is stored as a number, which means `str` methods are not allowed. No problem, we can convert it to a string using the `astype` method.

```
In [10]: pg['month'] = pg['gameid'].astype(str).str[4:6]

In [11]: pg[['month', 'gameid']].head()
Out[11]:
  month      gameid
0    09  2017090700
1    09  2017091705
2    09  2017092407
3    10  2017100107
4    10  2017100500
```

But now `month` is a string now too (you can tell by the leading 0). We can convert it back to an integer with another call to `astype`.

```
In [12]: pg['month'].astype(int).head()
Out[12]:
0     9
1     9
2     9
3    10
4    10
```

The DataFrame attribute `dtypes` tells returns the types of all of our columns.

```
In [13]: pg.dtypes.head()
Out[13]:
gameid            int64
player_id        object
carries         float64
rush_yards      float64
rush_fumbles    float64
```

Don't worry about the `64` after **`int`** and **`float`**; it's beyond the scope of this book. Also note Pandas refers to string columns as `object` (instead of `str`) in the `dtypes` output.

Review

This section was all about creating and manipulating columns. In reality, these are the same thing; the only difference is whether we make a new column (create) or overwrite and replace an existing column (manipulate).

We learned about number, string, and boolean columns and how to convert between them. We also learned how to apply our own functions to columns and work with missing data. Finally, we learned how to drop and rename columns.

Exercises

3.1.1 Load the player game data into a DataFrame named pg. You'll use it for the rest of the problems in this section.

3.1.2 Add a column to pg, 'rec_pts_ppr' that gives total receiving fantasy points, where the scoring system is 1 point for every 10 yards receiving, 6 points per receiving TD and 1 point per reception.

3.1.3 Add a column 'player_desc' to pg that takes the form, ' is the ', e.g. 'T.Brady is the NE QB' for tom brady

3.1.4 Add a boolean column to pg 'is_possesion_rec' indicating whether a players air yards were greater than his total yards after the catch.

3.1.5 Add a column 'len_last_name' that gives the length of the player's last name.

3.1.6 'gameid' is a numeric (int) column, but it's not really meant for doing math, change it into a string column.

3.1.7

a) Let's make the columns in pg more readable. Replace all the '_' with ' ' in all the columns.
b) This actually isn't good practice. Change it back.

3.1.8

a) Make a new column 'rush_td_percentage' indicating the percentage of a players carries that went for touchdowns.
b) There are missing values in this column, why? Replace all the missing values with -99.

3.1.9 Drop the column 'rush_td_percentage'. In another line, confirm that it worked.

2. Use Built-In Pandas Functions That Work on DataFrames

Note the examples for this section are in the file `03_02_functions.py`. We'll pick up right after you've loaded the DataFrame `adp` into your REPL.

Recall how analysis is the process of going from raw data to some statistic. Well, Pandas includes functions that operate on DataFrames and calculate certain statistics for you. In this section we'll learn about some of these and how to apply them to columns (the default) or rows.

Summary Statistic Functions

Pandas includes a variety of functions to calculate summary statistics. For example, to take the *average* (or *mean*) of every numeric column in your DataFrame you can do:

```
In [1]: adp.mean()
Out[1]:
adp                 88.582609
adp_formatted        7.897391
bye                  8.907609
high                67.108696
low                107.250000
player_id         1850.195652
stdev                8.338587
times_drafted      164.614130
```

We can also do `max`.

```
In [2]: adp.max()
Out[2]:
adp                  172.7
adp_formatted        15.05
bye                     12
high                   162
low                    180
name             Zay Jones
player_id             2523
position                WR
stdev                 21.3
team                   WAS
times_drafted          338
```

This returns the highest value of every column. Note unlike `mean`, `max` operates on string columns too (it treats "max" as latest in the alphabet, which is why we get Zay Jones for `name` in our ADP data).

Other summary statistic functions include `std`, `count`, `sum`, and `min`.

Axis

All of these functions take an axis argument which lets you specify whether you want to calculate the statistic on the *columns* (the default, `axis=0`) or the *rows* (`axis=1`).

Calculating the stats on the columns is usually what you want. Like this:

```
In [3]: adp[['adp', 'low', 'high', 'stdev']].mean(axis=0)
Out[3]:
adp        88.582609
low       107.250000
high       67.108696
stdev       8.338587
dtype: float64
```

(Note explicitly passing `axis=0` was unnecessary since it's the default, but I included it for illustrative purposes.)

Calling the function by rows, with `axis=1`, would give us nonsensical output. Remember, our ADP data is by *player*, so calling `mean` with `axis=1` would give us the average of each player's: adp, lowest pick, highest pick, and standard deviation.

```
In [4]: adp[['adp', 'low', 'high', 'stdev']].mean(axis=1).head()
Out[4]:
player_id
2297    1.725
1983    2.525
1886    3.175
1796    6.225
2343    6.750
dtype: float64
```

That number is meaningless here, but sometimes data is structured differently. For example, you might have a DataFrame where the columns are: `name`, `pts1`, `pts2`, `pts3` …, `pts17` — where each row represents a player and there are 17 columns, one for every week.

Then `axis=0` would give the average score across *all* players for *each week*, which could be interesting, and `axis=1` would give you *each player's* average weekly score for the *whole season*, which could also be interesting.

Summary Functions on Boolean Columns

When you use the built-in summary stats on boolean columns, Pandas will treat them as 0 for `False`, 1 for `True`.

What portion of our player-game sample are RBs who run for over 100 yards?

Picking up in line 26 of `03_02_functions.py` (after you've loaded `pg` in the REPL):

```
In [1]: pg['good_rb_game'] = ((pg['pos'] == 'RB') &
                              (pg['rush_yards'] >= 100))

In [2]: pg['good_rb_game'].mean()
Out[2]: 0.027952480782669462

In [3]: pg['good_rb_game'].sum()
Out[3]: 40
```

Two boolean specific summary functions are `all` — which returns `True` if *all* values in the column are `True`, and `any`, which returns `True` if *any* values in the column are `True`.

For example, did anyone here pass for over 400 yards?

```
In [4]: (pg['pass_yards'] > 400).any()
Out[4]: True
```

Yes. Did everyone finish their games with non-negative rushing yards?

```
In [5]: (pg['rush_yards'] >= 0).all()
Out[5]: False
```

No.

Like the other summary statistic functions, `any` and `all` take an `axis` argument.

For example, to look by row and check if each player went for over 100 rushing *or* receiving yards in a game we could do.

```
In [6]: (pg[['rush_yards', 'rec_yards']] > 100).any(axis=1)
Out[6]:
0       False
1       False
2       False
3       False
4       False
        ...
1426    False
1427    False
1428    False
1429    False
1430    False
```

If we want, we can then call another function on *this* column to see how often it happened.

```
In [7]: (pg[['rush_yards', 'rec_yards']] > 100).any(axis=1).sum()
Out[7]: 100
```

How often did someone go for *both* 100 rushing *and* receiving yards in the same game?

```
In [8]: (pg[['rush_yards', 'rec_yards']] > 100).all(axis=1).sum()
Out[8]: 0
```

Never, at least in our sample. Maybe we can lower the bar?

```
In [9]: (pg[['rush_yards', 'rec_yards']] > 75).all(axis=1).sum()
Out[9]: 4
```

Other Misc Built-in Summary Functions

Not all built-in, data-to-statistic Pandas functions return just one number. Another useful function is `value_counts`, which summarizes the frequency of individual values.

```
In [10]: adp['position'].value_counts()
Out[10]:
WR      63
RB      62
QB      21
TE      17
DEF     13
PK       8
```

We can **normalize** these frequencies — dividing each by the total so that they add up to 1 and represent proportions — by passing the `normalize=True` argument.

```
In [11]: adp['position'].value_counts(normalize=True)
Out[11]:
WR      0.342391
RB      0.336957
QB      0.114130
TE      0.092391
DEF     0.070652
PK      0.043478
```

So 34.2% (63/184) of the positions in our ADP data are WRs, 33.7% (62/184) are RBs, etc.

Also useful is `crosstab`, which shows the frequencies for all the combinations of *two* columns.

```
In [12]: pd.crosstab(adp['team'], adp['position']).head()
Out[12]:
position  DEF  PK  QB  RB  TE  WR
team
ARI         1   0   1   2   0   2
ATL         1   1   1   2   1   3
BAL         1   1   0   2   0   2
BUF         0   0   1   1   0   3
CAR         1   0   1   2   1   0
```

Crosstab also takes an optional `normalize` argument.

Just like we did with `str` methods in the last chapter, you should set aside some time to explore functions and types available in Pandas using the REPL, tab completion, and typing the name of a function followed by a question mark.

There are three areas you should explore. The first is high-level Pandas functions, which you can see by typing `pd.` into the REPL and tab completing. These include functions for reading various file formats, as well as the `DataFrame`, `Series`, and `Index` Python types.

You should also look at Series specific methods that operate on single columns. You can explore this by typing `pd.Series.` into the REPL and tab completing.

Finally, we have DataFrame specific methods — `head`, `mean` or `max` are all examples — which you can use on any DataFrame (we called them on `adp` above). You can view all of these by typing in `pd.DataFrame.` into the REPL and tab completing.

Review

In this section we learned about summary functions — `mean`, `max`, etc — that operate on DataFrames, including two — `any` and `all` — that operate on boolean data specifically. We learned how they can apply to columns (the default) or across rows (by setting `axis=1`).

We also learned about two other useful functions for viewing frequencies and combinations of values, `value_counts` and `pd.crosstab`.

Exercises

3.2.1 Load the player game data into a DataFrame named `pg`. You'll use it for the rest of the problems in this section.

3.2.2 Add a column to `pg` that gives the total rushing, receiving and passing yards for each player-game. Do it two ways, one with basic arithmetic operators and another way using a built-in pandas function. Call them '`total_yards1`' and '`total_yards2`'. Prove that they're the same.

3.2.3

a) What were the average values for rushing and receiving yards?

b) How many times in our data did someone throw for over at least 300 and at least 3 tds?

c) What % of qb performances was that?

d) How many rushing tds were there total in our sample?

e) What week is most represented in our sample? Least?

3. Filter Observations

Note the examples for this section are in the file `03_03_filter.py`. We'll pick up right after you've loaded the DataFrame `adp` into your REPL.

The third thing we can do with DataFrames is **filter** them, which means picking out a subset rows. In this section we'll learn how to filter based on criteria we set, as well as how to filter by dropping duplicates.

loc

One way to filter observations is to pass the *index value* you want to `loc[]` (note the brackets as opposed to parenthesis):

For example:

```
In [1]: tom_brady_id = 119

In [2]: adp.loc[tom_brady_id]
Out[2]:
adp                    29.6
adp_formatted          3.06
bye                      10
high                     14
low                      43
name             Tom Brady
position                 QB
stdev                   5.8
team                     NE
times_drafted           193
```

Similar to how you select multiple columns, you can pass multiple values via a list:

```
In [3]: my_player_ids = [119, 1886, 925]

In [4]: adp.loc[my_player_ids]
Out[4]:
            adp  adp_formatted  bye  ...  stdev  team times_drafted
player_id                            ...
119        29.6           3.06   10  ...    5.8    NE           193
1886        3.7           1.04    7  ...    1.0   PIT           338
925        69.9           6.10   12  ...    7.4   ARI           187
```

While not technically filtering by rows, you can also pass `loc` a second argument to limit which columns you return. This returns the `name`, `adp`, `stddev` columns for the ids we specified.

```
In [5]: adp.loc[my_player_ids, ['name', 'adp', 'stdev']]
Out[5]:
                      name   adp  stdev
player_id
119             Tom Brady  29.6    5.8
1886        Antonio Brown   3.7    1.0
925       Adrian Peterson  69.9    7.4
```

Like in other places, you can also pass the column argument of `loc` a single, non-list value and it'll return just the one column.

```
In [6]: adp.loc[my_player_ids, 'name']
Out[6]:
player_id
119             Tom Brady
1886        Antonio Brown
925       Adrian Peterson
```

Boolean Indexing

Though `loc` can take specific index values (a list of player ids in this case), this isn't done that often. More common is **boolean indexing**, where you pass `loc` a column (technically a Series, which recall is the Pandas type for a single column) of boolean values and it returns only rows that are `True`.

So say we're just interested in RBs. Let's create our Series of booleans that indicate whether a player is an RB:

```
In [7]: is_a_rb = adp['position'] == 'RB'

In [8]: is_a_rb.head()
Out[8]:
player_id
2297     True
1983     True
1886    False
1796    False
2343     True
```

And now pass this to `loc[]`. Again, note the brackets; calling `loc` is more like retrieving a value from a dictionary than calling a method.

```
In [9]: adp_rbs = adp.loc[is_a_rb]

In [10]: adp_rbs[['name', 'adp', 'position']].head()
Out[10]:
                       name  adp position
player_id
2297          David Johnson  1.3       RB
1983            LeVeon Bell  2.3       RB
2343        Ezekiel Elliott  6.2       RB
2144        Devonta Freeman  7.0       RB
1645           LeSean McCoy  7.8       RB
```

Boolean indexing requires that the column of booleans you're passing has the same index as the DataFrame you're calling `loc` on. In this case we already know `is_a_rb` has the same index as `adp` because we created it with `adp['pos'] == 'RB'` and that's how Pandas works.

We broke the process into two separate steps above, first creating `is_a_rb` and then passing it to `loc`, but that's not necessary. This does the same thing without leaving an `is_a_wr` Series lying around:

```
In [11]: adp_wrs = adp.loc[adp['position'] == 'WR']

In [12]: adp_wrs[['name', 'adp', 'position']].head()
Out[12]:
                         name   adp position
player_id
1886           Antonio Brown   3.7       WR
1796             Julio Jones   5.7       WR
2113        Odell Beckham Jr   6.4       WR
2111              Mike Evans   7.9       WR
1795              A.J. Green  10.0       WR
```

Having to refer to the name of your DataFrame (`adp` here) multiple times in one line may seem cumbersome at first. It can get a bit verbose, but this is a very common thing to do so get used to it.

Any boolean column or boolean operation works.

```
In [13]: is_a_te = adp['position'] == 'TE'

In [14]: adp_not_te = adp.loc[~is_a_te]

In [15]: adp_not_te[['name', 'adp', 'position']].head()
Out[15]:
                       name  adp position
player_id
2297          David Johnson  1.3       RB
1983            LeVeon Bell  2.3       RB
1886          Antonio Brown  3.7       WR
1796            Julio Jones  5.7       WR
2343        Ezekiel Elliott  6.2       RB
```

Duplicates

A common way to filter data is by removing duplicates. Pandas has built-in functions for this.

```
In [1]: adp.drop_duplicates(inplace=True)
```

In this case it didn't do anything since we had no duplicates, but it would have if we did. The `drop_duplicates` method drops duplicates across *all* columns, if you are interested in dropping only a subset of variables you can specify them:

```
In [2]: adp.drop_duplicates('position')[['name', 'adp', 'position']]
Out[2]:
                      name    adp position
player_id
2297         David Johnson    1.3       RB
1886         Antonio Brown    3.7       WR
1740        Rob Gronkowski   18.1       TE
1004         Aaron Rodgers   23.4       QB
1309        Denver Defense  105.5      DEF
1962         Justin Tucker  145.0       PK
```

Note, although it though it might look strange to have `[['name', 'adp', 'position']]` immediately after `.drop_duplicates('position')`, it works because the result of `adp.drop_duplicates(...)` is a DataFrame. We're just immediately using the multiple column bracket syntax after calling `drop_duplicates` to pick out and print certain columns.

Alternatively, to identify — but not drop — duplicates you can do:

```
In [3]: adp.duplicated().head()
Out[3]:
player_id
2297    False
1983    False
1886    False
1796    False
2343    False
```

The `duplicated` method returns a boolean column indicating whether the row is a duplicate (none of these are). Note how it has the same index as our original DataFrame.

Like `drop_duplicates`, you can pass it a subset of variables. Alternatively, you can just call it on the columns you want to check.

```
In [4]: adp['position'].duplicated().head()
Out[4]:
player_id
2297    False
1983     True
1886    False
1796     True
2343     True
```

By default, `duplicated` *only* identifies the duplicate observation — not the original — so if you have two "T. Smith"'s in your data, `duplicated` will indicate `True` for the second one. You can tell it to identify *both* duplicates by passing `keep=False`.

Combining Filtering with Changing Columns

Often you'll want to combine filtering with modifying columns and update columns *only* for certain rows.

For example, say we want a column `'primary_yards'` with passing yards for QBs, rushing yards for RBs, and receiving yards for WRs.

After loading the player-game data into a DataFrame `pg` (not shown here) we would do that using something like this:

```
In [1]: pg['primary_yards'] = np.nan

In [2]: pg.loc[pg['pos'] == 'QB', 'primary_yards'] = pg['pass_yards']

In [3]: pg.loc[pg['pos'] == 'RB', 'primary_yards'] = pg['rush_yards']

In [4]: pg.loc[pg['pos'] == 'WR', 'primary_yards'] = pg['rec_yards']
```

We start by creating an empty column, `primary_yards`, filled with missing values (remember, missing values have a value of `np.nan` in Pandas). Then we go through and use `loc` to pick out only the rows (where `pos` equals what we want) and the one column (`primary_yards`) and assign the correct value to it.

```
In [5]: pg[['player_name', 'pos', 'pass_yards', 'rush_yards',
            'rec_yards', 'primary_yards']].sample(5)
Out[5]:
     player_name pos  pass_yards  rush_yards  rec_yards  primary_yards
0        T.Brady  QB       267.0         0.0        0.0          267.0
798    T.Lockett  WR         0.0         0.0       25.0           25.0
1093    D.Thomas  WR         0.0         0.0       67.0           67.0
84        K.Hunt  RB         0.0       155.0       51.0          155.0
766     J.Graham  TE         0.0         0.0       45.0            NaN
```

The `query` Method is an Alternative Way to Filter

The `loc` method is flexible, powerful and can do everything you need — including letting you update columns only for rows with certain values. But, if you're *only* interested in filtering, there's a less verbose alternative: `query`.

To use `query` you pass it a string. Inside the string you can refer to variable names and do normal Python operations.

For example, to filter `pg` so it only includes RBs:

```
In [1]: pg.query("pos == 'RB'").head()
Out[1]:
       gameid   player_id  carries  ...  player_name  week  primary_yards
3  2017090700  00-0030288      3.0  ...   R.Burkhead     1           15.0
5  2017090700  00-0033923     17.0  ...       K.Hunt     1          148.0
7  2017091705  00-0030288      2.0  ...   R.Burkhead     2            3.0
8  2017091705  00-0025394      8.0  ...   A.Peterson     2           26.0
9  2017091705  00-0027966      8.0  ...     M.Ingram     2           52.0
```

Notice how inside the string we're referring to `pos` without quotes, like a variable name. We can refer to any column name like that. String values inside `query` strings (e.g. `'RB'`) still need quotes. If you normally tend to use single quotes for strings, it's good practice to wrap all your `query` strings in double quotes (e.g. `"pos == 'RB'"`) so that they work well together.

We can also call boolean columns directly:

```
In [2]: pg['is_a_rb'] = pg['pos'] == 'RB'

In [3]: pg.query("is_a_rb").head()
Out[3]:
       gameid   player_id  carries  ...  week  primary_yards  is_a_rb
3  2017090700  00-0030288      3.0  ...     1           15.0     True
5  2017090700  00-0033923     17.0  ...     1          148.0     True
7  2017091705  00-0030288      2.0  ...     2            3.0     True
8  2017091705  00-0025394      8.0  ...     2           26.0     True
9  2017091705  00-0027966      8.0  ...     2           52.0     True
```

Another thing we can do is use basic Pandas functions. For example, to filter on whether `raw_yac` is missing:

```
In [4]: pg.query("raw_yac.notnull()")[
                  ['gameid', 'player_id', 'raw_yac']].head()
Out[4]:
       gameid   player_id  raw_yac
0  2017090700  00-0019596      0.0
1  2017090700  00-0023436      0.0
2  2017090700  00-0026035     49.0
3  2017090700  00-0030288      7.0
4  2017090700  00-0030506     23.0
```

Note: if you're getting an error here, try passing `engine='python'` to `query`. That's required on some systems.

Again, `query` doesn't add anything beyond what you can do with `loc` (I wasn't even aware of `query` until I started writing this book), and there are certain things (like updating columns based on values in the row) that you can *only* do with `loc`. So I'd focus on that first. But, once you have `loc` down, `query` can let you filter data a bit more concisely.

Review

In this section we learned how to filter our data, i.e. take a subset of rows. We learned how to filter by passing both specific index values and a column of booleans to `loc`. We also learned about identifying and dropping duplicates. Finally, we learned about `query`, which is a shorthand way to filter your data.

Exercises

3.3.1 Load the ADP data into a DataFrame named `adp`. You'll use it for the rest of the problems in this section.

3.3.2 Make smaller DataFrame with just Dallas Cowboy players and only the columns: `'name'`, `'position'`, `'adp'`. Do it two ways: (1) using the `loc` syntax, and (b) another time using the `query` syntax. Call them `adp_cb1` and `adp_cb2`.

3.3.3 Make a DataFrame `adp_no_cb` that is everyone EXCEPT Dallas players, add the `'team'` column to it.

3.3.4

a) Are there any duplicates by last name AND position in our `adp` DataFrame? How many?

b) Divide `adp` into two separate DataFrames `adp_dups` and `adp_nodups`, one with dups (by last name and pos) one without.

3.3.5 Add a new column to `adp` called `'adp_description'` with the values:

- `'stud'` for adp's < 40
- `'scrub'` for adp's > 120
- missing otherwise

3.3.6 Make a new DataFrame with only observations for which '`adp_description`' is missing. Do this with both the (a) loc and (b) query syntax. Call them `adp_no_desc1` and `adp_no_desc2`.

4. Change Granularity

Note the examples for this section are in the file `03_04_granularity.py`. We'll pick up right after you've loaded the DataFrame `pbp` into your REPL.

The fourth thing to do with DataFrames is change the granularity.

Remember: data is a collection of structured information. Granularity is the level your collection is at. Our ADP data is at the player level; each row in our `adp` DataFrame is one player. In `pg` each row represents a single player-game.

Ways of Changing Granularity

Changing the granularity of your data is a very common thing to do. There are two ways to do it.

1. **Grouping** — sometimes called **aggreggating** — involves going from fine grained data (e.g. play) to less fine grained data (e.g. game). It necessarily involves a loss of information. Once my data is at the game level I have no way of knowing what happened on any particular play.
2. **Stacking** or **unstacking** — sometimes called **reshaping** — is less common than grouping. It involves no loss of information, essentially because it crams data that was formerly in unique rows into separate columns. For example: say I have a dataset of weekly fantasy points at the *player-game* level. I could move things around so my data is one line for every *player*, but now with 17 separate columns (week 1's fantasy points, week 2's, etc), one for each game.

Grouping

Aggregating data to be less granular via grouping is something data scientists do all the time. Examples: going from play-by-play to game data or from player-game to player-season data.

Grouping necessarily involves some function that says *how* your data gets to this less granular state.

So if we have have play-by-play level data with rushing yards for each play and wanted to group it to the game level we could take the:

- *sum* to get total rushing yards for the game
- *average* to get yards per rush for ypc
- *max* or *min* to get some level of floor/ceiling per carry
- *count* to get total number of rushes

Or we could do something more sophisticated, maybe the percentage of runs that went for more than 5 yards[3].

Let's use our play-by-play sample (every play from the 2018 KC-NE and KC-LA games, loaded earlier) to look at some examples.

groupby

Pandas handles grouping via the `groupby` function.

```
In [1]: pbp.groupby('game_id').sum()
Out[1]:
            play_id  posteam_score  ...         wp       wpa
game_id                             ...
2018101412   287794         2269.0  ...  72.384102  1.374290
2018111900   472385         3745.0  ...  76.677250  0.823359
```

This gives us a DataFrame where every column is summed (because we called `.sum()` at the end) over `game_id`. Note how `game_id` is the index of our newly grouped-by data. This is the default behavior; you can turn it off either by calling `reset_index` right away or passing `as_index=False` to `groupby`.

Also note `sum` gives us the sum of *every* column. Usually we'd only be interested in a subset of variables, maybe yards or attempts for sum.

```
In [2]: sum_cols = ['yards_gained', 'rush_attempt',
                    'pass_attempt', 'shotgun']

In [3]: pbp.groupby('game_id').sum()[sum_cols]
Out[3]:
            yards_gained  rush_attempt  pass_attempt  shotgun
game_id
2018101412           946          55.0          73.0       85
2018111900          1001          41.0         103.0      101
```

Or we might want to take the sum of yards, and use a different function for other columns. We can do that using the `agg` function, which takes a dictionary.

[3] In practice, this would involve multiple steps. First we'd create a boolean column indicating whether a rushing play went for more than 5 yards. Then we'd take the average of that column to get a percentage between 0-1.

```
In [4]: pbp.groupby('game_id').agg({
                      'yards_gained': 'sum',
                      'play_id': 'count',
                      'interception': 'sum',
                      'touchdown': 'sum'})
Out[4]:
            yards_gained  play_id  interception  touchdown
game_id
2018101412           946      144           2.0        8.0
2018111900          1001      160           3.0       14.0
```

Note how the new grouped by columns have the same names as the original, non-aggregated versions. But after a `groupby` that name may no longer be what we want. For instance, `play_id` isn't the best name for the total number of plays run, which is what this column tells us post grouping.

To fix this, Pandas let's you pass new variable names to `agg` as keywords, with the values being variable, function **tuple** pairs (for our purposes, a tuple is like a list but with parenthesis). The following code is the same as the above, but renames `play_id` to `nplays`.

```
In [5]:
pbp.groupby('game_id').agg(
    yards_gained = ('yards_gained', 'sum'),
    nplays = ('play_id', 'count'),
    interception = ('interception', 'sum'),
    touchdown = ('touchdown', 'sum'))

Out[5]:
            yards_gained  nplays  interception  touchdown
game_id
2018101412           946     144           2.0        8.0
2018111900          1001     160           3.0       14.0
```

Note you're no longer passing a dictionary, instead `agg` takes arguments, each in a `new_variable = ('old_variable', 'function-as-string-name')` format.

You can also group by more than one thing — for instance, game *and* team — by passing `groupby` a list.

```
In [6]:
yards_per_team_game = (pbp
                       .groupby(['game_id', 'posteam'])
                       .agg(
                           ave_yards_per_play = ('yards_gained', 'mean'),
                           total_yards = ('yards_gained', 'sum')))

In [7]: yards_per_team_game
Out[7]:
                      yards_gained
                               sum      mean
game_id    posteam
2018101412 KC                  446  7.689655
           NE                  500  6.250000
2018111900 KC                  546  7.479452
           LA                  455  5.617284
```

A Note on Multilevel Indexing

Grouping by two or more variables shows that it's possible in Pandas to have a *multilevel* index, where your data is indexed by two or more variables. In the example above, our index is a combination of `game_id` and `posteam`.

You can still use the `loc` method with multi-level indexed DataFrames, but you need to pass it a tuple (again, like a list but with parenthesis):

```
In [10]: yards_per_team_game.loc[[(2018101412, 'NE'), (2018111900, 'LA')]]
Out[10]:
                      yards_gained
                               sum  mean
game_id    posteam
2018101412 NE                  500  6.250000
2018111900 LA                  455  5.617284
```

I personally find multilevel indexes unwieldy and avoid them when I can by calling the `reset_index` method immediately after running a multi-column `groupby`.

However there are situations where multi-level indexes are the only way to do what you want, like in stacking and unstacking.

Stacking and Unstacking Data

I would say stacking and unstacking doesn't come up *that* often, so if you're having trouble with this section or feeling overwhelmed, feel free to make mental note of what it is broadly and come back to it later.

Stacking and unstacking data technically involves changing the granularity of our data, but instead of applying some function (sum, mean) to aggregate it, we're just moving data from columns to rows (stacking) or vis versa (unstacking).

For example, let's look at total passing yards by week in our player game data. Picking up in line 43 of `03_04_granularity.py` after you've loaded `pg`.

```
In [1]: qbs = pg.loc[pg['pos'] == 'QB',
                     ['player_name', 'week', 'pass_tds']]

In [1]: qbs.sample(5)
     player_name  week  pass_tds
214     T.Taylor    10       0.0
339       M.Ryan    14       1.0
220     T.Taylor    11       1.0
70       T.Brady    15       1.0
1192    C.Newton     1       2.0
```

This data is at the *player and game* level. Each row is a player-game combination, and we have the `pass_tds` column for number of passing touchdowns each QB threw that week.

But say instead we want this data to be at the *player* level and have up to 17 separate columns for number of touchdowns. Then we'd do:

```
In [2]: qbs_reshaped = qbs.set_index(['player_name', 'week']).unstack()

In [2]: qbs_reshaped.head()
Out[2]:
                 pass_tds       ...
week                    1    2  ...   12   13   14   15   16   17
player_name                     ...
A.Smith               4.0  1.0  ...  1.0  4.0  1.0  2.0  1.0  NaN
B.Bortles             1.0  1.0  ...  0.0  2.0  2.0  3.0  3.0  0.0
B.Hundley             NaN  NaN  ...  3.0  0.0  3.0  NaN  0.0  1.0
B.Roethlisberger      2.0  2.0  ...  5.0  2.0  2.0  3.0  2.0  NaN
C.Newton              2.0  0.0  ...  0.0  2.0  1.0  4.0  0.0  1.0
```

This move doesn't cost us any information. Initially, we find passing touchdowns for a particular QB and week by looking in the right row. After we unstack it, we can find total passing tds for a particular QB and week by first finding the player's row, then finding the column for the right week.

This lets us do things like calculate season totals:

```
In [3]: total_tds = qbs_reshaped.sum(axis=1).head()

In [4]: total_tds
Out[4]:
player_name
A.Smith             27.0
B.Bortles           22.0
B.Hundley           10.0
B.Roethlisberger    32.0
C.Newton            23.0
```

Or figure out maximum number of touchdowns thrown each week:

```
In [5]: qbs_reshaped.max(axis=0).head()
Out[5]:
          week
pass_tds  1       5.0
          2       3.0
          3       5.0
          4       3.0
          5       3.0
```

If we wanted to undo this operation and to stack it back up we could do:

```
In [6]: qbs_reshaped_undo = qbs_reshaped.stack()

In [7]: qbs_reshaped_undo.head()
Out[6]:
                  pass_tds
player_name week
A.Smith     1          4.0
            2          1.0
            3          2.0
            4          1.0
            5          3.0
```

Review

In this section we learned how to change the granularity of our data. We can do that two ways, by grouping — where the granularity of our data goes from fine to less-fine grained — and by stacking and unstacking, where we shift data from columns to row or vis versa.

Exercises

3.4.1 How does shifting granularities affect the amount of information in your data? Explain.

3.4.2

a) Load the play by data.

b) Figure out who the leading rusher in each game was and how many rushing yards they had.

c) Figure out everyone's ypc.

d) What portion of everyone's runs got 0 or negative yardage?

3.4.3 Using the play-by-play data, run `pbp.groupby('game_id').count()`.

Based on the results, explain what you think it's doing. How does `count` differ from `sum`? When would `count` and `sum` give you the same result?

3.4.4 In `pbp`, which team/game had the highest percentage of their plays go for first downs? Turnovers?

3.4.5 How does stacking or unstacking affect the amount of information in your data? Explain.

5. Combining Two or More DataFrames

The examples for this section are in the file `03_05_combine.py`*. We'll pick up right after loading the* `pg`*,* `games` *and* `player` *DataFrames.*

The last thing we need to know how to do with DataFrames is combine them.

Typically, by *combining* we mean sticking DataFrames together side by side, like books on a shelf. This is also called **merging**, **joining**, or **horizontal concatenation**.

The alternative (which we'll also learn) is stacking DataFrames on top of each other, like a snowman. This is called **appending** or **vertical concatenation**.

Merging

There are three questions to ask yourself when merging DataFrames. They are:

1. What columns are you joining on?
2. Are you doing a one to one (1:1), one to many (1:m or m:1), or many to many (m:m) type join?
3. What are you doing with unmatched observations?

Let's go over each of these.

Merge Question 1. What columns are you joining on?

Say we want to analyze whether QBs throw for more yards when they're playing at home vs playing away. We can't do it at the moment because we don't have a home or away column in our player-game data.

```
   player_name team  week      gameid  pass_yards  pass_tds
0      T.Brady   NE     1  2017090700       267.0       0.0
1      A.Smith   KC     1  2017090700       368.0       4.0
6      T.Brady   NE     2  2017091705       447.0       3.0
12     T.Brady   NE     3  2017092407       378.0       5.0
16     T.Brady   NE     4  2017100107       310.0       2.0
```

Recall our tabular data basics: each *row* is some item in a collection, and each *column* some piece of information.

Here, rows are player-game combinations (Tom Brady, week 1). And our information is: player, team, week, game id, passing yards and touchdowns. Information we *don't* have: whether the QB was home or away.

That information is in a different table, `games`:

```
       gameid home away
0  2017090700   NE   KC
1  2017091000  BUF  NYJ
2  2017091008  WAS  PHI
3  2017091007  TEN  OAK
4  2017091005  HOU  JAX
```

We need to link the home and away information in `games` with the passing statistics in `pg`. The end result will look something like this:

```
  player_name team  week      gameid  pass_yards  pass_tds home away
0     T.Brady   NE     1  2017090700       267.0       0.0   NE   KC
1     A.Smith   KC     1  2017090700       368.0       4.0   NE   KC
2     T.Brady   NE     2  2017091705       447.0       3.0   NO   NE
3     T.Brady   NE     3  2017092407       378.0       5.0   NE  HOU
4     T.Brady   NE     4  2017100107       310.0       2.0   NE  CAR
```

To link these two tables we need information in common. In this example, it's `gameid`. Both the `pg` and `games` DataFrames have a `gameid` column, and in both cases it refers to the same game.

So we can do:

```
In [1]: pd.merge(pg, games[['gameid', 'home', 'away']],
                 on='gameid').head()
Out[1]:
       gameid   player_id  carries  ...  week  home  away
0  2017090700  00-0019596      0.0  ...     1    NE    KC
1  2017090700  00-0023436      2.0  ...     1    NE    KC
2  2017090700  00-0026035      0.0  ...     1    NE    KC
3  2017090700  00-0030288      3.0  ...     1    NE    KC
4  2017090700  00-0030506      1.0  ...     1    NE    KC
```

Again, this works because `gameid` is in (and means the same thing) in both tables. Without it, Pandas would have no way of knowing which `pg` row was connected to which `game` row.

Here, we're explicitly telling Pandas to link these tables on `gameid` with the `on='gameid'` keyword argument. This argument is optional. If we leave it out, Pandas will default to using the columns the two DataFrames have in common.

Merging is Precise

Keep in mind that to merge successfully, the values in the columns you're linking need to be *exactly* the same.

If your `name` column in one DataFrame has "Odell Beckham Jr." and the other has "Odell Beckham" or just "O.Beckham" or "OBJ", they won't be merged. It's your job to modify one or both of them (using the column manipulation functions we talked about earlier) to make them the same so you can combine them properly. If you're new to working with data you might be surprised at how much of your time is spent doing things like this.

Another issue to watch out for is inadvertent duplicates. For example, if you're combining two DataFrames on a column `name` and you have two `'J.Jones'` (J.J. and Julio), it will lead to unexpected behavior. That's one reason it's best to merge on a unique id variable if you can.

So far we've been talking about merging on a single column, but merging on more than one column works too. For example, say we have separate rushing and receiving DataFrames:

```
In [2]: rush_df = pg[['gameid', 'player_id', 'rush_yards', 'rush_tds']]

In [3]: rec_df = pg[['gameid', 'player_id', 'rec_yards', 'rec_tds']]
```

Both of which are at the player-game level. To combine them by `player_id` *and* `gameid` we just pass a list of column names to `on`.

```
In [4]: combined = pd.merge(rush_df, rec_df, on=['player_id', 'gameid'])
```

Merge Question 2. Are you doing a 1:1, 1:many (or many:1), or many:many join?

After deciding which columns you're merging on, the next step is figuring out whether you're doing a one-to-one, one-to-many, or many-to-many merge.

In the previous example, we merged two DataFrames together on `player_id` and `gameid`. Neither DataFrame had duplicates on these columns. That is, they each had *one* row with a gameid of `2017090700` and player_id of `'00-0019596'`, *one* row with a gameid of `2017090700` and player_id of `'00-0023436'`, etc. Linking them up was a **one-to-one** (1:1) merge.

One-to-one merges are straightforward; all DataFrames involved (the two we're merging, plus the final, merged product) are at the same level of granularity. This is *not* the case with one-to-many (or many-to-one, same thing, order doesn't matter) merges.

Say we're working with our `combined` DataFrame from above. Recall this was *combined* rushing and receiving stats at the player-game level.

```
       gameid   player_id  rush_yards  rush_tds  rec_yards  rec_tds
0  2017090700  00-0019596         0.0       0.0        0.0      0.0
1  2017090700  00-0023436         9.0       0.0        0.0      0.0
2  2017090700  00-0026035         0.0       0.0      100.0      0.0
3  2017090700  00-0030288        15.0       0.0        8.0      0.0
4  2017090700  00-0030506         4.0       0.0       40.0      0.0
```

Now we want to add back in each player's name. We do this by merging it with the player table:

```
    player_id  season team pos player_name
0  00-0033951    2017  IND  RB      M.Mack
1  00-0028116    2017   SF  WR  A.Robinson
2  00-0033080    2017  CLE  TE   S.DeValve
3  00-0033553    2017  PIT  RB    J.Conner
4  00-0029615    2017  HOU  RB    L.Miller
```

The column we're merging on is `player_id`. Since the `player` data is at the player level, it has one row per `player_id`. There are no duplicates:

```
In [1]: player['player_id'].duplicated().any()
Out[1]: False
```

That's *not* true for `combined`, which is at the player-game level. Here, each player shows up multiple times: once in his week 1 game, another time for week 2, etc.

```
In [2]: combined['player_id'].duplicated().any()
Out[2]: True
```

In other words, every *one* `player_id` in our `player` table is being matched to *many* `player_id`s in the `combined` table. This is a **one-to-many** merge.

```
In [3]: pd.merge(combined, player).head()
Out[3]:
       gameid   player_id  rush_yards  ...  team  pos  player_name
0  2017090700  00-0019596         0.0  ...    NE   QB      T.Brady
1  2017091705  00-0019596         9.0  ...    NE   QB      T.Brady
2  2017092407  00-0019596         6.0  ...    NE   QB      T.Brady
3  2017100107  00-0019596         2.0  ...    NE   QB      T.Brady
4  2017100500  00-0019596         5.0  ...    NE   QB      T.Brady
```

(Note that even though we left out the `on='player_id'` keyword argument, Pandas defaulted to it since `player_id` was the one column the two tables had in common.)

One-to-many joins come up often, especially when data is efficiently stored. It's not necessary to store name, position and team for every single line in our player-game table when we can easily merge it back in with a one-to-many join on our `player` table when we need it.

Finally, although it's technically possible to do **many-to-many** (m:m) joins, in my experience this is almost always done unintentionally[4], usually when merging on columns with inadvertent duplicates.

Note how the Pandas `merge` command for 1:1 and 1:m merges looks exactly the same. Pandas automatically figures out which type you want depending on what your data looks like.

[4] There are rare situations where something like this might be useful that we'll touch on more in the SQL section.

You can pass the type of merge you're expecting using the `validate` keyword. If you do that, Pandas will throw an error if the merge isn't what you say it should be. It's a good habit to get into. It's much better to get an error right away than it is to continue working with data that isn't actually structured the way you thought it was.

Let's try that last `combined` to `player` example using `validate`. We know this isn't really a 1:1 merge, so if we set `validate='1:1'` we should get an error.

```
In [4]: pd.merge(combined, player, validate='1:1')
...
MergeError: Merge keys are not unique in left dataset; not a one-to-one
   merge
```

Perfect.

Merge Question 3. What are you doing with unmatched observations?

So you know which columns you're merging on, and whether you're doing a 1:1 or 1:m join. The final factor to consider: what are you doing with unmatched observations?

Logically, there's no requirement that two tables *have* to include information about the exact same observations.

To demonstrate, let's make some rushing and receiving data, keeping observations with positive yardage values only.

```
In [1]: rush_df = pg.loc[pg['rush_yards'] > 0,
          ['gameid', 'player_id', 'rush_yards', 'rush_tds']]

In [2]: rec_df = pg.loc[pg['rec_yards'] > 0,
          ['gameid', 'player_id', 'rec_yards', 'rec_tds']]

In [3]: rush_df.shape
Out[3]: (555, 4)

In [4]: rec_df.shape
Out[4]: (1168, 4)
```

Many players in the rushing table (not all of them) will also have some receiving stats. Many players in the receiving table (i.e. the TEs) won't be in the rushing table.

When you merge these, Pandas defaults to keeping only the observations in *both* tables.

```
In [5]: comb_inner = pd.merge(rush_df, rec_df)

In [6]: comb_inner.shape
Out[6]: (355, 6)
```

So `comb_inner` *only* has the player-game's where the player had at least one rushing *and* one receiving yard.

Alternatively, we can keep everything in the left (`rush_df`) or right (`rec_df`) table by passing `'left'` or `'right'` to the `how` argument.

```
In [7]: comb_left = pd.merge(rush_df, rec_df, how='left')

In [8]: comb_left.shape
Out[8]: (555, 6)
```

Where "left" and "right" just denote the order we passed the DataFrames into `merge` (first one is left, second right).

Now `comb_left` has everyone who had at least one rushing yard, whether they had any receiving yards or not. Rows in `rush_df` that weren't in `rec_df` get missing values for `rec_yards` and `rec_tds`.

```
In [9]: comb_left.head()
Out[9]:
       gameid   player_id  rush_yards  rush_tds  rec_yards  rec_tds
0  2017090700  00-0023436         9.0       0.0        NaN      NaN
1  2017090700  00-0030288        15.0       0.0        8.0      0.0
2  2017090700  00-0030506         4.0       0.0       40.0      0.0
3  2017090700  00-0033923       148.0       1.0       98.0      2.0
4  2017091705  00-0019596         9.0       0.0        NaN      NaN
```

We can also do an "outer" merge, which keeps everything: matches, and non-matches from both left and right tables.

One thing I find helpful when doing non-inner joins is to include the `indicator=True` keyword argument. This adds a column `_merge` indicating whether the observation was in the left DataFrame, right DataFrame, or both.

```
In [10]: comb_outer = pd.merge(rush_df, rec_df, how='outer',
                               indicator=True)

In [11]: comb_outer.shape
Out[11]: (1368, 7)

In [12]: comb_outer['_merge'].value_counts()
Out[12]:
right_only    813
both          355
left_only     200
```

This tells us that — out of the 1368 player-game observations in our sample — 813 didn't have any rushing yards, 200 didn't have any receiving yards, and 355 had both.

More on pd.merge

All of our examples so far have been neat merges on identically named id columns, but that won't always be the case. Often the columns you're merging on will have different names in different DataFrames.

To demonstrate, let's modify the rushing and receiving tables we've been working with, renaming `player_id` to `rusher_id` and `reciever_id` respectively.

```
In[1]: rush_df.columns = ['gameid', 'rusher_id', 'rush_yards', 'rush_tds']

In[2]: rec_df.columns = ['gameid', 'receiver_id', 'rec_yards', 'rec_tds']
```

(Recall assigning the `columns` attribute of a DataFrame a new list is one way to rename columns.)

But now if we want to combine these, the column is `rusher_id` in `rush_df` and `reciever_id` in `rec_df`. What to do? Simple, just use the `left_on` and `right_on` arguments instead of `on`.

```
In [3]:
pd.merge(rush_df, rec_df, left_on=['gameid', 'rusher_id'],
         right_on=['gameid', 'receiver_id']).head()
--
Out[3]:
       gameid   rusher_id  rush_yards  ... reciever_id  rec_yards  ...
0  2017090700  00-0030288        15.0  ...  00-0030288        8.0  ...
1  2017090700  00-0030506         4.0  ...  00-0030506       40.0  ...
2  2017090700  00-0033923       148.0  ...  00-0033923       98.0  ...
3  2017091705  00-0030288         3.0  ...  00-0030288       41.0  ...
4  2017091705  00-0027966        52.0  ...  00-0027966       18.0  ...
```

Sometimes you might want attach one of the DataFrames you're merging by its index. That's also no problem.

Here's an example. Say we want to find each player's maximum number of rushing yards and touchdowns.

```
In [4]: max_rush_df = (rush_df
                        .groupby('rusher_id')
                        .agg(max_rush_yards = ('rush_yards', 'max'),
                             max_rush_tds =  ('rush_tds', 'max')))
```

This is a `groupby` on `rusher_id`, which results in a new DataFrame where the index is `rusher_id`.

```
In [5]: max_rush_df.head()
Out[5]:
            max_rush_yards  max_rush_tds
rusher_id
00-0019596            14.0           1.0
00-0022924            25.0           0.0
00-0023436            70.0           1.0
00-0023500           130.0           1.0
00-0024389             1.0           1.0
```

What if we want to add this back into our original, `rush_df` DataFrame? They both have `rusher_id`, but one is an index, one a regular column. No problem. Instead of `right_on`, we pass `right_index=True`.

```
In [6]: pd.merge(rush_df, max_rush_df, left_on='rusher_id',
          right_index=True).head()
Out[6]:
         gameid   rusher_id  rush_yards  ...  max_rush_tds
1    2017090700  00-0023436         9.0  ...           1.0
86   2017091704  00-0023436        21.0  ...           1.0
93   2017092412  00-0023436         9.0  ...           1.0
99   2017100200  00-0023436        61.0  ...           1.0
102  2017100811  00-0023436        19.0  ...           1.0
```

`pd.merge()` Resets the Index

One thing to be aware of with `merge` is that the DataFrame it returns has a new, reset index. If you think about it, this makes sense. Presumably you're using `merge` because you want to combine two, non-identically indexed DataFrames. If that's the case, how is Pandas supposed know which of their indexes to use once they're combined? It doesn't, and so resets the index to the `0`, `1`, `2`, … default.

But if you're relying on Pandas indexing to automatically align everything for you, and doing some merging along the way, this is something you'll want to watch out for.

`pd.concat()`

If you're combining DataFrames with the same index, you can use the `concat` function (for concatenate) instead of `merge`.

To try it out, let's make our rushing and receiving DataFrames again, this time setting the index to `gameid` and `player_id`.

```
In [1]:
rush_df = (pg.loc[pg['rush_yards'] > 0,
                  ['gameid', 'player_id', 'rush_yards', 'rush_tds']]
           .set_index(['gameid', 'player_id']))

In [2]:
rec_df = (pg.loc[pg['rec_yards'] > 0,
                 ['gameid', 'player_id', 'rec_yards', 'rec_tds']]
          .set_index(['gameid', 'player_id']))
```

So `rush_df`, for example, looks like this:

```
In [3]: rush_df.head()
Out[3]:
                       rush_yards  rush_tds
gameid     player_id
2017090700 00-0023436         9.0       0.0
           00-0030288        15.0       0.0
           00-0030506         4.0       0.0
           00-0033923       148.0       1.0
2017091705 00-0019596         9.0       0.0
```

And concatenating `rush_df` and `rec_df` gives us:

```
In [4]: pd.concat([rush_df, rec_df], axis=1).head()
Out[4]:
                       rush_yards  rush_tds  rec_yards  rec_tds
gameid     player_id
2017090700 00-0023436         9.0       0.0        NaN      NaN
           00-0026035         NaN       NaN      100.0      0.0
           00-0030288        15.0       0.0        8.0      0.0
           00-0030506         4.0       0.0       40.0      0.0
           00-0033923       148.0       1.0       98.0      2.0
```

Note we're passing `concat` a *list* of DataFrames. Lists can contain as many items as you want, and `concat` let's you stick together as many DataFrames as you want. This is different than `merge`, which limits you to two.

For example, maybe we have a passing DataFrame.

```
In [5]:
pass_df = (pg.loc[pg['pass_yards'] > 0,
                  ['gameid', 'player_id', 'pass_yards', 'pass_tds']]
           .set_index(['gameid', 'player_id']))
```

And want to concatenate all three at once:

```
In [6]: pd.concat([rush_df, rec_df, pass_df], axis=1).head()
Out[6]:
                       rush_yards  rush_tds  ...  pass_yards  pass_tds
gameid     player_id                          ...
2017090700 00-0019596         NaN       NaN  ...       267.0       0.0
           00-0023436         9.0       0.0  ...       368.0       4.0
           00-0026035         NaN       NaN  ...         NaN       NaN
           00-0030288        15.0       0.0  ...         NaN       NaN
           00-0030506         4.0       0.0  ...         NaN       NaN
```

Like most Pandas functions, `concat` takes an `axis` argument. When you pass `axis=1`, `concat` sticks the DataFrames together side by side horizontally. Both `merge` and `concat` with `axis=1` provide similar functionality. I usually stick with `merge` for straightforward, two DataFrame joins since it's more powerful, and use `concat` if I need to combine more than two DataFrames.

When `axis=1`, you can tell `concat` how to handle mismatched observations using the `join` argument. Options are `'inner'` (the default) or `'outer'`. Unlike `merge` there's no `'left'` or `'right'` option, which makes sense because `concat` has to handle more than two DataFrames.

Combining DataFrames Vertically

When `axis=0` (which it is by default), `concat` sticks the DataFrames together on top of each other, like a snowman. Importantly, `concat` is the *only* way to do this. There's no `axis` equivalent in `merge`.

Let's pick up at line 110 in `03_05_combine.py` (after we've loaded our ADP data) to try it out. We'll make QB and RB only DataFrames:

```
In [1]: qbs = adp.loc[adp['position'] == 'QB']

In [2]: rbs = adp.loc[adp['position'] == 'RB']
```

We can see these DataFrames are 21 and 62 rows respectively:

```
In [3]: qbs.shape
Out[3]: (21, 11)

In [4]: rbs.shape
Out[4]: (62, 11)
```

Now let's use `pd.concat` (with its default `axis=0`) to stack these on top of each other. The resulting DataFrame should be `21 + 62 = 83` rows.

```
In [5]: pd.concat([qbs, rbs]).shape
Out[5]: (83, 11)
```

Perfect.

In this case, we *know* qbs and rbs don't have any index values in common (because we just created them using loc, which keeps original index), but often that's not the case.

For example, let's reset the indexes on both of these.

```
In [6]: qbs_reset = qbs.reset_index()

In [7]: rbs_reset = rbs.reset_index()
```

That resets each index to the default 0, 1, … etc. So now qbs_reset looks like this:

```
In [8]: qbs_reset.head()
Out[8]:
    adp  adp_formatted  ... stdev  team times_drafted
0  23.4           2.11  ...   6.1    GB           200
1  29.6           3.06  ...   5.8    NE           193
2  41.7           4.06  ...   8.7    NO           170
3  56.4           5.08  ...   7.8   ATL           110
4  64.3           6.04  ...   7.5   SEA           111
```

And when we concatenate qbs_reset and rbs_reset we get:

```
In [9]: pd.concat([qbs_reset
            rbs.reset_index()]).sort_index().head()
Out[9]:
    adp  adp_formatted   ...   position stdev  team times_drafted
0  23.4           2.11   ...         QB   6.1    GB           200
0   1.3           1.01   ...         RB   0.6   ARI           310
1  29.6           3.06   ...         QB   5.8    NE           193
1   2.3           1.02   ...         RB   0.8   PIT           303
2  41.7           4.06   ...         QB   8.7    NO           170
```

Now our index has duplicates — one 0 from our QB DataFrame, another from the RB DataFrame, etc. Pandas will technically let us do this, but it's probably not what we want. The solution is to pass ignore_index=True to concat:

```
In [10]:
(pd.concat([qbs.reset_index(), rbs.reset_index()], ignore_index=True)
 .sort_index()
 .head())

Out[10]:
    adp  adp_formatted  ...  position stdev  team times_drafted
0  23.4           2.11  ...        QB   6.1    GB           200
1  29.6           3.06  ...        QB   5.8    NE           193
2  41.7           4.06  ...        QB   8.7    NO           170
3  56.4           5.08  ...        QB   7.8   ATL           110
4  64.3           6.04  ...        QB   7.5   SEA           111
```

Review

In this section we learned about combining DataFrames. We first covered `pd.merge` for joining two DataFrames with one or more columns in common. We talked about specifying those columns in the `on`, `left_on` and `right_on` arguments, and how to control what we do with unmatched observations by setting how equal to `'inner'`, `'outer'`, `'left'` or ’`'right'`.

We also talked about `pd.concat` and how the default behavior is to stick two DataFrames on top of each other (optionally setting `ignore_index=True`). We covered how `pd.concat` can let you combine two or more DataFrames with the same index left to right via the `axis=1` keyword.

Let’s wrap up with a quick summary of the differences between `concat` and `merge`.

`merge`

- usually what you’ll use when you need to combine two DataFrames horizontally
- combines *two* DataFrames per `merge` (you can do more by calling `merge` multiple times)
- *only* combines DataFrames horizontally
- let’s you combine DataFrames with different indexes
- is more flexible in handling unmatched observations

`concat`

- the *only* way to stack DataFrames vertically on top of each other
- combines *any number* of DataFrames
- can combine horizontally (`axis=1`) *or* vertically (`axis=0`)
- *requires* every DataFrame has the same index
- let’s you keep observations in *all* DataFrames (`join='inner'`) or observations in *any* DataFrame (`join='outer'`)

Exercises

3.5.1

a) Load the three datasets in in `./data/problems/combine1/`.

They contain touch (carries and receptions), yardage (rushing and receiving), and touchdown (rushing and receiving) data.

Combine them: b) using `pd.merge`. c) using `pd.concat`.

Note players are only in the touchdown data if they got at least one rushing or receiving touchdowns. Make sure your final combined data includes all players, even if they didn't score any touchdowns. If a player didn't score a touchdown, make sure number of rushing and receiving touchdowns are set to 0.

d) Which do you think is better here, `pd.merge` or `pd.concat`?

3.5.2

a) Load the four datasets in in `./data/problems/combine2/`. It contains the same data, but split "vertically" by position instead of horizontally.

b) Combine them.

3.5.3.

a) Load the ADP data.

b) Write a two line for loop to save subsets of the ADP data frame for each position to the `DATA_DIR` .

c) Then using `pd.concat` and list comprehensions, write one line of Python that loads these saved subsets and combines them.

4. SQL

Introduction to SQL

This section is on **databases** and **SQL**, which cover the second (storing data) and third (loading data) sections of our high level data analysis process respectively.

They're in one chapter together because they go hand in hand (that's why they're sometimes called *SQL databases*): once you have data in a database, SQL — a mini programming language that is separate from Python — is how you get it out. Similarly, you can't *use* SQL unless you have a database to use it *on*.

This chapter might seem redundant given we've been storing and loading data already: the book came with some csv files, which we've already read into Pandas. What advantages do databases and SQL give us over that? Let's start there.

How to Read This Chapter

This chapter — like the rest of the book — is heavy on examples. All the examples in this chapter are included in the Python file `04_sql.py`. Ideally, you would have this file open in your Spyder editor and be running the examples (highlight the line(s) you want and press F9 to send it to the REPL/console) as we go through them in the book.

Databases

Why do we need databases — can't we just store all our data in one giant spreadsheet?

The main issue with storing everything in a single spreadsheet is that things can get unwieldy very quickly. For example, say we're building a model to project weekly fantasy points. This data is at the player and week level, but we might want to include less granular data — information about the *player* (position, years in league, height) or *game* (home or away, weather).

When it comes time to actually run the model, we'll want all those values filled in for every row, but there's no reason we need to *store* the data that way.

Think about it: a player's position (usually) and number of years in the league stay the same every week, and whether they're home or away is the same for every player playing in a given game. Instead of one giant table, it would be more efficient to store this data as:

- One player table with just name, team, position, height, weight, year they came in the league.
- One game table with week, home and away team.
- Another player-game table with ONLY the things that vary at this level: points, yards, number of touchdowns, etc.

In each one we would want an id column — i.e. the player table would have a "player id", the game table a "game id", and the player-game table both player and game id — so we could link them back together when it's time to run our model.

This process of storing the minimal amount of information necessary is called **normalizing** your data. There are at least two benefits:

First, storing data in one place makes it easier to update it. For example, what if our initial dataset incorrectly had the home and away teams wrong for Week 1, Chicago vs Green Bay. If that information is in a single games table, we can fix it there, rerun our code, and have it propagate through our analysis. That's preferable to having it stored on multiple rows in multiple tables, all of which would need to be fixed.

This applies to code as well as data. There's a programming saying, "don't repeat yourself" (abbreviated DRY). It's easier to change things in one spot than all over, which is why we use variable constants and reusable functions in our code.

The other advantage is a smaller storage footprint. Storage space isn't as big of a deal as it has been in the past, but data can get unwieldy. Take our play-by-play data; right now we have mostly play-specific information in there (the down, time left, how many yards it went for, pass or run). But imagine if we had to store every single thing we might care about — player height, weight, where they went to college, etc — on every single line.

It's much better to keep what varies by play in the play data, then link it up to other data when we need it.

OK, so everything in one giant table isn't ideal, but what about just storing each table (play, game, player-game etc) in its own csv file. Do things really need to be in a SQL database?

Multiple csv files is better than one giant csv, and honestly I don't care if you want to do it this way (I do it myself for quick, smaller projects). However, it does mean loading your data in Pandas, and *then* doing your merging there. That's fine, but joining tables is what SQL is good at. It's why they're called *relational databases*, they keep track of relationships between data.

The other thing is SQL is good at is letting you pick out individual columns and just the data you need. In Pandas that would be another extra step.

Finally, it doesn't matter that much for the size of the datasets we'll be working with, but it can be easier using SQL (or SQL-like tools) for very large datasets.

SQL Databases

SQL database options include Postgres, SQLite, Microsoft SQL Server, and MySQL, among others. Postgres is open source and powerful, and you might want to check it out if you're interested in going beyond this chapter.

Many databases can be complicated to set up and deal with. All of the above require installing a database *server* on your computer (or on another computer you can connect to), which runs in the background, interprets the SQL code you send it, and returns the results.

The exception is SQLite, which requires no server and just sits as a file on disk. There whatever analysis program you're using can access it directly. Because it's more straight forward, that's what we'll use here.

A Note on NoSQL

Sometimes you'll hear about NoSQL databases, the most common of which is MongoDB. We won't be using them, but for your reference, NoSQL databases are databases that store data as (nested) "documents" similar to Python's dictionaries. This dictionary-like data format is also called JSON (JavaScript object notation).

NoSQL databases are flexible and can be good for storing information suited to a tree-like structure. They also can be more performant in certain situations. But in modeling we're more interested in structured data in table shapes, so SQL databases are much more common.

SQL

SQL is short for Structured Query Language. I always pronounce it "sequal", but some people say the full "S-Q-L". It's not really a fully featured programming language, more of a simple way to describe data you want to load from a database.

It's also important to note SQL is its own thing, *not* part of Python. We'll be using it with Pandas and inside Python, but that's not necessary. Other languages have their own way of interacting with SQL, and some people do most of their work in SQL itself.

Pandas

While pretty much everything you can do in SQL you can also do in Pandas, there are a few things I like leaving to SQL. Mainly: initial loading; joining multiple tables; and selecting columns from raw data.

In contrast, though SQL does offer some basic column manipulation and grouping functionality, I seldom use it. Generally, Pandas is so powerful and flexible when it comes to manipulating columns and grouping data that I usually just load my data into it and do it there[1]. Also, though SQL has some syntax for updating and creating data tables, I also usually handle writing to databases inside Pandas.

But SQL is good for loading (not necessarily modifying) and joining your raw, initial, normalized tables. Its also OK for filtering, e.g. if you want to only load RB data or just want to look at a certain week.

There are a few benefits to limiting SQL to the basics like this. One is that SQL dialects and commands can change depending on the database you're using (Postgres, SQLite, MS SQL, etc), but most of the basics are the same.

Another benefit: when you stick to the basics, learning SQL is pretty easy and intuitive.

Creating Data

Remember, SQL and databases go hand-in-hand, so to be able to write SQL we need a database to practice on. Let's make one using SQLite, which is the simplest to set up.

The following code (1) creates an empty SQLite database, (2) loads the csv files that came with this book, and (3) puts them inside our database.

It relies on the `sqlite3` library, which is included in Anaconda. This code is in `04_sql.py`.

[1] One exception: SQL can be more memory efficient if your data is too large to load into Pandas, but that usually isn't a problem with the medium sized football datasets we'll be using.

```
import pandas as pd
from os import path
import sqlite3

# handle directories
DATA_DIR = '/Users/nathan/fantasybook/data'

# create connection
conn = sqlite3.connect(path.join(DATA_DIR, 'fantasy.sqlite'))

# load csv data
player_game = pd.read_csv(path.join(DATA_DIR, 'game_data_sample.csv'))
player = pd.read_csv(path.join(DATA_DIR, 'game_data_player_sample.csv'))
game = pd.read_csv(path.join(DATA_DIR, 'game_2017_sample.csv'))
team = pd.read_csv(path.join(DATA_DIR, 'teams.csv'))

# and write it to sql
player_game.to_sql('player_game', conn, index=False, if_exists='replace')
player.to_sql('player', conn, index=False, if_exists='replace')
game.to_sql('game', conn, index=False, if_exists='replace')
team.to_sql('team', conn, index=False, if_exists='replace')
```

You only have to do this once. Now we have a SQLite database with data in it.

Queries

SQL is written in **queries**, which are just instructions for getting data out of your database.

Every query has at least this:

```
SELECT <...>
FROM <...>
```

where in `SELECT` you specify the names of columns you want (`*` means all of them), and in `FROM` you're specifying the names of the tables.

So if you want all the columns from your teams table, you'd do:

```
SELECT *
FROM teams
```

Though not required, a loose SQL convention is to put keywords like SELECT and FROM in uppercase, as opposed to particular column or table names in lowercase.

Because the job of SQL is to get data into Pandas so we can work with it, we'll be writing all of our SQL within Pandas, i.e.:

```
In [1]:
df = pd.read_sql(
    """
    SELECT *
    FROM player
    """, conn)
```

The SQL query is written inside a Python string and passed to the Pandas `read_sql` method. I like writing my queries inside of multi-line strings, which start and end with three double quotation marks. In between you can put whatever you want and Python treats it like one giant string. In this, `read_sql` requires the string be valid SQL code, and will throw an error if it's not.

The first argument to `read_sql` is this query string; the second is the connection to your SQLite database. You create this connection by passing the location of your database to the `sqlite3.connect` method.

Calling `read_sql` returns a DataFrame with the data you asked for.

```
In [2]: df.head()
Out[2]:
    player_id  season team pos player_name
0  00-0031359    2017  BUF  WR  K.Benjamin
1  00-0028116    2017   SF  WR  A.Robinson
2  00-0031390    2017   TB  RB      C.Sims
3  00-0031228    2017  ATL  WR   T.Gabriel
4  00-0031382    2017  MIA  WR    J.Landry
```

In the example file, you'll notice this is how we run all of the queries in this chapter (i.e., as strings inside `read_sql`). And you should stick to that as you run your own queries and work through the book.

However, because the `pd.read_sql( ..., conn)` is the same every time, I'm going to leave it (as well as the subsequent call to `head` showing what it returns) off for the rest of examples in this chapter. Hopefully that makes it easier to focus on the SQL code.

Just remember, to actually run these yourself, you have to pass these queries to sqlite via Python. To actually view what you get back, you need to call `head`.

What if we want to modify the query above to only return a few columns?

In [3]:

```
SELECT player_id, player_name AS name, pos
FROM player
```

Out [3]:

```
    player_id         name pos
0  00-0031359  K.Benjamin  WR
1  00-0028116  A.Robinson  WR
2  00-0031390      C.Sims  RB
3  00-0031228   T.Gabriel  WR
4  00-0031382    J.Landry  WR
```

You just list the columns you want and separate them by commas. Notice the `player_name AS name` part of the `SELECT` statement. Though column is stored in the database as `player_name`, we're renaming it to `name` on the fly, which can be useful.

Filtering

What if we want to *filter* our rows, say — only get back Miami players? We need to add another clause, a `WHERE`:

In [4]:

```
SELECT player_id, player_name AS name, pos
FROM player
WHERE team = 'MIA'
```

Out [4]:

```
    player_id       name pos
0  00-0031382  J.Landry  WR
1  00-0033118   K.Drake  RB
2  00-0031609   A.Derby  TE
3  00-0031547  D.Parker  WR
```

A few things to notice here. First, note the single equals sign. Unlike Python, where = is assignment and == is testing for equality, in SQL just the one = tests for equality. Even though we're writing this query inside a Python string, we still have to follow SQL's rules.

Also note the single quotes around `'MIA'`. Double quotes won't work.

Finally, notice we're filtering on `team` (i.e. we're choosing which rows to return depending on the value they have for `team`), even though it's not in our `SELECT` statement. That's fine. We could include it if we wanted (in which case we'd have a column `team` with `'MIA'` for every row), but we don't have to.

We can use logic operators like `OR` and `AND` in our `WHERE` clause too.

In [5]:

```
SELECT player_id, player_name AS name, pos
FROM player
WHERE team = 'MIA' AND pos == 'WR'
```

Out [5]:

```
    player_id      name pos
0  00-0031382  J.Landry  WR
1  00-0031547  D.Parker  WR
```

In [6]:

```
SELECT player_id, player_name AS name, pos, team
FROM player
WHERE team = 'MIA' OR team == 'NE'
```

Out [6]:

```
    player_id      name pos team
0  00-0031382  J.Landry  WR  MIA
1  00-0033118   K.Drake  RB  MIA
2  00-0031609   A.Derby  TE  MIA
3  00-0028087   D.Lewis  RB   NE
4  00-0019596   T.Brady  QB   NE
```

That last query could also be rewritten as:

```
SELECT player_id, player_name AS name, pos, team
FROM player
WHERE team IN ('MIA', 'NE')
```

SQL also allows negation:

In [7]:

```
SELECT player_id, player_name AS name, pos, team
FROM player
WHERE team NOT IN ('MIA', 'NE')
```

Out [7]:

```
    player_id        name pos team
0  00-0031359  K.Benjamin  WR  BUF
1  00-0028116  A.Robinson  WR   SF
2  00-0031390      C.Sims  RB   TB
3  00-0031228   T.Gabriel  WR  ATL
4  00-0032209    T.Yeldon  RB  JAX
```

Joining, or Selecting From Multiple Tables

SQL is also good at combining multiple tables. Say we want to see a list of players (in the `player` table) and the division they play in (in the `team` table).

We might try adding a new table to our `FROM` clause like this:

In [8]:

```
SELECT
    player.player_name as name,
    player.pos,
    player.team,
    team.conference,
    team.division
FROM player, team
```

Note we now pick out the columns we want from each table using the `table.column_name` syntax.

But there's something weird going on here. Look at the first 10 rows of the table:

Out [8]:

```
         name pos team conference division
0  K.Benjamin  WR  BUF        NFC     West
1  K.Benjamin  WR  BUF        NFC    South
2  K.Benjamin  WR  BUF        AFC    North
3  K.Benjamin  WR  BUF        AFC     East
4  K.Benjamin  WR  BUF        NFC    South
5  K.Benjamin  WR  BUF        NFC    North
6  K.Benjamin  WR  BUF        AFC    North
7  K.Benjamin  WR  BUF        AFC    North
8  K.Benjamin  WR  BUF        NFC     East
9  K.Benjamin  WR  BUF        AFC     West
```

It's all Kelvin Benjamin, and he's in every division.

The problem is we haven't told SQL how the `player` and `team` tables are related.

When you don't include that information, SQL doesn't try to figure it out or complain and give you an error. Instead it returns a cross join, i.e. *every* row in the `player` table gets matched up with *every* row in the `team` table.

In this case we have two tables: `(1)` `player`, and `(2)` `team`. So we have our first row (`K.Benjamin`, `WR`, `BUF`) matched up with the first division in the team table (`NFC West`); then the second (`NFC South`), and so on.

To make it even clearer, let's add in the `team` column from the `team` table too.

In [9]:

```
SELECT
    player.player_name as name,
    player.pos,
    player.team as player_team,
    team.team as team_team,
    team.conference,
    team.division
FROM player, team
```

Out [9]:

```
         name pos player_team team_team conference division
0  K.Benjamin  WR         BUF       ARI        NFC     West
1  K.Benjamin  WR         BUF       ATL        NFC    South
2  K.Benjamin  WR         BUF       BAL        AFC    North
3  K.Benjamin  WR         BUF       BUF        AFC     East
4  K.Benjamin  WR         BUF       CAR        NFC    South
5  K.Benjamin  WR         BUF       CHI        NFC    North
6  K.Benjamin  WR         BUF       CIN        AFC    North
7  K.Benjamin  WR         BUF       CLE        AFC    North
8  K.Benjamin  WR         BUF       DAL        NFC     East
9  K.Benjamin  WR         BUF       DEN        AFC     West
```

This makes it clear it's a cross join — every line for Kelvin Benjamin (and also every other player once Benjamin is done) is getting linked up with every team in the `team` table.

Since we have a 100 row player table and 32 row team table, that means we should get back `100*32 = 3200` rows. Sure enough:

```
In [10]: df.shape
Out[10]: (3200, 6)
```

What if we added a third table, say a `conference` table with two rows: one for NFC, one for AFC. In that case, each of these 3,200 rows in the table above gets matched yet again with *each* of the two rows in the `conference` table. In other words, our table is `100*32*2 = 6400` rows.

This is almost never what we want[2] (in fact an inadvertent cross join is something to watch out for if a query is taking way longer to run than it should) but it's useful to think of the `FROM` part of a multi-table SQL query as doing cross joins initially.

But we're not interested in a full cross join and getting back a row where Kelvin Benjamin plays in the NFC North, so we have specify a `WHERE` clause to filter and keep only the rows that make sense.

In [11]:

[2] Can you think of a time when it would be what you want? I can think of one: if you had a table of teams, and another of weeks 1-17 and wanted to generate a schedule so that every team had a line for every week. That's it though.

```
SELECT
    player.player_name as name,
    player.pos,
    player.team,
    team.conference,
    team.division
FROM player, team
WHERE player.team = team.team
```

Out [11]:

```
         name pos team conference division
0  K.Benjamin  WR  BUF        AFC     East
1  A.Robinson  WR   SF        NFC     West
2      C.Sims  RB   TB        NFC    South
3   T.Gabriel  WR  ATL        NFC    South
4    J.Landry  WR  MIA        AFC     East
```

Let's walk through it:

First, SQL is doing the full cross join (with 3200 rows).

Then we have a `WHERE`, so we're saying after the cross join give us *only* the rows where the column `team` from the `players` table matches the column `team` from the `team` table. We go from having 32 separate rows for Kelvin Benjamin, to only the one row — where his team in the `player` table (`BUF`) equals `BUF` in the `team` table.

That gives us a table of 100 rows — the same number of players we originally started with — and includes the conference and division info for each.

Again, adding in the `team` column from table team makes it more clear:

In [12]:

```
SELECT
    player.player_name as name,
    player.pos,
    player.team as player_team,
    team.team as team_team,
    team.conference,
    team.division
FROM player, team
WHERE player.team = team.team
```

Out [12]:

```
         name pos player_team team_team conference division
0  K.Benjamin  WR         BUF       BUF        AFC     East
1  A.Robinson  WR          SF        SF        NFC     West
2      C.Sims  RB          TB        TB        NFC    South
3   T.Gabriel  WR         ATL       ATL        NFC    South
4    J.Landry  WR         MIA       MIA        AFC     East
```

I first learned about this cross join-then WHERE framework of conceptualizing SQL queries from the book, The Essence of SQL by David Rozenshtein. It's a great book, but out of print and going for $125 (as a 119 page paperback) on Amazon as of this writing. It covers more than just cross join-WHERE, but we can use Pandas for most of the other stuff. If you want you can think about this section as The Essence of The Essence of SQL.

What if we want to add a third table? We just need to add it to FROM and update our WHERE clause.

In [13]:

```
SELECT
    player.player_name as name,
    player.pos,
    team.team,
    team.conference,
    team.division,
    player_game.*
FROM player, team, player_game
WHERE
    player.team = team.team AND
    player_game.player_id = player.player_id
```

Out [13]:

```
         name  pos  team conference division      gameid   player_id ...
0  K.Benjamin   WR   BUF        AFC     East  2017091011  00-0031359 ...
1  K.Benjamin   WR   BUF        AFC     East  2017091701  00-0031359 ...
2  K.Benjamin   WR   BUF        AFC     East  2017092402  00-0031359 ...
3  K.Benjamin   WR   BUF        AFC     East  2017100107  00-0031359 ...
4  K.Benjamin   WR   BUF        AFC     East  2017100802  00-0031359 ...
```

This is doing the same as above (`player` + `team` tables) but also combining it with data from `player_games`. Note, that if we had left off our WHERE clause, SQL would have done a full, three table `player*team*player_game` cross join. Kelvin Benjamin would be matched with each division, then each of *those* rows would be matched with every row from the player-game table, giving us a `100*32*716=2,291,200` row result.

Also note the `player_games.*` syntax. This gives us all the columns from that table.

Sometimes table names can get long and unwieldy, especially when working with multiple tables. We could also write above as:

```
SELECT
    p.player_name as name,
    p.pos,
    t.team,
    t.conference,
    t.division,
    pg.*
FROM player AS p, team AS t, player_game AS pg
WHERE
    p.team = t.team AND
    pg.player_id = p.player_id
```

We just specify the full names once (in `FROM`), then add an alias with `AS`. Then in the `SELECT` and `WHERE` clauses we can use the alias instead.

Combing Joining and Other Filters

We can also add in other filters, e.g. maybe we want this same query but only the RBs:

```
SELECT
    p.player_name as name,
    p.pos,
    t.team,
    t.conference,
    t.division,
    pg.*
FROM player AS p, team AS t, player_game AS pg
WHERE
    p.team = t.team AND
    pg.player_id = p.player_id AND
    p.pos == 'RB'
```

Misc SQL

The basics of `SELECT`, `FROM` and `WHERE` plus the cross join-then filter way of conceptualizing joins + the fact you're leaving the other parts of SQL to Pandas should make learning SQL straightforward.

But there are a few additional minor features that can be useful and sometimes come up.

LIMIT/TOP

Sometimes want to make sure a query works and see what columns you get back before you just run the whole thing.

In that case you can do:

```
SELECT *
FROM player
LIMIT 5
```

Which will return the first five rows. Annoyingly, the syntax for this is something that changes depending on the database you're using, for Microsoft SQL Server it'd be:

```
SELECT TOP 5 *
FROM player
```

DISTINCT

Including `DISTINCT` right after `SELECT` drops duplicate observations.

For example, maybe we want to see a list of all the different calendar days NFL games were on.

In [14]:

```
SELECT DISTINCT season, week, date
FROM game
```

Out [14]

```
   season  week        date
0    2017     1  2017-09-07
1    2017     1  2017-09-10
2    2017     1  2017-09-11
3    2017     2  2017-09-14
4    2017     2  2017-09-17
```

UNION

`UNION` lets you stick data on top of each other to form one table. It's similar to `concat` with `axis=0` in Pandas.

Above and below `UNION` are two separate queries, and both queries *have* to return the same columns in their `SELECT` statements.

So maybe I want to do an analysis over the past two years and the data I'm inheriting is in separate tables. I might do:

```
SELECT *
FROM player_data_2018
UNION
SELECT *
FROM player_data_2019
```

Subqueries

Previously, we've seen how we can do `SELECT ... FROM table_name AS abbreviation`. In a subquery, we replace `table_name` with another, inner `SELECT ... FROM` query and wrap it in parenthesis.

LEFT, RIGHT, OUTER JOINS

You may have noticed our mental cross join-then `WHERE` framework can only handle inner joins. That is, we'll only keep observations in *both* tables. But this isn't always what we want.

For example, maybe we want 16 rows (one for each game) for every player, regardless of whether they played in every game. In that case we'd have to do a **left join**, where our left table is a full 16 rows for every player, and our right table is games they actually played. The syntax is:

```
SELECT *
FROM <left_table>
LEFT JOIN <right_table>
ON <left_table>.<common_column> = <right_table>.<common_column>
```

SQL Example — LEFT JOIN, UNION, Subqueries

I find left and right joins in SQL less intuitive than the cross join-then `WHERE` framework, and do most of my non-inner joins in Pandas. But writing this full, one row-for-every-game and player query using the tables we have does require using some of these miscellaneous concepts (unions and subqueries), so it might be useful to go through this as a final example.

Feel free to skip if you don't envision yourself using SQL that much and are satisfied doing this in Pandas.

This query gives us rushing and receiving yards and TDs for every player and game in our database, whether the player actually suited up or not. We'll walk through it below:

```
1  SELECT a.*, b.rec_yards, b.rush_yards, b.rec_tds, b.rush_tds
2  FROM
3      (SELECT
4          game.season, week, gameid, home as team, player_id,
5          player_name
6      FROM game, player
7      WHERE game.home = player.team
8      UNION
9      SELECT
10         game.season, week, gameid, away as team, player_id,
11         player_name
12     FROM game, player
13     WHERE game.away = player.team) AS a
14 LEFT JOIN player_game AS b
15 ON a.gameid = b.gameid AND a.player_id = b.player_id
```

Let's go through it. First, we need a full set of 16 rows for every player. We do that in a subquery (lines 3-13) and call the resulting table `a`.

This subquery involves a `UNION`, let's look at the top part (lines 3-7).

```
SELECT game.season, week, gameid, home as team, player_id,
       player_name
FROM game, player
WHERE game.home = player.team
```

Remember, the first thing SQL is doing when we query `FROM game` and `player` is a full cross join, i.e. we get back a line for *every* player in *every* game. So, after the `game`, `player` cross join here, not only is there a line for Aaron Rodgers, week 1, Green Bay vs Seattle, but there's a line for Aaron Rogers, week 1, Kansas City at New England too.

This is way more than we need. In the case of Aaron Rodgers, we want to filter the rows to ones where one of the teams is Green Bay. We do that in our `WHERE` clause. This is all review from above.

The problem is our `game` table is by week, not team and week. If it were the latter, GB-SEA week 1 would have *two* lines, one for Green Bay, one for Seattle. Instead it's just the one line, with Green Bay in the `home` field, Seattle in `away`.

```
        gameid        date home away  season  week
11  2017091010  2017-09-10   GB  SEA    2017     1
0   2017090700  2017-09-07   NE   KC    2017     1
1   2017091000  2017-09-10  BUF  NYJ    2017     1
2   2017091008  2017-09-10  WAS  PHI    2017     1
3   2017091007  2017-09-10  TEN  OAK    2017     1
```

What this means is, to match up Aaron Rodgers to only the Green Bay games, we're going to have to run this part of the query twice: once when Green Bay is home, another time when Green Bay is away, then stick them together with a UNION clause

That's what we're doing here:

```
SELECT game.season, week, gameid, home as team, player_id, player_name
FROM game, player
WHERE game.home = player.team
UNION
SELECT game.season, week, gameid, away as team, player_id, player_name
FROM game, player
WHERE game.away = player.team
```

Above the UNION gives us a line for every player's home games (so 8 per player), below a line for every away game. Stick them on top of each other and we have what we want.

It's all in a subquery, which we alias as a. So once you understand that, you can ignore it and mentally replace everything in parenthesis with full_player_by_week_table if you want.

In fact, let's do that, giving us:

```
SELECT a.*, b.rec_yards, b.rush_yards, b.rec_tds, b.rush_tds
FROM
    full_player_by_week_table AS a
LEFT JOIN
    player_game AS b ON
        a.gameid = b.gameid AND
        a.player_id = b.player_id
```

From there it's the standard left join syntax: LEFT JOIN table_name ON ...

And the result

```
In [15]: df.loc[df['player_name'] == 'M.Sanu']
Out[15]:
     season  week player_name  rec_yards  rush_yards  rec_tds  rush_tds
7      2017     1      M.Sanu       47.0         0.0      0.0       0.0
89     2017     2      M.Sanu       85.0         0.0      0.0       0.0
110    2017     3      M.Sanu       27.0         0.0      1.0       0.0
152    2017     4      M.Sanu        3.0         4.0      0.0       0.0
243    2017     6      M.Sanu        NaN         NaN      NaN       NaN
324    2017     7      M.Sanu       65.0         0.0      0.0       0.0
350    2017     8      M.Sanu       74.0         0.0      1.0       0.0
373    2017     9      M.Sanu       23.0         0.0      1.0       0.0
443    2017    10      M.Sanu       29.0         0.0      0.0       0.0
495    2017    11      M.Sanu       34.0         3.0      1.0       0.0
503    2017    12      M.Sanu       64.0         0.0      0.0       0.0
552    2017    13      M.Sanu       54.0         0.0      0.0       0.0
600    2017    14      M.Sanu       83.0         0.0      1.0       0.0
721    2017    16      M.Sanu       31.0         0.0      0.0       0.0
747    2017    17      M.Sanu       83.0         0.0      1.0       0.0
```

Mohamed Sanu missed game 6 in 2017, yet we still have a row for him. So this is returning what we'd expect.

End of Chapter Exercises

4.1a

Using the same sqlite database we were working with in this chapter, use SQL to make a DataFrame that's only AFC QBS with the following columns:

`season`, `week`, `player_name`, `team`, `attempts`, `completions`, `pass_yards`, `pass_tds`, `interceptions`

Since we know we're only dealing with QBs, rename `pass_yards` and `pass_tds` to just `yards` and `tds`.

4.1b

Now pretend your data is normalized and `player_game` doesn't have the `team`, `pos` or `player_name` columns. How do you have to modify your query to get the same result as in (a)? Use abbreviations too (`t` for the team table, `pg` for `player_game`, etc).

4.2

Using the same sqlite database, make a DataFrame that's the same as the `game` table, with two new columns: `home_mascot` and `away_mascot`.

Hint: you can include the same table multiple separate times in your `FROM` statement as long as you use a different alias for it each time.

5. Web Scraping and APIs

Introduction to Web Scraping and APIs

This chapter is all about the first section of the high level pipeline: collecting data. Sometimes you'll find structured, ready-to-consume tabular data directly available in a spreadsheet or a database. Other times you have to get it yourself.

Here we'll learn how to write programs that grab data for you. There are two situations where these programs are especially useful.

The first is when you want to take regular snapshots of data that's changing over time. For example, you could write a program that gets the current weather at every NFL stadium and run it every week.

Second is when you need to grab a lot of data at once. Scrapers scale really well. You want annual fantasy point leaders by position for the past 10 years? Write a function that's flexible enough to get this data given some position and year. Then run it 60 times (10 years * 6 positions — QB, RB, WR, TE, K, DST). Copying and pasting that much data would be slow, tedious and error prone.

This chapter covers two ways to get data: web scraping and APIs.

Web Scraping

Most websites — including websites with data — are designed for human eyeballs. A web scraper is a program built to interact with and collect data from these sites. Once they're up and running, you usually can run them without visiting the site in your browser.

HTML and CSS

Building web scrapers involves understanding basic HTML + CSS, which — along with JavaScript — is most of the code behind websites today. We'll focus on the minimum required for scraping. So while this section won't teach you how to build your own site, it will make getting data a lot easier.

HTML is a *markup* language, which means it includes both the content you see on the screen (the text) along with built in instructions (the markup) for how the browser should show it.

These instructions come in **tags**, which are wrapped in arrow brackets (<>) and look like this:

```
<p>
<b>
<div>
```

Most tags come in pairs, e.g. a starting tag of <p> and an ending tag </p>. We say any text in between is *wrapped* in the tags. For example, the `p` tag stands for paragraph and so:

```
<p>This text is a paragraph.</p>
```

Tags themselves aren't visible to regular users, though the text they wrap is. You can view the HTML tags on a website by right clicking in your browser and selecting 'view source'.

Tags can be nested. The `i` tag stands for italics, and so:

```
<p><i>This part</i> of the paragraph is in italics.</p>
```

Tags can also have one or more *attributes*, which are just optional data and are also invisible to the user. Two common attributes are `id` and `class`:

```
<p id="intro">This is my intro paragraph.</p>
<p id="2" class="main-body">This is is my second paragraph.</p>
```

These ids and classes are there so web designers can specify — separately in a **CSS file** — more rules about how things should look. Maybe the CSS file says intro paragraphs are a larger font. Or paragraphs with the class "main-body" get a different color, etc.

As scrapers, we don't care how things look, and we don't care about CSS itself. But these tags, ids, and classes are a good way to tell our program which parts of the website to scrape, so it's useful to know what they are.

Common HTML tags include:

p paragraph

div this doesn't really do anything directly, but they're a way for web designer's to divide up their HTML however they want to assign classes and ids to particular sections

table tag that specifies the start of a table

th header in a table

tr denotes table row

td table data

a link, always includes the attribute `href`, which specifies where the browser should go when you click on it

HTML Tables

As analysts, we're usually interested in tabular data, so it's worth exploring HTML tables in more detail.

Tables are good example of nested HTML. Everything is between `table` tags. Inside those, `tr`, `td` and `th` tags denote rows, columns and header columns respectively.

So if we had a table with weekly fantasy points, the HTML for the first two rows (plus the header) might look something like this:

```
<html>
  <table>
    <tr>
     <th>Name</th>
     <th>Pos</th>
     <th>Week</th>
     <th>Pts</th>
    </tr>
    <tr>
     <td>Todd Gurley</td>
     <td>RB</td>
     <td>1</td>
     <td>22.6</td>
    </tr>
    <tr>
     <td>Christian McCaffrey</td>
     <td>RB</td>
     <td>1</td>
     <td>14.8</td>
    </tr>
  </table>
</html>
```

Note columns (`td` and `th` elements) are always nested inside rows (`tr`).

If you were to save this code in an html file and open it in your browser you'd see:

Name	Pos	Week	Pts
Todd Gurley	RB	1	22.6
Christian McCaffrey	RB	1	14.8

Figure 0.1: Simple HTML Table

BeautifulSoup

The library BeautifulSoup (abbreviated BS4) is the Python standard for working with HTML. It lets you turn HTML tags into standard data structures like lists and dicts, which you can then put into Pandas.

Let's take our HTML from above, put it in a multi-line string, and load it into BeautifulSoup. Note the following code is in `05_01_scraping.py`, and we start from the top of the file.

```
In [1]: from bs4 import BeautifulSoup as Soup

In [2]:
table_html = """
<html>
  <table>
    <tr>
     <th>Name</th>
     <th>Pos</th>
     <th>Week</th>
     <th>Pts</th>
    </tr>
    <tr>
     <td>Todd Gurley</td>
     <td>RB</td>
     <td>1</td>
     <td>22.6</td>
    </tr>
    <tr>
     <td>Christian McCaffrey</td>
     <td>RB</td>
     <td>1</td>
     <td>14.8</td>
    </tr>
  </table>
<html>
"""

In [3]: html_soup = Soup(table_html)
```

Note we're using BeautifulSoup with a regular Python string. BS4 is a *parsing* library. It helps us take a *string* of HTML and turn it into Python data. It's agnostic about where this string comes from. Here, I wrote it out by hand and put it in a file for you. You could use BS4 on this string even if you weren't connected to the Internet, though in practice we almost always get our HTML in real time.

The key type in BeautifulSoup is called a *tag*. Like lists and dicts, tags are containers, which means they hold things. Often they hold other tags.

Once we call `Soup` on our string, *every* pair of tags in the HTML gets turned into some BS4 tag. Usually they're nested.

For example, our first *row* (the header row) is in a `tr` tag:

```
In [4]: tr_tag = html_soup.find('tr')

In [5]: tr_tag
Out[5]:
<tr>
<th>Name</th>
<th>Pos</th>
<th>Week</th>
<th>Pts</th>
</tr>

In [6]: type(tr_tag)
Out[6]: bs4.element.Tag
```

(Note: here the `find('tr')` method "finds" the first `tr` tag in our data and returns it.)

We could also have a tag object that represents the whole table.

```
In [7]: table_tag = html_soup.find('table')

In [8]: table_tag
Out[8]:
<table>
<tr>
<th>Name</th>
<th>Pos</th>
<th>Week</th>
<th>Pts</th>
</tr>
...
<tr>
<td>Christian McCaffrey</td>
<td>RB</td>
<td>1</td>
<td>14.8</td>
</tr>
</table>

In [9]: type(table_tag)
Out[9]: bs4.element.Tag
```

Or just the first `td` element.

```
In [10]: td_tag = html_soup.find('td')

In [11]: td_tag
Out[11]: <td>Todd Gurley</td>

In [12]: type(td_tag)
Out[12]: bs4.element.Tag
```

They're all tags. In fact, the whole page — all the zoomed out HTML — is just one giant `html` tag.

Simple vs Nested Tags

I've found it easiest to mentally divide tags into two types. BeautifulSoup doesn't distinguish between these, so this isn't official terminology, but it's helped me.

Simple Tags

Simple tags are BS4 tags with just text inside. No other, nested tags. Our `td_tag` above is an example.

```
In [13]: td_tag
Out[13]: <td>Todd Gurley</td>
```

On simple tags, the key attribute is `string`. This returns the data inside.

```
In [14]: td_tag.string
Out[14]: 'Todd Gurley'
```

Technically, `string` returns a BeautifulSoup string, which carries around a bunch of extra data. It's good practice to convert them to regular Python strings like this:

```
In [15]: str(td_tag.string)
Out[15]: 'Todd Gurley'
```

Nested Tags

Nested BS4 tags contain other tags. The `tr`, `table` and `html` tags above were all nested.

The most important method for nested tags is `find_all`. It takes the name of an HTML tag (`'tr'`, `'p'`, `'td'` etc) and returns all the matching sub-tags in a list.

So to find all the `th` tags in our first row:

```
In [16]: tr_tag.find_all('th')
Out[16]: [<th>Name</th>, <th>Pos</th>, <th>Week</th>, <th>Pts</th>]
```

Again, nested tags contain other tags. These sub-tags themselves can be simple or nested, but either way `find_all` is how you access them. Here, calling `find_all('th')` returned a list of three simple `th` tags. Let's call `string` to pull their data out.

```
In [17]: [str(x.string) for x in tr_tag.find_all('th')]
Out[17]: ['Name', 'Pos', 'Week', 'Pts']
```

Note the list comprehension. Scraping is another situation where basic Python comes in handy.

Other notes on `find_all` and nested tags.

First, find_all works *recursively*, which means it searches multiple levels deep. So we could find all the `td` tags in our `table`, even though they're in multiple rows.

```
In [18]: all_td_tags = table_tag.find_all('td')
```

The result is in one flat list:

```
In [19]: all_td_tags
Out[19]:
[<td>Todd Gurley</td>,
 <td>RB</td>,
 <td>1</td>,
 <td>22.6</td>,
 <td>Christian McCaffrey</td>,
 <td>RB</td>,
 <td>1</td>,
 <td>14.8</td>]
```

Second, `find_all` is a *method* that you call on a particular tag. It only searches in the tag its called on. So, while calling `table_tag.find_all('td')` returned data on Gurley *and* McCaffrey (because they're both in the table), calling `tr_tag.find_all('td')` on just the last, single row returns data for McCaffrey only.

```
In [20]: all_rows = table_tag.find_all('tr')

In [21]: first_data_row = all_rows[1]  # all_rows[0] is header

In [22]: first_data_row.find_all('td')
Out[22]: [<td>Todd Gurley</td>, <td>RB</td>, <td>1</td>, <td>22.6</td>]
```

Third, you can search multiple tags by passing `find_all` a *tuple* (for our purposes a tuple is a list with parenthesis instead of brackets) of tag names.

```
In [23]: all_td_and_th_tags = table_tag.find_all(('td', 'th'))

In [24]: all_td_and_th_tags
Out[24]:
[<th>Name</th>,
 <th>Pos</th>,
 <th>Week</th>,
 <th>Pts</th>,
 <td>Todd Gurley</td>,
 <td>RB</td>,
 <td>1</td>,
 <td>22.6</td>,
 <td>Christian McCaffrey</td>,
 <td>RB</td>,
 <td>1</td>,
 <td>14.8</td>]
```

Finally, remember `find_all` can return lists of both simple and nested tags. If you get back a simple tag, you can run `string` on it:

```
In [25]: [str(x.string) for x in all_td_tags]
Out[25]: ['Todd Gurley', 'RB', '1', '22.6', 'Christian McCaffrey', 'RB',
          '1', '14.8']
```

But if you get back a list of nested tags, you'll have to call `find_all` again.

```
In [26]: all_rows = table_tag.find_all('tr')
In [27]: list_of_td_lists = [x.find_all('td') for x in all_rows[1:]]

In [28]: list_of_td_lists
Out[28]:
[[<td>Todd Gurley</td>, <td>RB</td>, <td>1</td>, <td>22.6</td>],
 [<td>Christian McCaffrey</td>, <td>RB</td>, <td>1</td>, <td>14.8</td>]]
```

Fantasy Football Calculator ADP - Web Scraping Example

Note the examples for this section are in the file `05_02_ffc.py`. We'll pick up from the top of the file.

Let's build a scraper to get all the ADP data off fantasyfootballcalculator.com and put it in a DataFrame.

We'll start with the imports

```
from bs4 import BeautifulSoup as Soup
import requests
from pandas import DataFrame
```

Besides BeautifulSoup, we're also importing the `requests` library, which we'll use to programatically visit Fantasy Football Calculator. We're going to put our final result in a DataFrame, so we've imported that too.

After you've loaded those imports in your REPL, the first step is using `requests` to visit the URL and store the raw HTML it returns:

```
In [1]: ffc_response = requests.get('https://fantasyfootballcalculator.com
    /adp/ppr/12-team/all/2017')
```

Let's look at (part of) this HTML.

```
In [2] print(ffc_response.text)
Out[2]:

      <tr class='PK'>
        <td align='right'>178</td>
        <td align='right'>14.07</td>
        <td class="adp-player-name"><a style="color: rgb(30, 57, 72); font
           -weight: 300;" href="/players/mason-crosby">Mason Crosby</a></
           td>
        <td>PK</td>
        <td>GB</td>


          <td class="d-none d-sm-table-cell" align='right'>162.6</td>
          <td class="d-none d-sm-table-cell" align='right'>5.9</td>
          <td class="d-none d-sm-table-cell" align='right'>13.06</td>
          <td class="d-none d-sm-table-cell" align='right'>15.10</td>
          <td class="d-none d-sm-table-cell" align='right'>44</td>
          <td align='center'>

        </td>
        </tr>
```

The `text` attribute of `ffc_response` is a string with all the HTML on this page. This is just a small snippet of what we get back — there are almost 250k lines — but you get the picture.

Now let's parse it:

```
In [3]: adp_soup = Soup(ffc_response.text)
```

Remember, we can treat this top level `adp_soup` object as a giant nested tag. What do we do with nested tags? Run `find_all` on them.

We can never be 100% sure when dealing with sites that we didn't create, but looking at the page, it's probably safe to assume the data we want is on an HTML table.

Let's find all the `table` tags in this HTML.

```
In [3]: tables = adp_soup.find_all('table')
```

Remember `find_all` always returns a list. In this case a list of BS4 `table` tags. Let's check how many tables we got back.

```
In [4]: len(tables)
Out[4]: 1
```

It's just the one here, which is easy, but it's not at all uncommon for sites to have multiple tables. In that case we'd have to pick out the one we wanted from the list. Technically we still have to pick this one out, but since it's just the one it's easy.

```
In [5]: adp_table = tables[0]
```

Looking at it in the REPL, we can see it has the same `<tr>`, `<th>` and `<td>` structure we talked about above, though — being a real website — the tags have other attributes (**`class`**, `align`, `style` etc).

`adp_table` is still a nested tag, so let's run another `find_all`:

```
In [6]: rows = adp_table.find_all('tr')
```

This gives us a list of all the `tr` tags inside our table. Let's look at the first one.

```
In [7]: rows[0]
Out[7]:
<tr>
<th>#</th>
<th>[Pick](Pick)</th>
<th>Name</th>
<th>Pos</th>
<th>Team</th>
<th class="d-none d-sm-table-cell">Overall</th>
<th class="d-none d-sm-table-cell">Std.<br/>Dev</th>
<th class="d-none d-sm-table-cell">High</th>
<th class="d-none d-sm-table-cell">Low</th>
<th class="d-none d-sm-table-cell">Times<br/>Drafted</th>
<th></th>
</tr>
```

It's the header row, good. That'll be useful later for knowing what columns are what.

Now how about some data.

```
In [8]: first_data_row = rows[1]

In [9]: first_data_row
Out[9]:
<tr class="RB">
<td align="right">1</td>
<td align="right">1.01</td>
<td class="adp-player-name"><a href="/players/christian-mccaffrey" style="
   color: rgb(30, 57, 72); font-weight: 300;">Christian McCaffrey</a></td>
<td>RB</td>
<td>CAR</td>
<td align="right" class="d-none d-sm-table-cell">1.2</td>
<td align="right" class="d-none d-sm-table-cell">0.5</td>
<td align="right" class="d-none d-sm-table-cell">1.01</td>
<td align="right" class="d-none d-sm-table-cell">1.04</td>
<td align="right" class="d-none d-sm-table-cell">936</td>
<td align="center">
</td>
</tr>
```

It's the first, lowest-ADP pick — Christian McCaffrey for 2020 — nice. Note this is *still* a nested tag, so we need to use `find_all` again. The end is in site though.

```
In [10]: first_data_row.find_all('td')
Out[10]:
[<td align="right">1</td>,
 <td align="right">1.01</td>,
 <td class="adp-player-name"><a href="/players/christian-mccaffrey" style=
    "color: rgb(30, 57, 72); font-weight: 300;">Christian McCaffrey</a></
    td>,
 <td>RB</td>,
 <td>CAR</td>,
 <td align="right" class="d-none d-sm-table-cell">1.2</td>,
 <td align="right" class="d-none d-sm-table-cell">0.5</td>,
 <td align="right" class="d-none d-sm-table-cell">1.01</td>,
 <td align="right" class="d-none d-sm-table-cell">1.04</td>,
 <td align="right" class="d-none d-sm-table-cell">936</td>,
 <td align="center">
 </td>]
```

This returns a list of simple `td` tags. Now we can call `string` to get the data out.

```
In [11]: [str(x.string) for x in first_data_row.find_all('td')]
Out[11]:
['1',
 '1.01',
 'Christian McCaffrey',
 'RB',
 'CAR',
 '1.2',
 '0.5',
 '1.01',
 '1.04',
 '936',
 '\n']
```

Again note the list comprehension. Now that we've got this working, let's put it inside a function that will work on any row.

```
def parse_row(row):
    """
    Take in a tr tag and get the data out of it in the form of a list of
    strings.
    """
    return [str(x.string) for x in row.find_all('td')]
```

We have to apply `parse_row` to each row in our data. Since the first row is the header, that data is `rows[1:]`.

```
In [12]: list_of_parsed_rows = [parse_row(row) for row in rows[1:]]
```

Working with lists of lists is a pain, so let's get this into Pandas. The DataFrame constructor is pretty flexible. Let's try passing it `lists_of_parsed_rows` and seeing what happens:

```
In [13]: df = DataFrame(list_of_parsed_rows)

In [14]: df.head()
Out[14]:
   0     1                    2   3    4    5    6     7     8    9  10
0  1  1.01  Christian McCaffrey  RB  CAR  1.2  0.5  1.01  1.04  936  \n
1  2  1.03       Saquon Barkley  RB  NYG  2.5  0.7  1.01  1.06  960  \n
2  3  1.03      Ezekiel Elliott  RB  DAL  3.4  1.6  1.01  1.11  521  \n
3  4  1.05         Alvin Kamara  RB   NO  4.9  1.3  1.01  1.12  960  \n
4  5  1.06      Michael Thomas  WR   NO  5.6  1.6  1.01  1.11  811  \n
```

Great. It just doesn't have column names. Let's fix that. We could parse them, but it's easiest to just name them what we want.

```
In [15]:
df.columns = ['ovr', 'pick', 'name', 'pos', 'team', 'adp', 'std_dev',
              'high', 'low', 'drafted', 'graph']
```

We're almost there. Our one remaining issue is that all of the data is in string form, like numbers stored as text in Excel. It's an easy fix via the `astype` method.

```
In [16]: float_cols =['adp', 'std_dev']

In [17]: int_cols =['ovr', 'drafted']

In [18]: df[float_cols] = df[float_cols].astype(float)

In [19]: df[int_cols] = df[int_cols].astype(int)
```

It's debatable whether `pick`, `high` and `low` should be numbers or strings. Technically they're numbers, but I kept them strings because the decimal in draft picks (e.g. pick `1.12`) doesn't have the usual math-like interpretation.

Also let's get rid of the graph column, which we can see on the website is a UI checkbox and not real data.

```
In [23]: df.drop('graph', axis=1, inplace=True)
```

And we're done:

```
In [24]: df.head()
Out[24]:
   ovr  pick               name  ... adp  std_dev  high   low  drafted
0    1  1.01  Christian McCaffrey  ... 1.2      0.5  1.01  1.04      936
1    2  1.03       Saquon Barkley  ... 2.5      0.7  1.01  1.06      960
2    3  1.03      Ezekiel Elliott  ... 3.4      1.6  1.01  1.11      521
3    4  1.05        Alvin Kamara  ... 4.9      1.3  1.01  1.12      960
4    5  1.06      Michael Thomas  ... 5.6      1.6  1.01  1.11      811
```

There we go, we've built our first real web scraper!

Exercises

5.1.1

Put everything we did in the Fantasy Football ADP Calculator example inside a function `scrape_ffc` that takes in `scoring` (a string that's one of: 'ppr', 'half', 'std'), `nteams` (number of teams) and `year` and returns a DataFrame with the scraped data.

Your function should work on all types of scoring systems leagues, 8, 10, 12 or 14 team leagues, between 2010-2020.

Caveats:

- Fantasy Football Calculator only has half-ppr data going back to 2018, so you only need to be able to get std and ppr before that.
- All of Fantasy Football Calculators archived data is for 12 teams. URLs with other numbers of teams will work (return data), but if you look closely the data is always the same.

5.1.2

On the Fantasy Football Calculator page we're scraping, you'll notice that each player's name is a clickable link. Modify `scrape_ffc` to store that as well, adding a column named 'link' for it in your DataFrame.

Hint: bs4 tags include the `get` method, which takes the name of an HTML attribute and returns the value.

5.1.3

Write a function `ffc_player_info` that takes one of the urls we stored in 5.1.2, scrapes it, and returns the player's team, height, weight, birthday, and draft info (team and pick) as a dict.

APIs

Above, we learned how to scrape a website using BeautifulSoup to work with HTML. While HTML basically tells the browser what to render onscreen, an API works differently.

Two Types of APIs

In practice, people mean at least two things by API.

The trouble comes from the acronym, *Application Programming Interface*. It all depends on what you mean by "application". For example, the application might be the Pandas library. Then the API is just the exact rules (the functions, what they take and return, etc) of Pandas.

A more specific example: part of the Pandas API is the `pd.merge` function. The `merge` API specifies that it requires two DataFrames, has optional arguments (with defaults) for `how`, `on`, `left_on`, `right_on`, `left_index`, `right_index`, `sort`, `suffixes`, `copy`, and `indicator` and returns a DataFrame.

This `merge` API isn't quite the same thing as the `merge` documentation. Ideally, an API is accurately documented (and Pandas is), but it's not required. Nor is the API the `merge` function itself exactly. Instead, it's how the function interacts with the outside world and the programmer. Basically what it takes and returns.

Web APIs

The other, more common way the term is used is as a web API. In that case the website is the "application" and we interact with it via it's URL. Everyone is familiar with the most basic urls, e.g. www.fantasymath.com, but urls can have extra stuff too, e.g. api.fantasymath.com/v2/players-wdis/?wdis=aaron-rodgers&wdis=drew-brees.

At a very basic level: a web API lets you specifically manipulate the URL (e.g. maybe you want to put `kirk-cousins` in instead of `aaron-rodgers`) and get data back. It does this via the same mechanisms (HTTP) that regular, non-API websites use.

It's important to understand web APIs are specifically designed, built and maintained by website owners with the purpose of providing data in an easy to digest, predictable way. You can't just tack on "api" to the front of any URL, play around with parameters, and start getting back useful data. Any API you use should give you some instructions on what to do and what everything means.

Not every API is documented and meant for public consumption. More commonly, they're built for a website's own, internal purposes. The Fantasy Math API, for example, is only called by the Fantasy Math site. You can go to fantasymath.com, and pick two players from the dropdown (Aaron Rodgers and Drew Brees). When you click submit, the site accesses the API via that URL, then collects and displays the results. Decoupling the website (front-end) from the part that does the calculations (the back-end) makes things simpler and easier to program.

But some web APIs are public, which means anyone can access them to get back some data. A good example is the Fantasy Football Calculator API.

Fantasy Football Calculator ADP - API Example

Let's get the same data we scraped up above via Fantasy Football Calculator's public API. This example is in `05_03_api.py`. Because APIs are *designed* to make grabbing data as easy as possible, it's a lot shorter than what we did with scraping above. Let's run through it quick and then do a more in depth explanation after.

First we need to import requests and DataFrame.

```
In [1]: import requests

In [2]: from pandas import DataFrame
```

Then we need to call the URL. We can see via Fantasy Football Calculator's documentation's that for 12 team, PPR scoring we want to call.

```
In [3]: fc_url = 'https://fantasyfootballcalculator.com/api/v1/adp/ppr?
    teams=12&year=2020'
```

Then we access it with the `get` method from requests. The data it returns gets assigned to 'resp.

```
In [4]: resp = requests.get(fc_url)
```

Finally, we call the `json` method on `resp`, pass that to Pandas and we're good to go.

```
In [5]: df = DataFrame(resp.json()['players'])

In [6]: df.head()
Out[6]:
              name  adp  times_drafted team  ...  position bye  stdev
0    David Johnson  1.3            310  ARI  ...        RB  12    0.6
1      LeVeon Bell  2.3            303  PIT  ...        RB   7    0.8
2    Antonio Brown  3.7            338  PIT  ...        WR   7    1.0
3      Julio Jones  5.7            131  ATL  ...        WR   9    3.2
4  Ezekiel Elliott  6.2            180  DAL  ...        RB   8    2.8
```

Easy.

Let's wrap it in a function to make calling this API a little more flexible.

```
def fc_adp(scoring='ppr', teams=12, year=2020):
    ffc_com = 'https://fantasyfootballcalculator.com'
    resp = requests.get(
        f'{ffc_com}/api/v1/adp/{scoring}?teams={teams}&year={year}'
    )
    df = DataFrame(resp.json()['players'])

    # data doesn't come with teams, year columns, let's add them
    df['year'] = year
    df['teams'] = teams
    return df
```

Now we can get any arbitrary ADP — 10 team standard scoring for 2019 say — in one line.

```
In [8]: df_10_std = fc_adp('standard', 10, 2019)

In [9]: df_10_std.head()
Out[9]:
                  name  adp  times_drafted  ... stdev  year  teams
0      Adrian Peterson  1.3            529  ...   0.6  2009     10
1  Maurice Jones-Drew  2.6            292  ...   1.0  2009     10
2       Michael Turner  2.9            218  ...   1.1  2009     10
3           Matt Forte  3.8            512  ...   1.2  2009     10
4     Larry Fitzgerald  6.1            274  ...   1.9  2009     10
```

Or maybe we want to get 10 years worth of ADP results in a few lines of code:

```
In [10]: df_history = pd.concat(
            [fc_adp('standard', 12, year=y) for y in range(2009, 2020)],
            ignore_index=True)

In [11]: df_history.head()
Out[11]:
                  name  adp  times_drafted  ... stdev  year  teams
0      Adrian Peterson  1.3            529  ...   0.6  2009     12
1  Maurice Jones-Drew  2.6            292  ...   1.0  2009     12
2       Michael Turner  2.9            218  ...   1.1  2009     12
3           Matt Forte  3.8            512  ...   1.2  2009     12
4     Larry Fitzgerald  6.1            274  ...   1.9  2009     12
```

HTTP

This isn't a web programming book, but working with APIs will be easier if you know a bit about HTTP.

Anytime you visit a website, your browser makes an HTTP *request* to some web server. We can think about a request as consisting of the URL we want to visit, plus some optional data. The web server handles the request, then — based on what's in it — sends an HTTP *response* back.

There are different types of requests. The one you'll use most often is *GET*. This just indicates you want to read ("get") some data.

There are other types of requests (e.g. a *POST* request is for sending data to the server), but *GET* is the main one for public APIs.

JSON

When you visit (request) a normal site in your browser, the response comes back as HTML, and you see it on the screen. But with an API you usually get data instead of HTML.

There are different data formats, but the most common is **JSON**, which stands for JavaScript Object Notation. Technically, JSON is a string of characters, (i.e. it's wrapped in `""`), which means we can't do anything to it until we convert (*parse*) it to a more useful format.

Luckily that's really easy, because inside that format is just a (likely nested) combination of Python's `dict` and `list`.

```
"""
{
    "players": ["aaron-rodgers", "aaron-jones"],
    "positions": ["qb", "rb"],
    "season": 2018
}
"""
```

To convert our JSON string to something useful to Python we just do `resp.json()`. But note, this won't work on just anything. For example, if we were missing the closing `]` on players like this:

```
"""
{
    "players": ["aaron-rodgers", "aaron-jones",
    "positions": ["qb", "rb"],
    "season": 2018
}
"""
```

We'd get an error when trying to parse it.

Once we do parse the JSON, we're back in Python, working with our usual data structures. Assuming we're working with tabular data, our goal should be to get it in Pandas ASAP.

In the FCC data this data happened to be in a format Pandas could read easily (a list of dicts, where each dict has the same fields). It's easy to convert that into a DataFrame, but not all data is like that. In more complicated cases you'll have to use your basic Python skills to get data into a format Pandas can handle.

APIs have some benefits over scraping HTML. Most importantly, because they're specifically designed to convey data, they're usually much easier to use and require much less code. We saw that when we rewrote our web scraper to use Fantasy Football Calculator's API.

Also, sometimes data is available via an API that you can't get otherwise. In the past, website content was primarily HTML + CSS, which meant you could generally get data out of it. In the past few years, however, much of what used to be done in HTML and CSS is now loaded — and hidden to scrapers — in JavaScript. If you try right clicking and viewing source in your Gmail inbox for example, you'll see mainly nonsensical, minified JavaScript code. As more and more websites are built like this, sometimes getting data via an API is the only good option.

That's not to say APIs don't have their disadvantages. For one, they aren't as common. A website builder has to explicitly design, build and expose it to the public for it to be useful. Also even when a public API exists, it's not always clear on how to go about using it; documentation for APIs can be out of date or non-existant.

Exercises

5.2.1

The league hosting site myfantasyleague.com has an api available for (limited) use.

The endpoints for ADP and player info are:

https://api.myfantasyleague.com/2019/export?TYPE=adp&JSON=1

https://api.myfantasyleague.com/2019/export?TYPE=players&JSON=1

respectively.

Connect to them, grab the data, and use it to make an ADP table of top 200, non-IDP players.

6. Data Analysis and Visualization

Introduction

In the first section of the book we defined *analysis* as "deriving useful insights from data".

One way to derive insights is through *modeling*. We'll cover that in the next chapter.

This chapter is about everything else. Non-modeling analysis usually takes one of three forms:

1. Understanding the **distribution** of a single variable.
2. Understanding the **relationship** between two or more variables.
3. Summarizing a bunch of variables via one **composite** score.

Distributions

A distribution conveys the *frequency* of outcomes for some variable.

Take fantasy points. Here are 25 random RB point performances from 2017:

```
player_name team  week  pts
  D.Freeman  ATL     2   24
   M.Ingram   NO     9    9
   A.Ekeler  LAC    13    6
     C.Sims   TB     2    0
   M.Ingram   NO    14   13
   J.Conner  PIT    13    1
   L.Murray  MIN    16    8
     C.Sims   TB     7    4
 C.Anderson  DEN    15   16
     M.Mack  IND     1    9
  T.Riddick  DET    14   28
   L.Murray  MIN    17   25
L.Fournette  JAX     6   22
   M.Breida   SF     2    5
     F.Gore  IND    12   16
   A.Ekeler  LAC    11   14
    L.McCoy  BUF    10    6
.Cunningham  CHI    12    2
   A.Kamara   NO     7   16
    J.Ajayi  PHI     2   15
  J.Charles  DEN    14    4
  D.Freeman  ATL    16    7
     F.Gore  IND    17   14
      C.Ham  MIN    15    2
     L.Bell  PIT    11   27
```

Let's arrange these smallest to largest, marking each with an `x` and stacking `x`'s when a score shows up multiple times. Make sense? Like this:

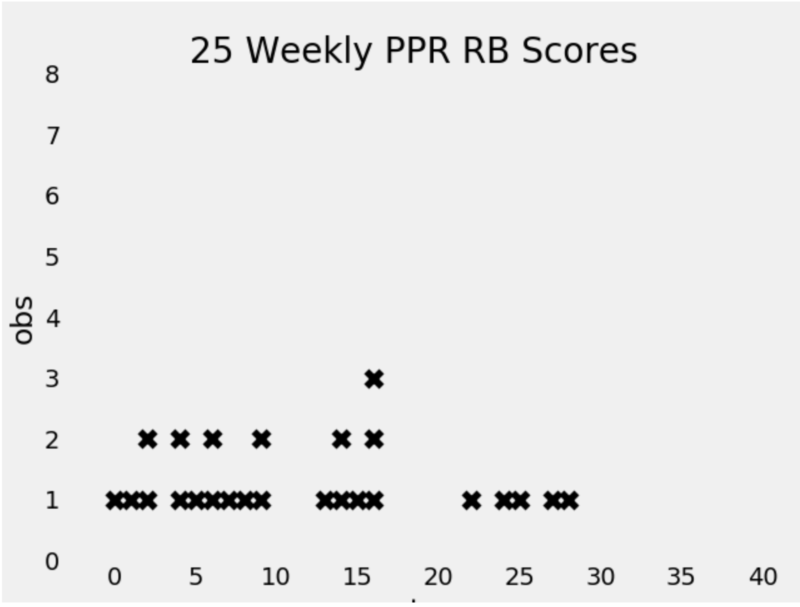


Figure 0.1: 25 RB Performances from 2017

Interesting, but why should we limit ourselves to just 25 x's? Let's see all of them:

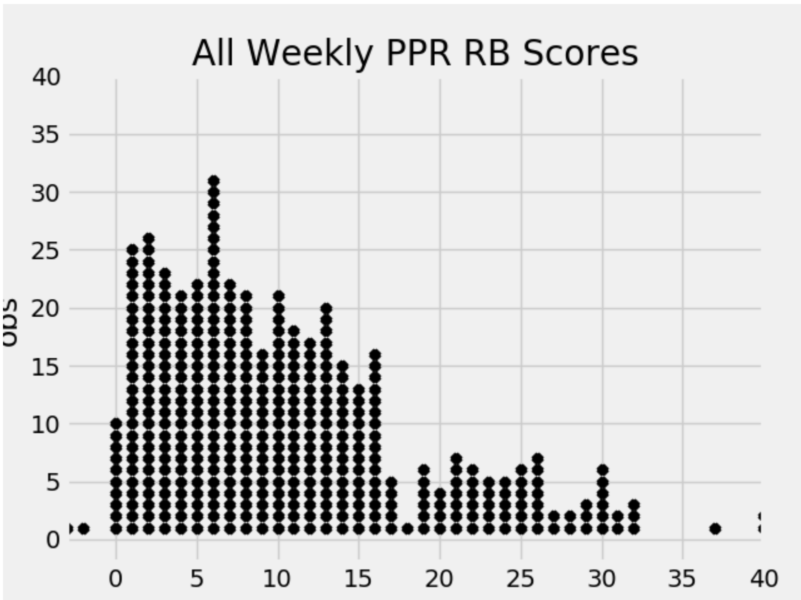


Figure 0.2: All RB Performances from 2017

These stacked x's show the *distribution* of RB points in 2017. Distributions are the key to statistics. When you start a RB (or take a draw from any random variable), you're picking one of these x's at random. Each x is equally likely to get picked. Each *score* is not. There are lot more x's between 0-10 points than there are between 20 and 30.

In this case, we rounded points to the nearest whole number and stacked x's on top of each other. But it may make more sense to treat points as a *continuous* variable, one that can take on any value. In that case, we'd move from stacked x's to area under a curve, like this:

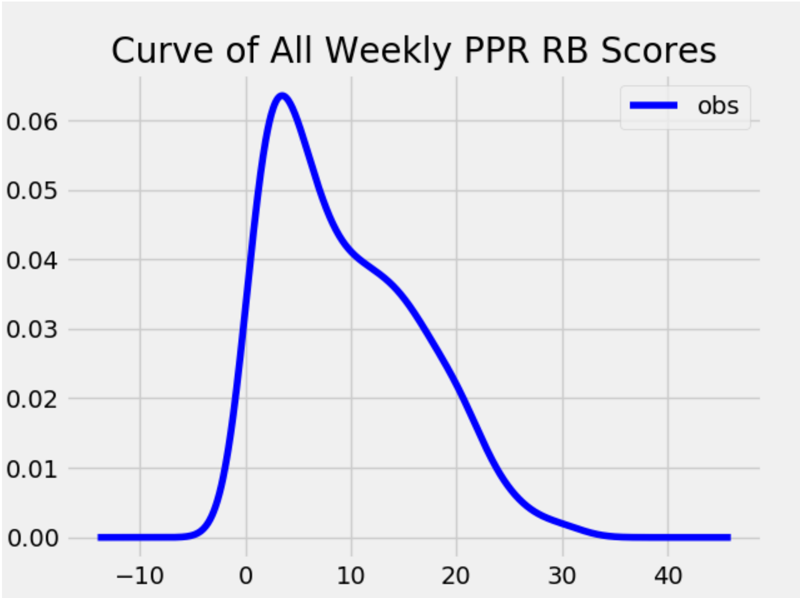


Figure 0.3: Kernel Density - All RB Performances from 2017

The technical name for these curves are **kernel densities**[1].

We're not going to get into the math, but for our purposes (mainly plotting them), we can mentally treat these curves as smoothed out stacks of x's.

Don't worry about the values of the y-axis (0.06, 0.05, etc). They're just set (or *scaled*) so that the whole area under the curve equals 1. That's convenient — half the area under the curve is 0.5, a quarter is 0.25, etc — but it doesn't change the shape. We could take this exact same curve and double the y values. It wouldn't look any different, but the area under it would be 2 instead of 1.

Summary Stats

Let's look at another example, say the distribution of RB rushing yards per game:

[1] Kernel densities are more flexible than traditional probability density functions like the normal or student T distribution. They can follow the "bumpiness" of our stacked x's — but they're more complicated mathematically.

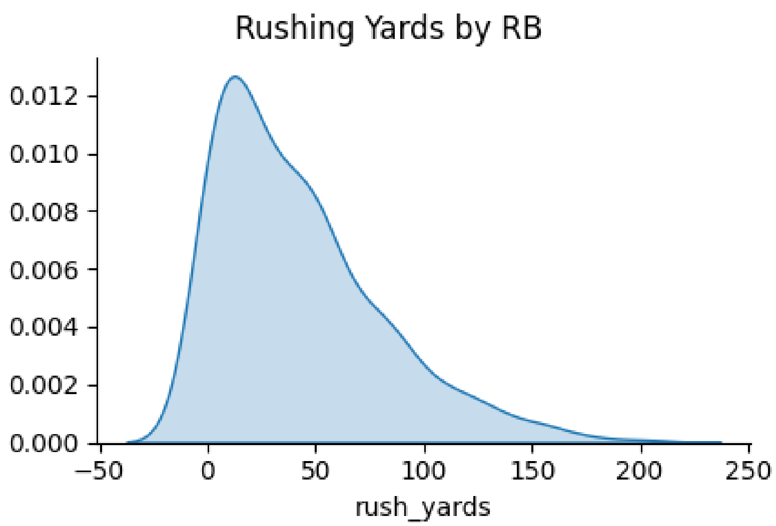


Figure 0.4: Distribution of Rushing Yards

At a glance, this gives us a good overview. Most RBs in our sample run for under 50 yards; running for over 200 yards is incredibly rare; and it's not out of the question for RBs to finish with negative yards.

Viewing and working with the distributions like this is the gold standard, but it isn't always practical.

Summary statistics describe (or *summarize*) a distribution with just a few numbers. Sometimes they're called *point estimates*. This makes sense because they're reducing the entire two dimensional distribution to a single number (or *point*).

For example, at the **median**, half area under the curve is above, half below. In this distribution, the median is 34 rushing yards.

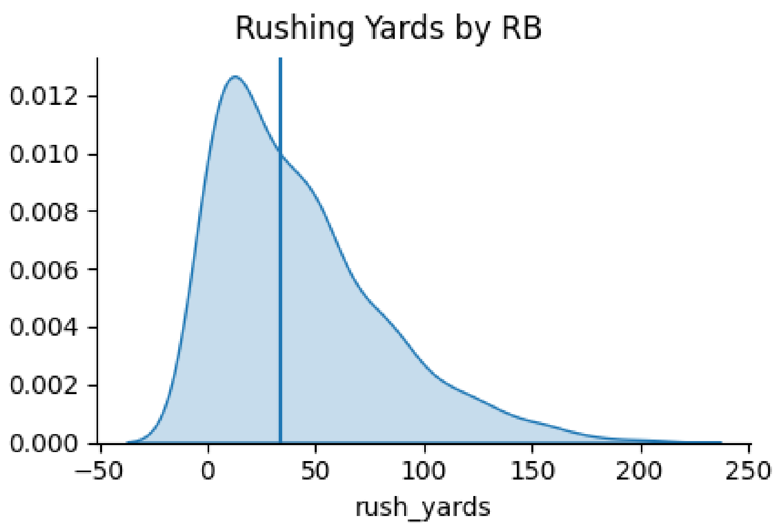


Figure 0.5: Distribution of Rushing Yards with Median

The median splits the distribution 50-50, but you can divide it wherever you want. 10-90, 90-10, 79.34-20.66, whatever.

These are called **percentiles**, and they denote the area to the *left* of the curve. So at the 10th percentile, 10% of the area under the curve is to the left. In this distribution, the 10th percentile is about 1 yard.

Summary Statistics in Pandas

Note: the code for this section is in the file `06_summary.py`*. We'll pick up right after loading the player-game data into* `df`*.*

Pandas lets us calculate any percentile we want with the `quantile` function.

```
In [1]: df.loc[df['pos'] == 'RB', 'rush_yards'].quantile(.95)
Out[1]: 118.0
```

So 95% of the time, RBs rush for less than 118 yards. And 95% of the area under our curve is to the left of a line extending up at 118 yards. This looks about right:

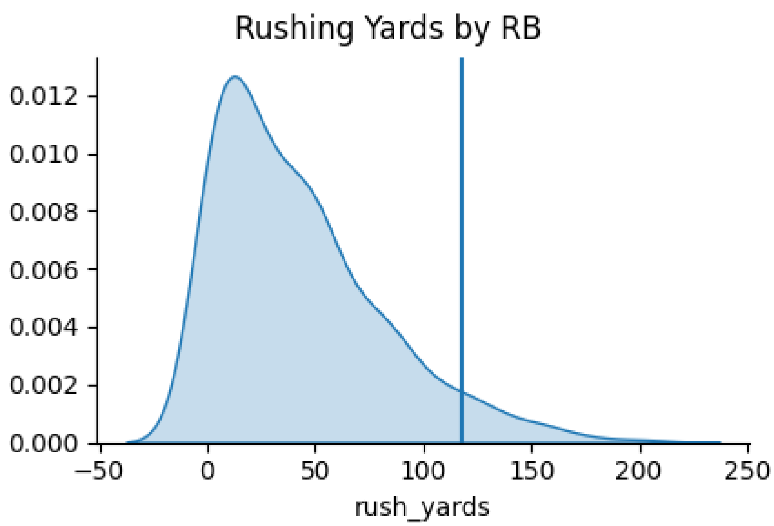


Figure 0.6: Distribution of Rushing Yards with 95% Percntile

Pandas also lets us calculate multiple summary statistics, including several percentiles, all at once with `describe`.

```
In [2]: df.loc[df['pos'] == 'RB', ['rush_yards', 'rec_yards']].describe()
Out[2]:
       rush_yards   rec_yards
count  426.000000  426.000000
mean    42.507042   19.253521
std     38.458181   20.292022
min     -3.000000   -4.000000
25%     12.000000    4.250000
50%     34.000000   13.000000
75%     61.000000   26.750000
max    203.000000  109.000000
```

Mean aka Average aka Expected Value

The second line of `describe` gives the **mean**. Other terms for the mean include *average* or *expected value*. You learned about averages in elementary school. Expected value refers to the fact that the mean is the probability weighted sum of all outcomes.

Take fantasy points. If 2% of RBs score 1 pt, 3% score 2 pts … etc, the expected value (and mean, and average) of RB points would be: `0.02*1 + 0.03+2 ...`

The normal, elementary school average is just a special case when every observation's probability is the same. Say we want to calculate the average weight of the Green Bay Packers 2020 starting offensive line. There are five starting linemen, so the "probability" of each is `1/5=0.2`.

Then we have:

```
0.2*310 + 0.2*311 + 0.2*301 + 0.2*313 + 0.2*310 = 309
```

This isn't a coincidence, it's just math. When you manipulate the algebra, multiplying every term by the probability it occurs and adding them all up is another way of saying, "add up all the `x` values and divide by the total number of `x`'s".

Variance

Other summary stats summarize dispersion — how close or far apart the observations are to each other. The standard deviation, for instance, is (basically) the average *distance to the mean*. To calculate it you (1) figure out the average of all your observations, (2) figure out how far each observation is from that average, and (3) take the average of that[2]. It's smaller when values are tightly clustered around their mean, larger when values are more dispersed.

Distributions vs Summary Stats

There are times when using summary statistics in place of distributions is useful. Usually it's because distributions are difficult to manipulate mathematically.

For example, say you've projected each player's point distribution for the week. And you want to use these player distributions to predict a total score for your whole team. Summary stats make this easy. You: (1) figure out the mean for each player, then (2) add them up the. That's lot easier than trying to combine player distributions and take the mean of that.

But although summary statistics are convenient, I think working with distributions directly is underrated.

First, understanding them will make you a better fantasy player. Recognizing that a player's weekly score is a random draw from some distribution helps you make better decisions in the long run. It makes it clear that your job in building a fantasy team is to send out a lineup with curves as far to the right as possible.

Does that mean you won't ever start the "wrong" guy? No. Fantasy point distributions — especially for tight who-do-I-start decisions — are very close, with a lot of overlap. It's normal that occasionally you'll get a bad draw from your starter, a good draw from your backup, or both. In fact, it'd be weird if this *didn't* ever happen. When it does, understanding distributions leads to less point chasing and second guessing, and hopefully more optimal decisions in the future.

[2] Technically, there are some slight modifications, but it's the general idea.

But we're not just interested in becoming better fantasy players, we're interested in getting insights from data via code. And plotting probability densities is one of the best ways to do this. In the next section we'll learn how.

Density Plots with Python

Unlike data manipulation, where Pandas is the only game in town, data visualization in Python is more fragmented.

The most common tool is *matplotlib*, which is very powerful, but is also trickier to learn[3]. One of the main problems is that there are multiple ways of doing the same thing, which can get confusing.

So instead we'll use the *seaborn* library, which is built on top of matplotlib. Though not as widely used, seaborn is still very popular and comes bundled with Anaconda. We'll go over some specific parts that I think provide the best mix of functionality and ease of use.

Again, the code below is in `06_summary.py`. We'll pick up after we've imported the libraries and loaded the player-game data. Note the convention is to import seaborn as `sns`.

Let's first use the raw stat categories to calculate fantasy points using a few common scoring systems:

```
In [1]:
# add fantasy points to data
df['std'] = (0.1*(df['rush_yards'] + df['rec_yards']) +
             0.04*df['pass_yards'] +
             -3*(df['rush_fumbles'] +df['rec_fumbles'] +
                 df['interceptions']) +
             6*(df['rush_tds'] + df['rec_tds']) + 4*df['pass_tds'])
df['ppr'] = df['std'] + 1*df['receptions']
df['half_ppr'] = df['std'] + 0.5*df['receptions']

In [2]: df[['player_name', 'week', 'std', 'ppr', 'half_ppr']].head()
Out[2]:
  player_name  week    std    ppr  half_ppr
0     T.Brady     1  10.68  10.68     10.68
1     A.Smith     1  31.62  31.62     31.62
2  D.Amendola     1   7.00  13.00     10.00
3  R.Burkhead     1   2.30   3.30      2.80
4     T.Kelce     1   4.40   9.40      6.90
```

When making density plots in seaborn you basically have three big "levers" to work with. All three are columns in your data. Two of them are optional.

[3] Note: "trickier" is relative, if after reading this book you wanted to sit down with the matplotlib documentation and master it, you'd be able to do it.

Basic, One-Variable Density Plot

The only thing we *have* to tell seaborn is the name of the variable we're plotting.

Say we want to plot the distribution of standard fantasy points (our column `std` in `df`). This is how we'd do it:

```
In [3]: g = sns.displot(df, x='std', kind='kde', fill=True)
```

The `displot` function is new in seaborn as of version 0.11, which came out in September 2020, so if you get an error, make sure you're using that. The shading is done with `fill=True` and is optional, but I think it looks better.

Here's what it looks like:

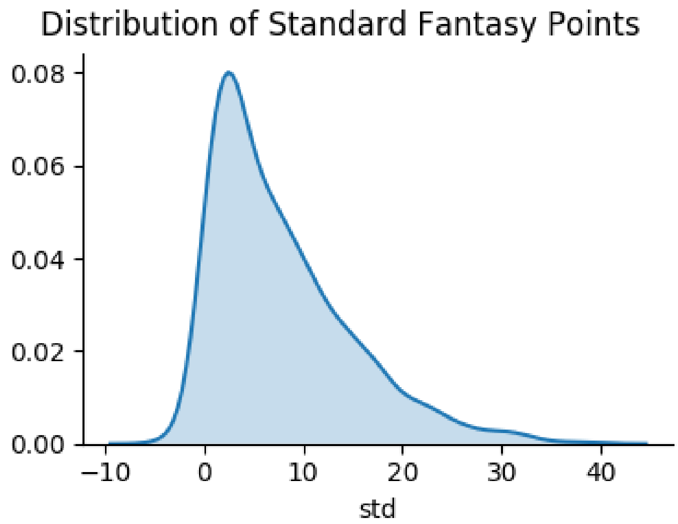


Figure 0.7: Distribution of Standard Fantasy Pts

Note, I've added a title and changed some height and width options to make things clearer. Yours won't show that yet. We'll cover them later.

Seaborn "Levers" - Slicing and Dicing Plots

Seaborn's killer feature is how easy it makes creating and comparing multiple plots.

For example, say we want separate plots for position. Now we can introduce our second lever, the `hue` keyword.

```
In [4]:
g = (sns.displot(df, x='std', kind='kde', fill=True, hue='pos'))
```

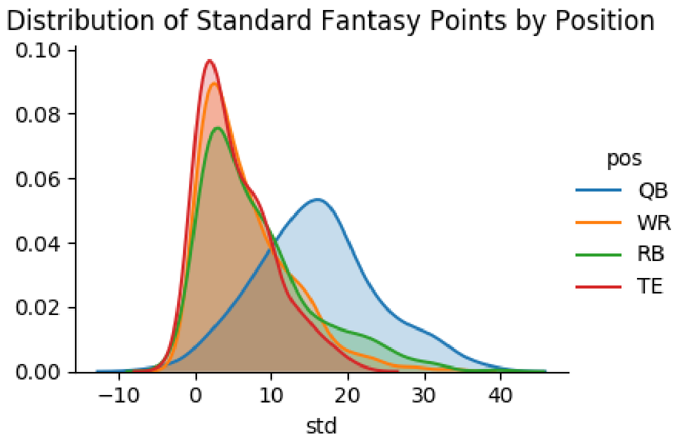


Figure 0.8: Distribution of Standard Fantasy Pts by Position

Again: hue always takes a *column* of data. By passing it my `pos` column, I've told it to make different plots of `std` (with different colors, or hues) for each value of `pos`. So now we can see we have one density plot when `pos='RB'`, another when `pos='QB'` etc.

This plot does a nice job showing fantasy point distributions by position. What if we wanted to add in another dimension, say position *and* week? We can use our third lever — the `col` keyword.

```
In [5]:
g = sns.displot(df, x='std', kind='kde', fill=True, hue='pos', col='week',
                col_wrap=4, height=2)
```

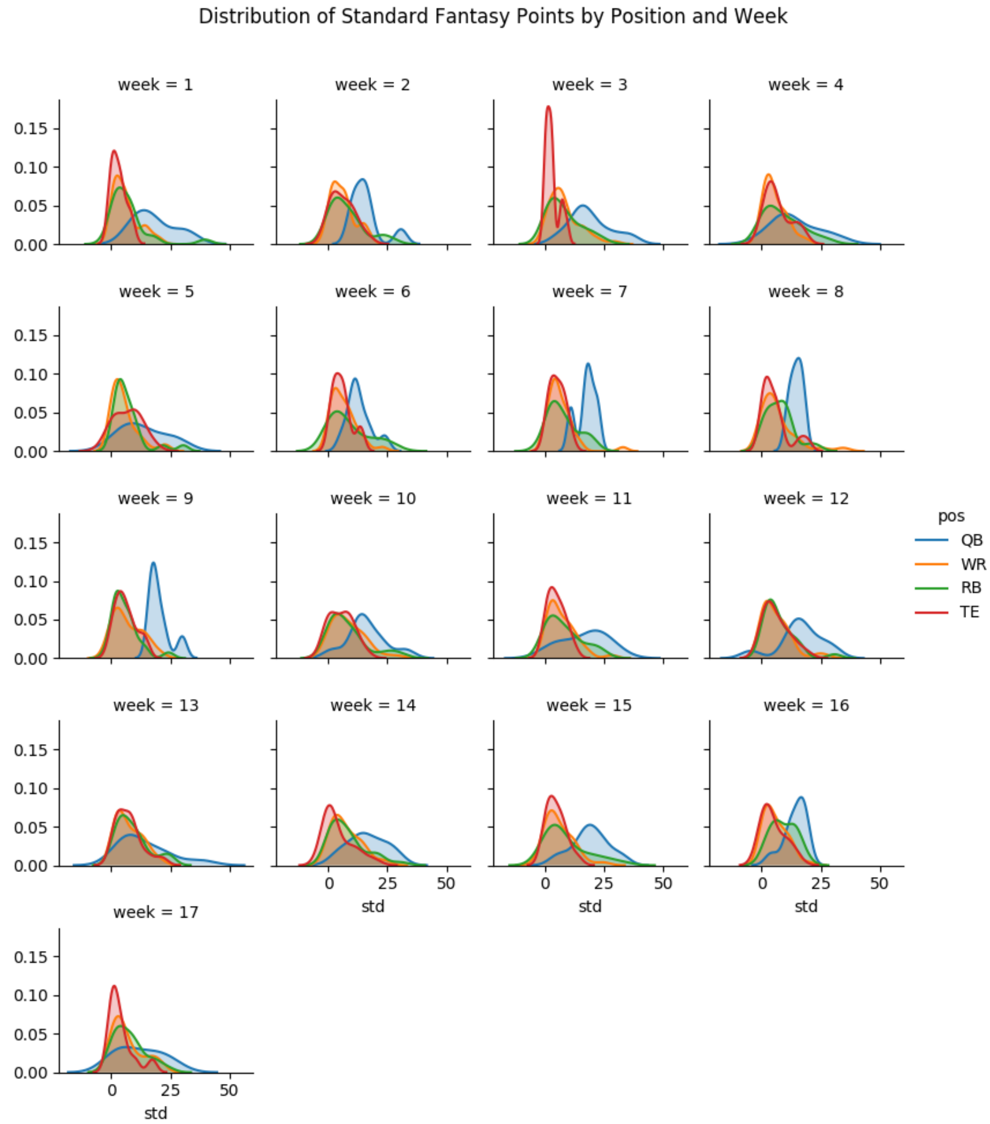


Figure 0.9: Distribution of Standard Fantasy Pts by Position and Week

(Don't worry about the `col_wrap` and `height` options for right now, they're aesthetic and we'll cover them later.)

This draws separate sub-plots for every value of whatever we pass to `col`. So we have one plot for `week=1`, another for `week=2` etc.

Within each of these, the `hue=pos` draws separate curves for each position.

Again all three of these variables — `std`, `pos`, and `week` are columns in our data. Seaborn *needs* the data in this format to make these types of plots. It's not guaranteed that your data will automatically come like this.

For example, what if — instead of plots by week — we want separate plots by scoring system. That's no problem conceptually, except our points data for our three scoring systems (standard, ppr, and half-ppr) are in three separate columns.

We currently have this:

```
In [6]: df[['pos', 'std', 'ppr', 'half_ppr']].head()
Out[6]:
  pos    std    ppr  half_ppr
0  QB  10.68  10.68     10.68
1  QB  31.62  31.62     31.62
2  WR   7.00  13.00     10.00
3  RB   2.30   3.30      2.80
4  TE   4.40   9.40      6.90
```

But seaborn needs something more like this:

```
  pos   scoring    pts
0  QB       std  10.68
1  QB       std  31.62
2  WR       std   7.00
3  RB       std   2.30
4  TE       std   4.40
0  QB       ppr  10.68
1  QB       ppr  31.62
2  WR       ppr  13.00
3  RB       ppr   3.30
4  TE       ppr   9.40
0  QB  half_ppr  10.68
1  QB  half_ppr  31.62
2  WR  half_ppr  10.00
3  RB  half_ppr   2.80
4  TE  half_ppr   6.90
```

They contain the same information, we've just changed the granularity (from player-game to player-game-scoring system) and shifted data from columns to rows.

If you've read the Python and Pandas section, you should know everything you need to do this, but let's walk through it for review.

First let's build a function that — given our data (`df`) and a scoring system (say, `std`) — moves that score to a points column, then adds in another column indicating what type of points they are. So this:

```
def score_type_df(_df, scoring):
    _df = _df[['pos', scoring]]
    _df.columns = ['pos', 'pts']
    _df['scoring'] = scoring
    return _df
```

And to use it with `std`:

```
In [7]: score_type_df(df, 'std').head()
Out[7]:
  pos    pts scoring
0  QB  10.68     std
1  QB  31.62     std
2  WR   7.00     std
3  RB   2.30     std
4  TE   4.40     std
```

That's what we want, we just need to call it on all three of our scoring systems, then stick the resulting DataFrames on top each other (like a snowman). Recall vertical stacking is done with the `concat` function, which takes a list of DataFrames.

So we need a list of DataFrames: one with standard scoring, another with ppr, and another with half-ppr. Then we need to pass them to `concat`. Let's do it using a list comprehension.

```
In [8]:
df_pts_long = pd.concat(
    [score_type_df(df, scoring) for scoring in ['std', 'ppr', 'half_ppr'
      ]],
    ignore_index=True)
```

Now we have what we want: the same position, points, and scoring information we had before, but in three separate columns. We can passing it to seaborn:

```
In [9]:
g = sns.displot(df_pts_long,  x='pts', col='pos', hue='scoring', kind='kde
    ',
                fill=True, col_wrap=2, aspect=1.3)
```

The plot is easy once our data is in the right format. This is a good example of how data manipulation is most of the work (both in time and lines of code) compared to analysis.

The final result:

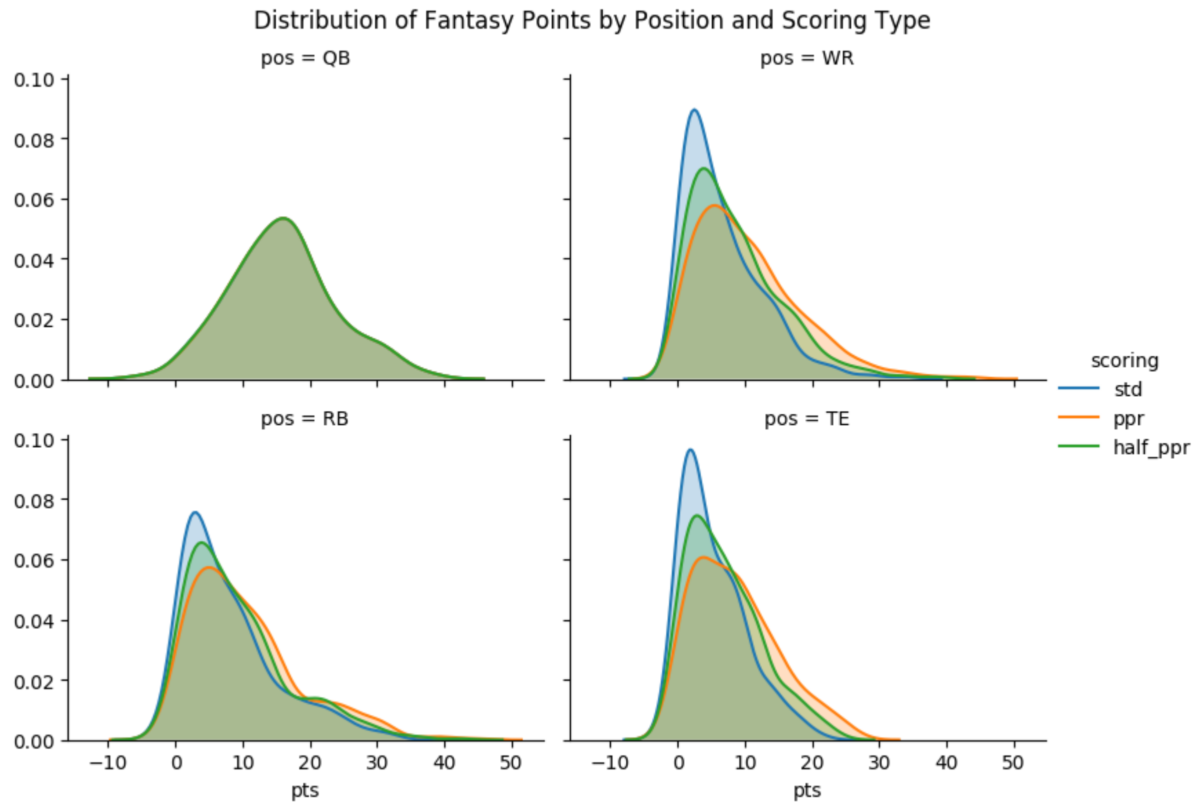


Figure 0.10: Distribution of Fantasy Points by Position and Scoring System

Relationships Between Variables

Another common analysis task is to look at the *relationship* between two (or more) variables. Do they tend to move together, or not?

For example, in our player-game data we can break out a players receiving yards into two parts: air yards (how long the pass was in the air before the player caught it), and yards after the catch (YAC).

We might be wondering about the relationship between these — do players who have games with more air yards tend to have less yards after the catch and vis versa? Are there such things as "possession receivers"?

Let's check it out.

Scatter Plots with Python

The most useful tool for visualizing relationships is a *scatter* plot. Scatter plots are just plots of points on a standard coordinate system. One of your variables is your x axis, the other your y axis. Each observation gets placed on the graph. The result is a sort of "cloud" of points. The more the cloud moves from one corner of the graph to another, the stronger the relationship between the two variables.

The process of actually making scatter plots in seaborn is a lot like the density plots we've already covered. We just use a new function: `relplot` (for *relationship* plot).

Like density plots, seaborn lets you pick out columns for `hue` and `col`.

So say we want to look at the relationship between air yards and receiving yards.

```
In [1]: g = sns.relplot(x='caught_airyards', y='raw_yac', data=df)
```

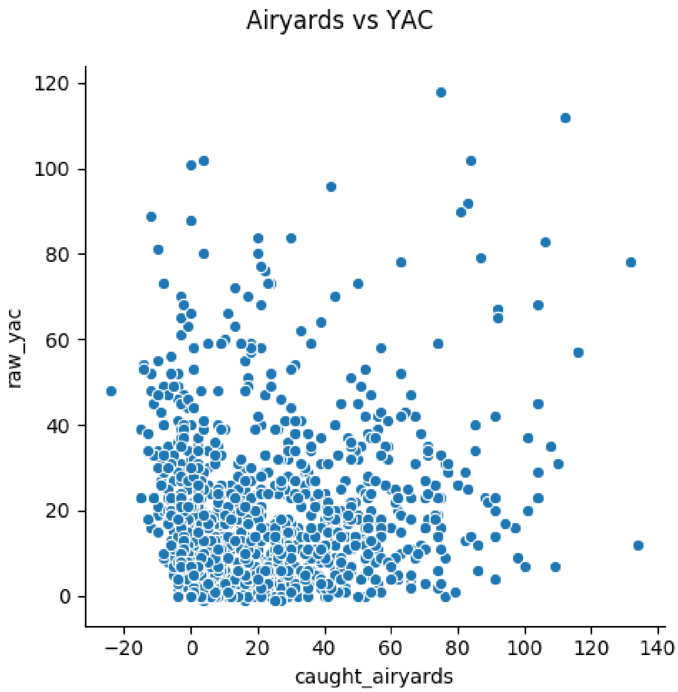


Figure 0.11: Air Yards vs YAC

Is this cloud of points moving up and to the right? It's hard for me to tell. If it is, the relationship isn't *that* strong. Later, we'll look at other, numeric ways of quantifying the strength of a relationship, but for now let's color our plots by position. Just like the density plots, we do this using the `hue` keyword.

```
In [2]: g = sns.relplot(x='caught_airyards', y='raw_yac', hue='pos',
                        data=df)
```

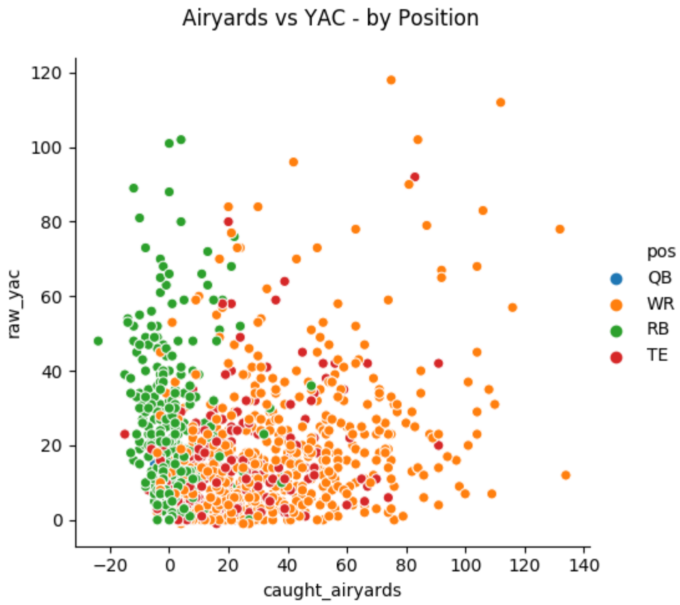


Figure 0.12: Air Yards vs YAC - by Position

This graph makes it obvious how running backs get most of their receiving yards on YAC on short dump offs compared to WRs and TEs who catch the ball further down field. Note these are player-game *totals*, not plays, which is why some of the points are more than 100.

Like density plots, scatter plots also take an optional `col` argument.

Correlation

Just like a median or mean summarizes a variable's distribution, there are statistics that summarize the strength of the relationship between variables.

The most basic is **correlation**. The usual way of calculating correlation (called *Pearson*'s) summarizes the tendency of variables to move together with a number between -1 and 1.

Variables with a -1 correlation move perfectly together in opposite directions; variables with a 1 correlation move perfectly together in the same direction.

Note: "move perfectly together" doesn't necessarily mean "exactly the same". Variables that are exactly the same *are* perfectly correlated, but so are simple, multiply-by-a-number transformations. For example, number of touchdowns (say `n`) is perfectly correlated with points from touchdowns (`6*n`).

A correlation of 0 means the variables have no relationship. They're *independent*. Finding variables with no correlation isn't as easy as you might think. For example, is the total score of the NYG-PHI game in NYC correlated with the score of OAK-NE in Foxborough? You wouldn't think so, but what if there's a snow storm moving through the Northeast that puts a damper on scoring in both games? In that case they'd be positively correlated.

One interesting way to view correlations across multiple variables at once (though still in pairs) is with a *correlation matrix*. In a correlation matrix, the variables you're interested in are the rows and columns. To check the correlation between any two variables, you find the right row and column and look at the value.

For example, let's look at a correlation matrix for WR: air yards, targets, rushing carries, receiving TDs, and PPR points.

In Pandas you get a correlation matrix with the `corr` function.

```
In [3]:
df.loc[df['pos'] == 'WR',
       ['rec_raw_airyards', 'targets', 'carries', 'ppr', 'std']].corr()

Out[3]:
          airyards   targets   carries       ppr       std
airyards  1.000000  0.791787 -0.042175  0.589707  0.553359
targets   0.791787  1.000000 -0.063028  0.723363  0.612425
carries  -0.042175 -0.063028  1.000000  0.008317  0.013609
ppr       0.589707  0.723363  0.008317  1.000000  0.976131
std       0.553359  0.612425  0.013609  0.976131  1.000000
```

Note that the diagonal elements are all 1. Every variable is perfectly correlated with itself. Also note the matrix is symmetrical around the diagonal. This makes sense. Correlation is like multiplication; order doesn't matter. The correlation between targets and carries is the same as the correlation between carries and targets.

To pick out any individual correlation pair, we can look at the row and column we're interested in. So we can see the correlation between air yards and PPR points is `0.5897`.

Let's look at that on a scatter plot (note the `query` method on `df`, which we covered at the end of the filtering section on Pandas).

```
In [4]:
g = sns.relplot(x='rec_raw_airyards', y='ppr',
                data=df.query("pos == 'WR'"))
```

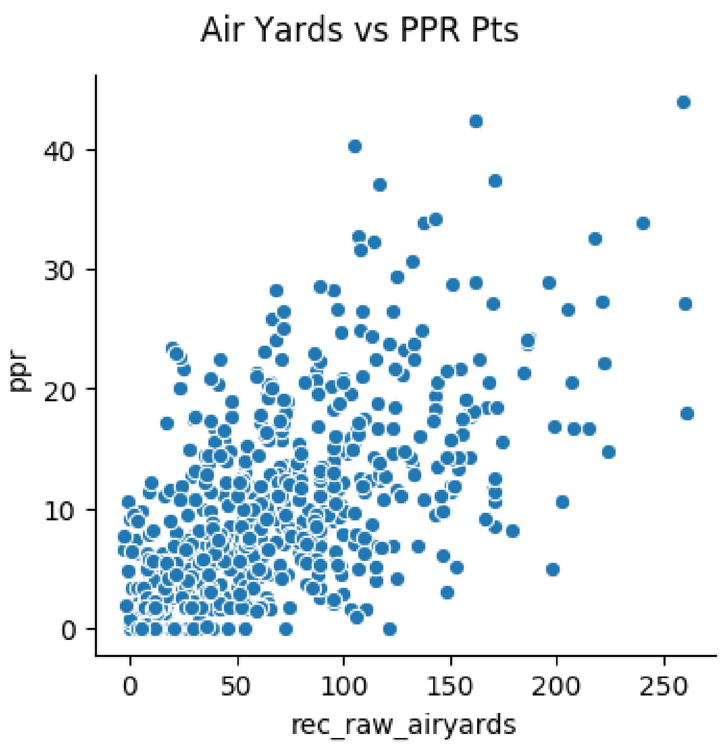


Figure 0.13: Air Yards vs PPR Points

We can see the cloud of points generally goes from bottom left to top right. This is a correlation of 0.59. What about something like standard vs PPR points, which is 0.98?

```
In [5]:
sns.relplot(x='std', y='ppr', data=df.query("pos == 'WR'"))
```

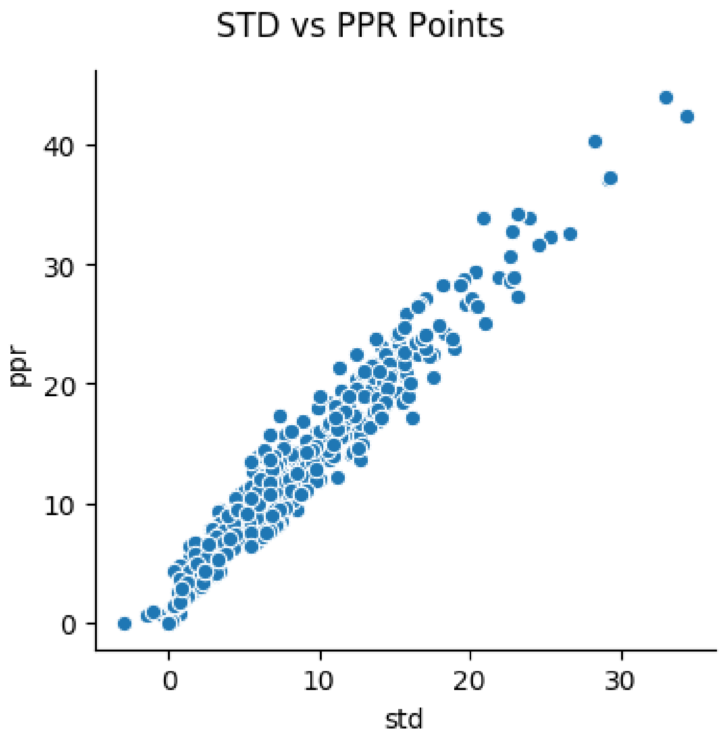


Figure 0.14: Standard vs PPR Pts

These points are much more clustered around an upward trending line.

Line Plots with Python

Scatter plots are good for viewing the relationship between two variables in general. But when one of the variables is some measure of *time* (e.g. week 1-17, year 2009-2020) a lineplot is usually more useful.

You make a lineplot by passing the argument `kind='line'` to `relplot`. When working with line plots, you'll want your time variable to be on the x axis.

Because it's still seaborn, we still have control over `hue` and `col` just like our other plots.

Let's try plotting points by position over the 2017 season.

```
In [6]:
g = sns.relplot(x='week', y='std', kind='line', hue='pos', data=df)
```

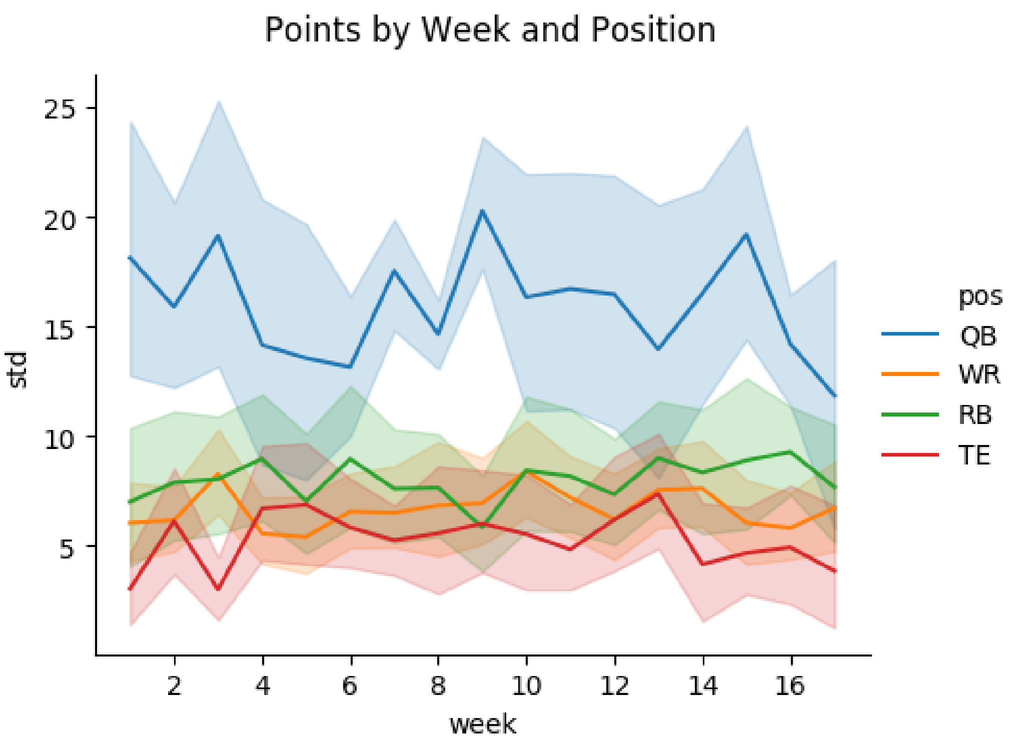


Figure 0.15: Points by Week, Position

Woah. What's happening here? We told seaborn we wanted week on the x axis and standard points on the y axis and that we wanted different plots (hues) for each position.

But remember, our data is at the *player-game* level, so for any given week (our x axis) and position (hue) there are multiple observations. Say we're looking at week 1 QBs:

```
In [7]:
df.loc[(df['pos'] == 'QB') & (df['week'] == 1),
       ['player_name', 'week', 'std']].head()—

Out[7]:
          player_name  week    std
0             T.Brady     1  10.68
1             A.Smith     1  31.62
174          T.Taylor     1  18.30
287            M.Ryan     1  18.14
512   B.Roethlisberger    1  15.72
```

Instead of plotting separate lines for each player, seaborn automatically calculates the mean (the line) and 95% confidence intervals (the shaded part), and plots that.

If we pass seaborn data with just one observation for any week and position — say the maximum score by position each week, it'll plot just the single lines.

```
In [8]:
max_pts_by_pos_week = (df.groupby(['pos', 'week'], as_index=False)
                       ['std'].max())

In [9]:
g = sns.relplot(x='week', y='std', kind='line', hue='pos', style='pos',
                data=max_pts_by_pos_week, height=4, aspect=1.2)
```

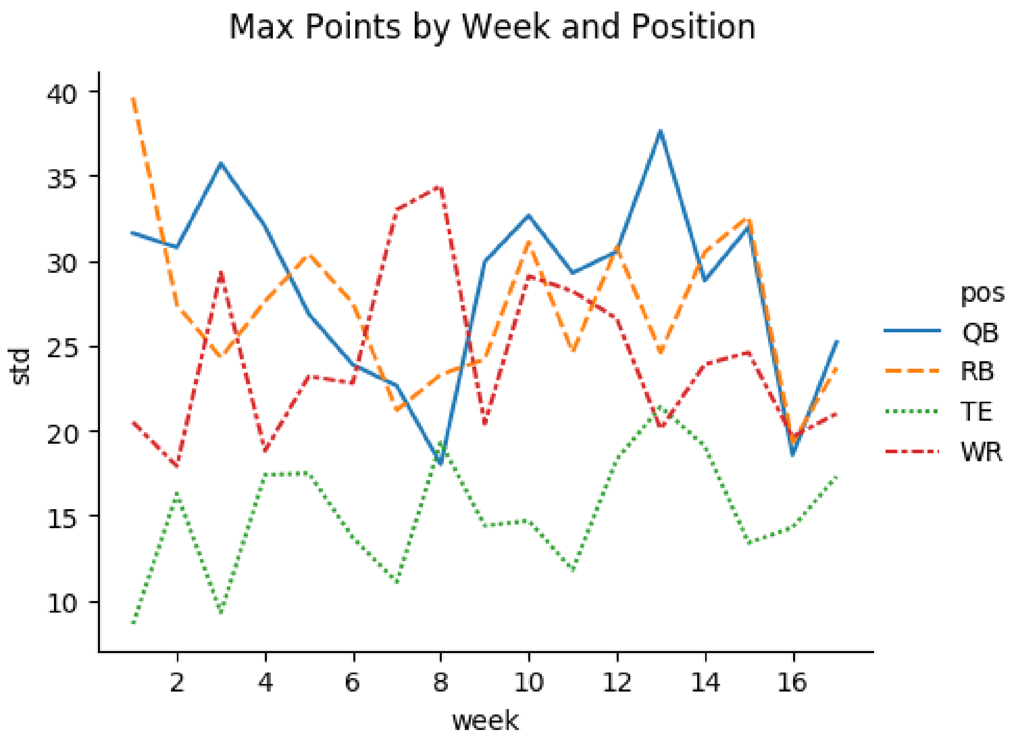


Figure 0.16: Max Points by Week, Position

Note: if you look close, you'll see we included an additional fourth, lineplot only lever: style. It controls how the lines look (dotted, dashed, solid etc).

Like the density examples, `relplot` includes options for separating plots by columns.

```
g = sns.relplot(x='week', y='std', kind='line', hue='player_name',
                col='player_name', height=2, aspect=1.2, col_wrap=3,
                legend=False, data=df.query("pos == 'QB'"))
```

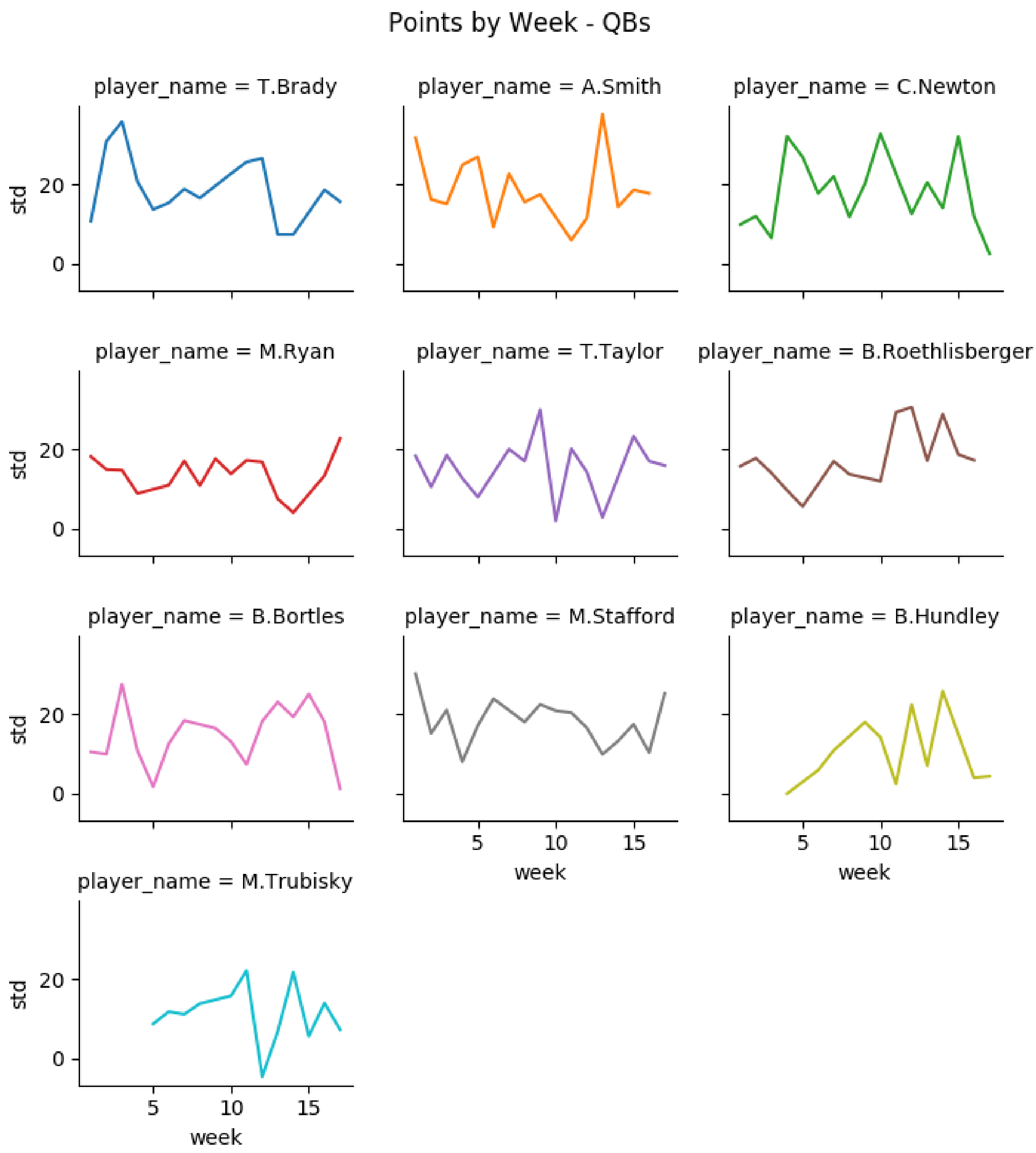


Figure 0.17: Points by Week - QBs

Again, these plots includes some other options — height, aspect, col_wrap, etc — we'll cover below.

Composite Scores

Another type of analysis you sometimes see are **composite scores**. Examples would be something like passer rating (the 0 to 158.3 scale for rating QBs) or SPARQ (speed, power, agility, reaction and quickness), which comes up around the NFL draft.

Most of these composite scores make use of two statistical concepts: **weighting** and **rescaling**.

Weighting is fairly common in statistical work. The idea is you take the average of a bunch of variables, but — rather than treating everything as equal — give more weight to certain columns. For example, maybe you're aggregating expert rankings and want to weight certain experts more than others.

The other concept that comes up when combining variables into composite scores is *scale*. Different variables have different ranges of plausible values.

For example, the SPARQ score is a combination of 40 yard dash, 20 yard shuttle, and vertical jump, among others. It'd make no sense to just take the average of these, weighted or otherwise. The solution is to make them on the same scale, usually by converting the raw number to a percentile. So if a 6'5", 260 pound outside rusher runs a 4.6 40 yard dash, that might be in the 98% percentile (he'd run faster than 98% of NFL players with a similar height and weight), and that would get combined with his other percentiles.

Personally, I don't do much with composite scores. I don't like that it's not obvious how they're calculated (do you know how to calculate QBR?) and would usually rather just work with multiple columns of real data instead.

Plot Options

Seaborn provides a powerful, flexible framework that — when combined with the ability to manipulate data in Pandas — should let you get your point across efficiently and effectively.

We covered the most important parts of these plots above. But there are a few other cosmetic options that are useful. These are mostly the same for every type of plot we've looked at, so we'll go through them all with one example.

Let's use our scoring system distribution plot from earlier. We'll start with no extra formatting options:

```
In [1]:
g = sns.displot(df_pts_long,  x='pts', col='pos', hue='scoring', kind='kde
    ',
                fill=True)
```

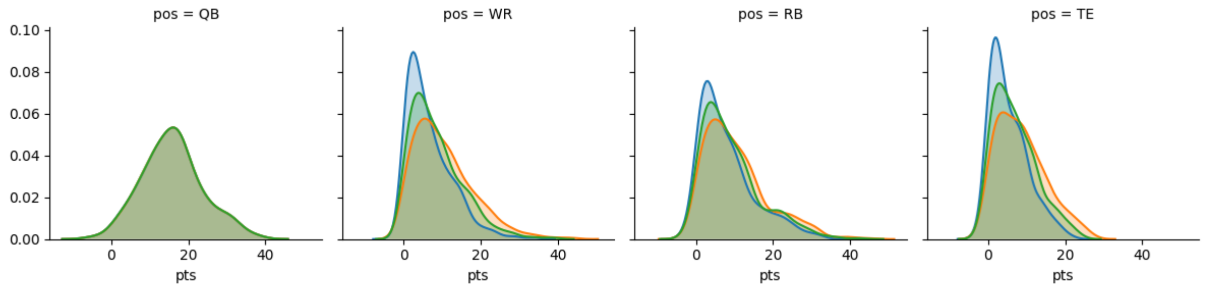


Figure 0.18: Plot with no options

Wrapping columns

By default, seaborn will spread all our columns out horizontally. We can change that with the `col_wrap` keyword, which will make seaborn start a new row after `n` number of columns.

```
In [2]:
g = sns.displot(df_pts_long,  x='pts', col='pos', hue='scoring', kind='kde
    ',
                fill=True, col_wrap=2)
```

Adding a title

Adding a title is a two step process. First you have to make room, then you add the title. The method is `suptitle` (for super title) because `title` is reserved for individual plots.

```
In [3]:
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Fantasy Points by Position, Scoring System')
```

This is something that seems like it should be easier, but it's a small price to pay for the overall flexibility of seaborn. I'd recommend just memorizing it and moving on.

Modifying the axes

Though by default seaborn will try to show you whatever data you have — you can decide how much of the x and y axis you want to show.

You do that via the `set` method.

```
In [4]:
g.set(xlim=(-10, 40), ylim=(0, 0.014))
```

Use `set` for anything you want to change on *every* plot. There are a bunch of options, but — apart from `xlim` and `ylim` — the ones I could see being useful include: `yscale` and `xscale` (can set to 'log') and `xticks` and `yticks`.

To change the x and y labels you can use the special `set_xlabels` and `set_ylabels` methods.

```
In [5]:
g.set_xlabels('points')
g.set_ylabels('density')
```

Legend

Seaborn will automatically add a legend you use the `hue` keyword. If you don't want it you can pass it `legend=False`.

Plot size

The size of plots in seaborn is controlled by two keywords: `height` and `aspect`. Height is the height of each of the individual, smaller plots (denoted by `col`). Width is controlled indirectly, and is given by `aspect*height`. I'm not positive why they do it this way, but it seems to work.

Whether you want your `aspect` to be greater, less than or equal to 1 (the default) depends on the type of data you're plotting.

I usually make plots smaller when making many little plots.

Saving

To save your plot you just call the `savefig` method on it, which takes the file path to where you want to save it. There are a few options for saving; I usually use `png`.

```
g.savefig('points_by_type_pos.png')
```

There are many more options you can set when working with seaborn visualizations, especially because it's built on top of the extremely customizable matplotlib. But this covers most of what I need.

If you do find yourself needing to do something — say modify the legend say — you should be able to find it in the seaborn and matplotlib documentation (and stackoverflow) fairly easily.

Here's our final plot after adjusting all those options.

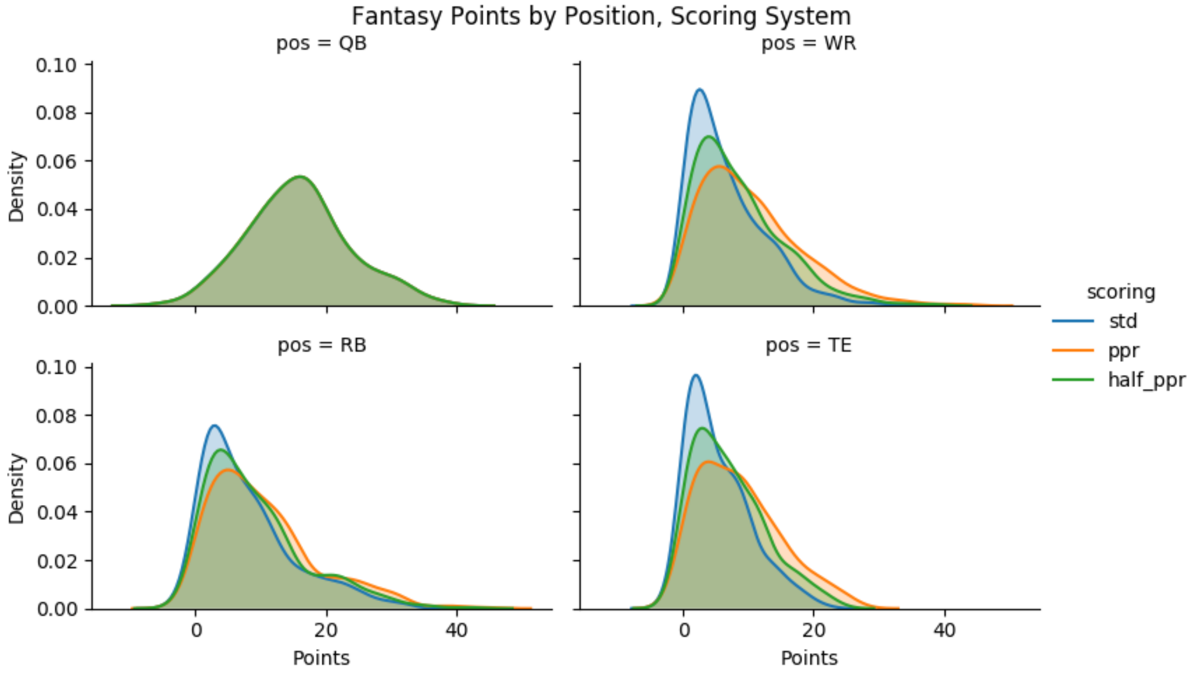


Figure 0.19: Formatted Basic Density Plot

End of Chapter Exercises

6.1

a) Using the play-by-play data, plot the distribution of yards gained. Make sure to give your plot a title.

Now modify your plot to show the distribution of yards gained by down. Restrict your analysis to downs 1-3. Do it (b) with down as separate colors on the same plot, and (c) also with downs as separate plots.

(d) Using your down as columns plot from (c) add `row='posteam'` keyword. We didn't cover this in the chapter, but what's is it doing?

(e) Sometimes it's effective to use the multiple keywords ("levers") to display redundant information, experiment with this.

6.2

Load the player-game data.

(a) Plot the relationship between carries and rushing yards by position. Again, make sure your plot has a title.

Based on this plot, which position do you think averages the most yards per carry?

(b) Verify this in Pandas.

7. Modeling

Introduction to Modeling

In the first section of the book we talked about how a **model** is the details of a relationship between an *output variable* and one or more *input variables*. In this chapter, we'll look at models more in depth and learn how to build them in Python.

The Simplest Model

Let's say we want a model that takes in distance to the end zone in yards and predicts whether a play from there will be a touchdown or not. So we might have something like:

```
touchdown or not = model(yards to endzone)
```

Terminology

First some terminology: the variable "touchdown or not" is our **output variable**[1]. There's always exactly one output variable.

The variable "yards to endzone" is our **input variable** [2]. In this case we just have one, but we could have as many as we want. For example:

```
touchdown or not = model(yards to endzone, time left in game)
```

OK. Back to:

```
touchdown or not = model(yards to endzone)
```

Here's a question: what is the simplest implementation for `model(...)` we might come up with?

How about:

[1]Other terms for this variable include: *left hand side variable* (it's to the left of the equals sign); *dependent* variable (its value *depends* on the value of yards to endzone), or *y* variable (traditionally output variables are denoted with y, inputs with x's).

[2]Other words for input variables include: *right hand side*, *independent*, *explanatory*, or *x* variables.

`model(...)= No`

So give it any yards to go, and our model spits out: "no, it will not be a touchdown". Since the vast majority of plays are not touchdowns, this model will be very accurate! But since it never says anything besides no, it's not that interesting or useful.

What about:

`prob td = 1 + -0.01*yards to go + -0.0000001*yards to go ^ 2`

So from 1 yard out we'd get a probability of 0.99, 3 yards 0.97, 10 yards 0.90 and 99 yards 0.000002. This is more interesting. I made the numbers up, so it isn't a *good* model (for 50 yards it gives about a 0.50 probability of a play being a TD, which is way too high). But it shows how a model transforms inputs to an output using some mathematical function.

Linear regression

This type of model format:

```
output variable =
    some number + another number*data + yet another number*other data
```

is called **linear regression**. It's *linear* because when you have one piece of data (input variable), the equation is a line on a set of x, y coordinates, like this:

`y = m*x + b`

If you recall math class, `m` is the slope, `b` the intercept, and `x` and `y` the horizontal and vertical axes.

Notice instead of saying *some number*, *another number* and *input* and *output data* we use `b`, `m`, `x` and `y`. This shortens things and gives you an easier way to refer back to parts of the equation. The particular letters don't matter (though people have settled on conventions). The point is to provide an abstract way of thinking about and referring to parts of our model.

A linear equation can have more than one data term in it, which is why statisticians use `b0` and `b1` instead of `b` and `m`. So we can have:

`y = b0 + b1*x1 + b2*x2 + ... + ... bn*xn`

Up to any number n you can think of. As long as it's a bunch of `x*b` terms added together it's a linear equation. Don't get tripped up by the notation: `b0`, `b1`, and `b2` are different numbers, and `x1` and `x2` are different columns of data. The notation just ensures you can include as many variables as you need to (just add another number).

In our probability-of-touchdown model that I made up, `x1` was yards to go, and `x2` was yards to go squared. We had:

`prob td = b0 + b1*(yards to go)+ b2*(yards to go ^ 2)`

Let's try running this model in Python and see if we can get better values for `b0`, `b1`, and `b2`.

Remember: the first step in modeling is making a dataset where the columns are your input variables and one output variable. So we need a three column DataFrame with yards, yards squared, and touchdown or not. We need it at the play level. Let's do it.

Note: the code for this section is in the file `07_01_ols.py`. We'll pick up from the top of the file.

```
1  import pandas as pd
2  import statsmodels.formula.api as smf
3  from os import path
4
5  DATA_DIR = '/Users/nathan/ltcwff-files/data'
6
7  # load
8  df = pd.read_csv(path.join(DATA_DIR, 'play_data_sample.csv'))
9
10 # process
11 df = df.loc[(df['play_type'] == 'run') | (df['play_type'] == 'pass')]
12 df['offensive_td'] = (
13     (df['touchdown'] == 1) & (df['yards_gained'] > 0))
14 df['offensive_td'] = df['offensive_td'].astype(int)
15
16 df['yardline_100_sq'] = df['yardline_100'] ** 2
```

Besides loading our libraries and the data, this first section of the code also does some minor processing:

First, we've limited our analysis to regular offensive plays (line 11) — no punts or field goals.

Next — although there is a `touchdown` field in our data — it includes both offensive and defensive touchdowns (e.g. an interception returned for a touchdown). Lines 12-13 create a new version that's offensive touchdowns only.

This initial offensive touchdown variable is a column of booleans (`True` if the play resulted in an offensive TD, `False` otherwise). That's fine except our model can only operate on actual numbers. We need to convert this boolean column into its numeric equivalent.

The way to do this while making everything easy to interpret is by transforming `offensive_td` into a **dummy variable**. Like a column of booleans, a dummy variable only has two values. Instead of `True` and `False` it's just `1` and `0`. Calling `astype(int)` on a boolean column will automatically do that conversion (line 13) [3].

[3] Notice even though we have two outcomes — touchdown or not — we just have the one column. There'd be no benefit to

Finally, our play-by-play data doesn't actually have yards to go squared built in, so we have to create it (line 16).

Now we have our data. In many ways, getting everything to this point is the whole reason we've learned Pandas, SQL, scraping data and everything else. All for this:

```
In [1]:
df[['offensive_td', 'yardline_100', 'yardline_100_sq']].head()

Out[1]:
      offensive_td  yardline_100  yardline_100_sq
0                0          75.0           5625.0
1                0          63.0           3969.0
2                0          58.0           3364.0
3                0          47.0           2209.0
4                0          47.0           2209.0
```

Now we just need to pass it to our modeling function, which we get from the third party library `statsmodels`. We're using the `ols` function. OLS stands for Ordinary Least Squares, and is another term for basic, standard linear regression.

We have to tell `smf.ols` which column is the output variable and which are the inputs, then run it. We do that in two steps like this:

```
In [2]: model = smf.ols(
    formula='offensive_td ~ yardline_100 + yardline_100_sq', data=df)

In [3]: results = model.fit()
```

Once we've done that, we can look at the results:

including an extra column `not_a_td` because it'd be the complete opposite of td; it doesn't add any information. In fact, including two perfectly correlated variables like this in your input variables breaks the model, and most statistical programs will drop the unnecessary variable automatically.

```
In [4]: results.summary2()
Out[4]:
<class 'statsmodels.iolib.summary2.Summary'>
"""
                 Results: Ordinary least squares
=================================================================
Model:              OLS              Adj. R-squared:     0.083
Dependent Variable: touchdown        AIC:                29.3048
Date:               2019-07-15 15:34 BIC:                40.3351
No. Observations:   292              Log-Likelihood:     -11.652
Df Model:           2                F-statistic:        14.25
Df Residuals:       289              Prob (F-statistic): 1.26e-06
R-squared:          0.090            Scale:              0.064073
-----------------------------------------------------------------
                  Coef.  Std.Err.    t    P>|t|   [0.025  0.975]
-----------------------------------------------------------------
Intercept         0.2950   0.0438  6.7421 0.0000  0.2089  0.3811
yardline_100     -0.0110   0.0023 -4.7287 0.0000 -0.0156 -0.0064
yardline_100_sq   0.0001   0.0000  3.9885 0.0001  0.0001  0.0002
-----------------------------------------------------------------
Omnibus:             185.464      Durbin-Watson:         2.140
Prob(Omnibus):       0.000        Jarque-Bera (JB):      1008.120
Skew:                2.797        Prob(JB):              0.000
Kurtosis:            10.180       Condition No.:         11073
=================================================================
* The condition number is large (1e+04). This might indicate
strong multicollinearity or other numerical problems.
"""
```

We get back a lot of information from this regression. The part we're interested in — the values for `b0`, `b1`, `b2` — are under Coef (for coefficients). They're also available in `results.params`.

Remember the intercept is another word for `b0`. It's the value of `y` when all the data is `0`. In this case, we can interpret as the probability of scoring a touchdown when you're right on the edge — the 0 yards away — of the goal line. The other coefficients are next to `yardline_100` and `yardline_100_sq`.

So instead of my made up formula from earlier, the formula that best fits this data is:

`0.2950 + -0.011*yards to go + 0.0001*(yards to go ^ 2)`.

Let's test it out with some values:

```
In [5]:
def prob_of_td(yds):
    b0, b1, b2 = results.params
    return (b0 + b1*yds + b2*(yds**2))

In [6]: prob_of_td(75)
Out[6]: 0.017520991820126786

In [7]: prob_of_td(25)
Out[7]: 0.10310069303712123

In [8]: prob_of_td(5)
Out[8]: 0.2695666142114951
```

Seems reasonable. Let's use the `results.predict` method to predict it for every value of our data.

```
In [9]: df['offensive_td_hat'] = results.predict(df)

In [10]: df[['offensive_td', 'offensive_td_hat']].head()
Out[10]:
   offensive_td  offensive_td_hat
0             0          0.017521
1             0         -0.005010
2             0         -0.006370
3             0          0.007263
4             0          0.007263
```

We can see the first five plays were not touchdowns, and our predictions were all pretty close to 0.

It's common in linear regression to predict a newly trained model on your input data. The convention is to write this variable with a ^ over it, which is why it's often suffixed with "hat".

The difference between the predicted values and what actually happened is called the **residual**. The math of linear regression is beyond the scope of this book, but basically the computer is picking out `b0`, `b1`, `b2` to make the residuals as small as possible[4].

The proportion of variation in the output variable that your model "explains" (the rest of variation is in the residuals) is called R^2 ("R squared", often written R2). It's always between 0-1. An R2 of 0 means your model explains nothing; an R2 of 1 means your model is perfect: your `yhat` always equals `y`; every residual is 0.

[4] Technically, OLS regression finds the coefficients that make the total sum of each squared residual (in part so they're all positive) as small as possible. In fact, "squares as small as possible" is partly the name, ordinary "least squares" regression.

Statistical Significance

If we look at our regression results, we can see there are a bunch of columns in addition to the coefficients. All of these are getting at the same thing, the **significance** of each coefficient.

Statistical significance is bit tricky to explain, but it basically gets at: is the effect we're observing real? Or is just luck of the draw?

To wrap our heads around this we need to distinguish between two things: the *true*, real relationship between variables — which we usually can't observe, and the observed/measured relationship, which we *can* see.

For example, consider flipping a fair coin.

What if we wanted to run a regression:

```
prob of winning toss = model(whether you call heads)
```

Now, we *know* in this case (because of the way the world, fair coins, and probability work) that whether you call heads or tails has no impact on your odds of winning the toss. That's the *true* relationship.

But data is noisy, and — if we actually guess, then flip a few coins — we probably will observe *some* relationship in our data.

Measures of statistical significance are meant to help you tell whether any result you observe is "true" or just a result of random noise.

They do this by saying: (1) assume the *true* effect of this variable is that there is none, i.e. it doesn't effect the outcome. Assuming that's the case, (2) how often would we observe what we're seeing in the data?

Make sense? Let's actually run a regression on some fake data that does this.

To make the fake data, we'll "flip a coin" coin using Python's built-in `random` library. Then we'll guess the result (via another call to `random`) and make a dummy indicating whether we got it right or not. We'll do that 100 times.

The code for this section is in the file `07_02_ols.py`.

```
import random
from pandas import DataFrame
import statsmodels.formula.api as smf

coin = ['H', 'T']

# make empty DataFrame
df = DataFrame(index=range(100))

# now fill it with a "guess" and a "flip"
df['guess'] = [random.choice(coin) for _ in range(100)]
df['result'] = [random.choice(coin) for _ in range(100)]

# did we get it right or not?
df['right'] = (df['guess'] == df['result']).astype(int)
```

Now let's run a regression on it:

```
model = smf.ols(formula='right ~ C(guess)', data=df)
results = model.fit()
results.summary2()
"""
                 Results: Ordinary least squares
=================================================================
Model:              OLS              Adj. R-squared:     0.006
Dependent Variable: right            AIC:                146.5307
Date:               2019-07-22 14:09 BIC:                151.7411
No. Observations:   100              Log-Likelihood:     -71.265
Df Model:           1                F-statistic:        1.603
Df Residuals:       98               Prob (F-statistic): 0.208
R-squared:          0.016            Scale:              0.24849
------------------------------------------------------------------
                Coef.   Std.Err.     t     P>|t|    [0.025  0.975]
------------------------------------------------------------------
Intercept       0.6170    0.0727   8.4859  0.0000   0.4727  0.7613
C(guess)[T.T]  -0.1265    0.0999  -1.2661  0.2085  -0.3247  0.0717
-----------------------------------------------------------------
Omnibus:              915.008       Durbin-Watson:          2.174
Prob(Omnibus):        0.000         Jarque-Bera (JB):       15.613
Skew:                 -0.196        Prob(JB):               0.000
Kurtosis:             1.104         Condition No.:          3
=================================================================

"""
```

Since we're working with randomly generated data you'll get something different, but according to *my* results guessing tails lowers your probability of correctly calling the flip by almost 0.13.

This is huge if true!

But, let's look at the significance columns. The one to pay attention to is `P>|t|`. It says: (1) start by assuming no true relationship between your guess and probability of calling the flip correctly. Then (2), *if* that were the case, you'd see a relationship as "strong" as the one we observed about 21% of the time.

So looks like we had a semi-unusual draw, about 80th percentile, but nothing *that* crazy.

(Note: if you want to get a feel for how often we should expect to see a result like this, try running `random.randint(1, 10)` a couple times in the REPL and see how often you get a 9 or 10.)

Traditionally, the rule has been for statisticians and social scientists to call a result **significant** if the P value is less than 0.05, i.e. — if there were no true relationship — you'd only see those type of results 1/20 times.

But in recent years, P values have come under fire.

Usually, people running regressions *want* to see an interesting, significant result. This is a problem because there are many, many people running regressions. If we have 100 researchers running a regression on relationships that don't actually exist, you'll get an average of five "significant" results (1/20) just by chance. Then those five analysts get published and paid attention to, even though they're describing statistical noise.

The real situation is worse, because usually even one person can run enough variations of a regression — adding in variables here, making different data assumptions there — to get an interesting and significant result.

But if you keep running regressions until you find something you like, the traditional interpretation of a P value goes out the window. Your "statistically significant" effect may be a function of you running many models. Then, when someone comes along trying to replicate your study with new data, they find the relationship and result doesn't actually exist (i.e., it's not significant). This appears to have happened in quite a few scientific disciplines, and is known as the "replicability crisis".

There are a few ways to handle this. The best option would be to write out your regression before you run it, so you have to stick to it no matter what the results are. Some scientific journals are encouraging this by committing to publish based only on a "pre-registration" of the regression.

It also is a good idea — particularly if you're playing around with different regressions — to have much stricter standards than just 5% for what's significant or not.

Finally, it's also good to mentally come to grips with the fact that no effect or a statistically insignificant effect still might be an interesting result.

So, back to yardline and probability of scoring a touchdown. Yardline clearly has an effect. Looking at `P>|t|` it says:

1. Start by assuming no true relationship between yards to the endzone and probability of scoring a TD.
2. *If* that were the case, we'd see our observed results — where teams *do* seem to score more as they get closer to the goal — less than 1 in 100,000 times.

So either this was a major, major fluke, or how close you are to the goal line actually is related to the probability you score.

Regressions hold things constant

One neat thing about the interpretation of any particular coefficient is it allows you to check the relationship between some input variable and your output holding everything else constant.

Let's go through another example. Our play-by-play data comes with a variable called `wpa`, which stands for win probability added. It's a measure for how much each play added or subtracted to a teams probability of winning.

Now, win probability itself is modeled — but for now let's take it as given and assume it's accurate. It might be fun to run a regression on `wpa` to see how different kinds of plays impact a team's probability of winning.

Let's start with something simple.

The code for this example is in `07_03_ols2.py`*. We'll pick up after you've loaded the play by play data into a DataFrame named* `df` *and created the variable* `offensive_td`*.*

```
model = smf.ols(formula=
        """
        wpa ~ offensive_td + turnover + first_down
        """, data=df)
results = model.fit()

print(results.summary2())
```

That gives us:

```
                      Results: Ordinary least squares
====================================================================
Model:                    OLS               Adj. R-squared:     0.612
Dependent Variable:  wpa                 AIC:                -942.2190
Date:                     2019-08-11 20:23  BIC:                -927.8402
No. Observations:    269               Log-Likelihood:     475.11
Df Model:                 3                 F-statistic:        141.7
Df Residuals:             265               Prob (F-statistic): 8.74e-55
R-squared:                0.616             Scale:              0.0017375
--------------------------------------------------------------------
                      Coef.  Std.Err.    t     P>|t|   [0.025  0.975]
--------------------------------------------------------------------
Intercept             -0.0136   0.0033  -4.1272 0.0000 -0.0201 -0.0071
offensive_td[T.True]   0.1323   0.0101  13.0786 0.0000  0.1124  0.1522
turnover[T.True]      -0.1599   0.0136 -11.7704 0.0000 -0.1867 -0.1332
first_down[T.True]     0.0573   0.0057  10.0369 0.0000  0.0460  0.0685
--------------------------------------------------------------------
Omnibus:                117.758        Durbin-Watson:           2.198
Prob(Omnibus):          0.000          Jarque-Bera (JB):        1492.616
Skew:                   1.383          Prob(JB):                0.000
Kurtosis:               14.203         Condition No.:           6
====================================================================
```

Let's look at a few coefficients to practice reading them. According to this, the *benefit* to a team from scoring a touchdown (`0.1323`) is smaller in magnitude than the *loss* in win probability from turning the ball over (`-0.1599`). Both are statistically significant (by a lot).

Then look at the coefficient on a first down. It's fairly large — almost a `0.06` increase in win probability.

If you think about it, there are two reasons plays that gain first downs are helpful: (1) the team gets a new set of downs, (2) plays that get first downs go for more yards than usual.

To verify the second claim we can use a groupby function in Pandas:

```
In [1]: df.groupby('first_down')['yards_gained'].mean()
Out[1]:
first_down
False     3.670270
True     15.130952
```

First down plays gain an average of 15 yards, vs non-first down plays, which average under four. But what if we want to quantity *just* the impact of a new set of downs on win probability?

The neat thing about regression is the interpretation of a coefficient — the effect of that variable — assumes all the other variables in the model are held constant.

So, in this first version we're saying, *controlling* (holding constant) for whether the play was touchdown or turnover, how much do plays that result in a first down add to win probability? We know first down plays go for more yards on average, but we're not explicitly controlling for it.

To do so, we can add yards gained to the model. Let's run it:

```
model = smf.ols(formula=
        """
        wpa ~ offensive_td + turnover + first_down + yards_gained
        """, data=df)
results = model.fit()
results.summary2()
```

```
                      Results: Ordinary least squares
=====================================================================
Model:                  OLS                 Adj. R-squared:     0.751
Dependent Variable:     wpa                 AIC:                -1061.1756
Date:                   2019-08-11 20:23 BIC:                   -1043.2021
No. Observations:       269                 Log-Likelihood:     535.59
Df Model:               4                   F-statistic:        203.4
Df Residuals:           264                 Prob (F-statistic): 2.31e-79
R-squared:              0.755               Scale:              0.0011125
---------------------------------------------------------------------
                       Coef.  Std.Err.    t     P>|t|   [0.025  0.975]
---------------------------------------------------------------------
Intercept             -0.0205   0.0027  -7.6111 0.0000 -0.0258 -0.0152
offensive_td[T.True]   0.0825   0.0091   9.1079 0.0000  0.0647  0.1003
turnover[T.True]      -0.1400   0.0110 -12.7333 0.0000 -0.1616 -0.1183
first_down[T.True]     0.0224   0.0054   4.1577 0.0000  0.0118  0.0330
yards_gained           0.0028   0.0002  12.2430 0.0000  0.0023  0.0032
---------------------------------------------------------------------
Omnibus:                71.033         Durbin-Watson:           2.217
Prob(Omnibus):          0.000          Jarque-Bera (JB):        2199.522
Skew:                   -0.006         Prob(JB):                0.000
Kurtosis:               17.009         Condition No.:           73
=====================================================================
```

Now we're saying, controlling for whether the play was a TD, turnover, *and* how many yards it gained, what is the effect of a first down on win probability?

Now that yards is explicitly accounted for, we know that the `first_down` coefficient measures *only* the effect of new set of downs. And we can see the effect drops by more than half. It's still positive — a new set of downs adds a little over 0.02 to a team's win probability on average — but it's less useful than getting a new set of downs *and* a long gain.

Other examples of holding things constant

This idea of holding variables constant is useful and one of the major reasons people run regressions. To drive the point home, let's look at some other hypothetical examples. I personally don't have the data to analyze these, so if you can find it feel free run with them (and let me know the results!).

Say we wanted to do know whether the fantasy community properly evaluates players who finished the prior season on IR. In that case we might do something like:

```
ave points = b0 + b1*adp + b2*ended_last_season_on_ir
```

Where `ended_last_season_on_ir` is `1` if a player ended the previous season on IR, `0` otherwise. Note: this data would be at the player-season level.

If `b2` is 0 or not significantly different from 0, that suggests — *controlling* for ADP — there's no systemic gain or loss from drafting a player who ended last season on IR.

If `b2` was < 0, it would imply players on IR do worse than their ADP would suggest; > 0, better. Depending on the results we could adjust our strategy accordingly.

You could do this analysis with any other data you had and wanted to test whether the crowd controlled for — rookies, players changing teams, etc.

Aside: I don't know this for sure, but my prediction is any coefficient wouldn't be statistically significant from 0. That is, I would guess the fantasy market is pretty efficient and the crowd doesn't systematically under or over value guys in predictable ways.

Holding things equal is also useful for comparing players' performance in different situations. For example, you could:

- Measure RB performance holding the quality of offensive line constant.
- Measure WR performance holding the quality of the quarterback constant.
- Measure a fantasy players points scored holding the amount of garbage time they get constant.

Fixed Effects

We've seen how dummy variables work for binary, true or false data, but what about something with more than two categories?

Not just `ended_season_on_ir` or `offensive_td`, but say, position (`QB`, `RB`, `WR`, `TE`, `K`, `DST`) or down (`1`, `2`, `3`, `4`).

These are called categorical variables or "fixed effects" and the way we handle them is by putting our one categorical variable (position) into a series of dummies that give us the same information (`is_qb`, `is_rb`, `is_wr`, `is_te`, `is_k`, `is_dst`).

So `is_qb` is `1` if player is a qb, `0` otherwise, etc. Except we don't need *all* of these. There are only 6 fantasy positions, and assuming we're working with fantasy data, a player has to be one — if a player isn't a QB, RB, WR, TE, or K, then we know it must be a DST. That means we can (by *can* I mean have to so that the math will work) leave out one of the categories.

Fixed effects are very common in right hand side variables, and Pandas has built in functions to make them for you:

```
In [1]: pd.get_dummies(df['down']).head()
Out[1]:
   1.0  2.0  3.0  4.0
0    1    0    0    0
1    1    0    0    0
2    0    1    0    0
3    1    0    0    0
4    0    1    0    0
```

Again, *all* of these variables would be redundant — there are only four downs, so you can pass the `drop_first=True` argument to `get_dummies` to have it return only three columns.

In practice, programs like `statsmodels` can automatically convert categorical data to a set of fixed effects, but it's useful to know what's going on behind the scenes.

Squaring Variables

When we run a linear regression, we're assuming certain things about how the world works, namely that a change in one of our `x` variables always means the *same* change in `y`.

Say for example we're looking at:

`ave points = b0 + b1*adp`

By modeling this as a linear relationship, we're assuming a one unit change in ADP always has the *same* effect on average points. This effect (`b1`) is the same whether we're going from pick 1 to pick 2, or pick 171 to 172.

Is that that a good assumption? In this case probably not. I'd expect the difference in early ADP to matter a lot more for final points than ADP later on.

Does this mean we have to abandon linear regression?

No, because there are tweaks we can make that — while keeping things linear — help make our model more realistic. All of these tweaks basically involve keeping the linear framework (`y = b0 + x1*b1 + x2*b2 ... xn*bn`), while transforming the `x`'s to model different situations.

In this case — where we think the relationship between points and ADP might vary — we could square ADP and include it in the model.

```
ave points = b0 + b1*adp + b2*adp^2
```

This allows the effect to change depending on where we are in ADP. For early values, ADP^2 is relatively small, and `b2` doesn't come into play as much — later it does.

Including squared (sometimes called *quadratic*) variables is common when you think the relationship between an input and output might depend where you are on the input.

Logging Variables

Another common transformation is to take the natural log of the output, inputs, or both. This let's you move from absolute to relative differences and interpret coefficients as percent changes.

So if we had a regression like:

```
rookie qb passing yards = b0 + b1*college passing yards
```

We'd interpret `b1` as the number of yards passing yards associated with 1 more passing yard in college. If we did:

```
ln(passing yards)= b0 + b1*ln(college passing yards)
```

We'd interpret `b1` as a *percent change* in rookie passing yards, given a one *percent change* in college yards. It works for dummy variables too, for example if you're doing:

```
ln(passing yards)= b0 + b1*ln(college passing yards)+ b2*is_under_6_ft
```

Then `b2` is the expected percentage change in rookie passing yards for quarterbacks under 6 ft.

Interactions

Again, in a normal linear regression, we're assuming the relationship between some `x` variable and our `y` variable is always the same for every type of observation.

For example, earlier we ran a regression on win probability and found that a turnover reduced a team's probability of winning by about `0.16`.

But that assumes the impact of a turnover is the same whenever it happens. Is that true? I could see turnovers being more costly in certain situations, e.g. in a close game or maybe towards the end of a game.

To test this, we can add in an **interaction** — which allow the effect of a variable to vary depending on the value of another variable.

In practice, it means our regression goes from this:

```
wpa = b0 + b1*offensive_td + b2*turnover + ...
```

To this:

```
wpa = b0 + b1*offensive_td + b2*turnover + b3*(is_4th_q*turnover)+ ...
```

Then b2 is the impact of a normal, non-4th quarter turnover and b2 + b3 is the effect of a 4th quarter turnover.

Let's run that regression:

```
df['is_4'] = (df['qtr'] == 4)
df['turnover'] = df['turnover'].astype(int)

model = smf.ols(formula=
        """
        wpa ~ offensive_td + turnover + turnover:is_4 + yards_gained +
            first_down
        """, data=df)
results = model.fit()
results.summary2()
```

And the results:

```
                  Results: Ordinary least squares
====================================================================
Model:                 OLS                Adj. R-squared:     0.762
Dependent Variable:    wpa                AIC:                -1072.4398
Date:                  2019-08-11 20:33 BIC:                -1050.8715
No. Observations:      269                Log-Likelihood:     542.22
Df Model:              5                  F-statistic:        173.0
Df Residuals:          263                Prob (F-statistic): 5.50e-81
R-squared:             0.767              Scale:              0.0010630
--------------------------------------------------------------------
                      Coef.  Std.Err.    t     P>|t|   [0.025  0.975]
--------------------------------------------------------------------
Intercept            -0.0205   0.0026 -7.7938 0.0000 -0.0257 -0.0154
offensive_td[T.True]  0.0824   0.0089  9.3014 0.0000  0.0649  0.0998
first_down[T.True]    0.0223   0.0053  4.2343 0.0000  0.0119  0.0326
turnover             -0.1153   0.0127 -9.0811 0.0000 -0.1403 -0.0903
turnover:is_4        -0.0820   0.0225 -3.6460 0.0003 -0.1263 -0.0377
yards_gained          0.0028   0.0002 12.5600 0.0000  0.0023  0.0032
--------------------------------------------------------------------
Omnibus:               78.617       Durbin-Watson:          2.139
Prob(Omnibus):         0.000        Jarque-Bera (JB):       1103.675
Skew:                  0.712        Prob(JB):               0.000
Kurtosis:              12.820       Condition No.:          162
====================================================================
```

So we can see a turnover in 4th quarter is indeed worse than a turnover in quarters 1-3. The latter lowers win probability by `-0.12`, the former by `-0.12 + -0.08 = -0.20`.

Logistic Regression

Earlier we went through an example where we built a model to calculate the probability of a touchdown given some value for yardline and yardline squared.

That model worked OK — especially since it was built on data from only two games — but for some yardlines around the middle of the field it returned negative probabilities.

We can avoid this by running a **logistic** regression instead of OLS.

You can use all the same tricks (interactions, fixed effects, squared, dummy and logged variables) on the right hand side, we're just working with a different model.

Logit:

`1/(1 + exp(-(b0 + b1*x1 + ... + bn*xn)))`

Vs Ordinary Least Squares:

`b0 + b1*x1 + ... + bn*xn`

In `statsmodels` it's just a one line change.

The logit example is in `07_04_logit.py`. We're picking up with the line that actually runs the logit.

```
In [1]:
smf.logit(formula='touchdown ~ yardline_100 + yardline_100_sq', data=df)
results = model.fit()
```

```
"""
                          Results: Logit
=================================================================
Model:              Logit            Pseudo R-squared: 0.196
Dependent Variable: offensive_td     AIC:              116.3669
Date:               2019-07-23 21:50 BIC:              127.1511
No. Observations:   269              Log-Likelihood:   -55.183
Df Model:           2                LL-Null:          -68.668
Df Residuals:       266              LLR p-value:      1.3926e-06
Converged:          1.0000           Scale:            1.0000
No. Iterations:     8.0000
-----------------------------------------------------------------
                   Coef.  Std.Err.    z     P>|z|   [0.025  0.975]
-----------------------------------------------------------------
Intercept         -0.2686   0.4678 -0.5743 0.5658 -1.1855  0.6482
yardline_100      -0.1212   0.0381 -3.1824 0.0015 -0.1958 -0.0465
yardline_100_sq    0.0010   0.0005  2.0822 0.0373  0.0001  0.0019
=================================================================
"""
```

Now to get the probability for any yardage, we need to multiply our data by our coefficients (like before), then run them through the logistic function.

```
In [2]:
def prob_of_td_logit(yds):
    b0, b1, b2 = logit_results.params
    value = (b0 + b1*yds + b2*(yds**2))
    return 1/(1 + math.exp(-value))

In [3]: prob_of_td_logit(75)
Out[3]: 0.02008026676665306

In [4]: prob_of_td_logit(25)
Out[4]: 0.063537736346553

In [5]: prob_of_td_logit(5)
Out[5]: 0.2993805493398434
```

A logit model guarantees our predicted probability will be between 0 and 1. You should always use a logit instead of OLS when you're modeling some yes or no type outcome.

Random Forest

Both linear and logistic regression are useful for:

1. Analyzing the relationships between data (looking at the coefficients).

2. Making predictions (running new data through a model to see what it predicts).

Random Forest models are much more of a black box. They're more flexible and make fewer assumptions about your data. This makes them great for prediction (2), but almost useless for analyzing relationships between variables (1).

Unlike linear or logistic regression, where your `y` variable has to be continuous or 0/1, Random Forests work well for classification problems. Later we'll build our own model to predict player's positions based on their stats.

But let's start with some theory.

Classification and Regression Trees

The foundation of Random Forest models is the **classification and regression tree (CART)**. A CART is a single tree made up of a series of splits on some numeric variables. So, in our position example, maybe the first split in the tree is on "targets". We start with all of our player-game combinations, and look at their number of targets. If the split point is at (say) 1, players with 0 targets go one direction, 1+ targets another.

Let's follow the players on the 0 target branch. They'll go on to be divided by another split that looks at a different variable. Maybe it's "passing yards". If it's above the split point (say 40 yards) they get classified as QBs, below Ks.

Meanwhile the 1+ target branch also continues onto its own, different split. Maybe it's carries. Players with more than X carries go one direction, less, another.

CART trees involve many split points. Details on how these points are selected are beyond the scope of this book, but essentially the computer goes through all possible variables and potential splits and picks the one that separates the data the "best". Then it sets that data aside and starts the process over with each subgroup. The final result is a bunch of if-then decision rules.

You can tell your program when to stop doing splits, either by: (1) telling it to keep going until all observations in a branch are "pure" (all classified the same thing), (2) telling it to split only a certain number of times, or (3) splitting until a branch reaches a certain number of samples.

Python seems to have sensible defaults for this, and I don't find myself changing them too often.

Once you stop, the end result is a tree where the endpoints (the *leaves*) are one of your output classifications, or — if your output variable is continuous — the average of your output variable for all the observations in the group.

Regardless, you have a tree, and you can follow it through till the end and get some prediction.

Random Forests are a Bunch of Trees

That's one CART tree. The **Random Forest** algorithm consists of multiple CARTs combined together for a sort of wisdom-of-crowds approach.

Each CART is trained on a subset of your data. This subsetting happens in two ways: using a random sample of *observations* (rows), but also by limiting each CART to a random subset of *columns*. This helps makes sure the trees are different from each other, and provides the best results overall.

The default in Python is for each Random Forest to create 100 CART trees, but this is a parameter you have control over.

So the final result is stored as some number of trees, each trained on a different, random sample of your data. If you think about it, *Random Forest* is the perfect name for this model.

Using a Trained Random Forest to Generate Predictions

Getting a prediction depends on whether your output variable is categorical (classification) or continuous (regression).

When it's a classification problem, you just run it through each of the trees (say 100), and see what the most common outcome is.

So for one particular observation, 80 of the trees might say QB, 15 RB and 5 K or something.

For a regression, you run it through the 100 trees, then take the average of what each of them says.

In general, a bunch of if … then tree rules make this model way more flexible than something like a linear regression, which imposes a certain structure. This is nice for accuracy, but it also means random forests are much more susceptible to things like overfitting. It's a good idea to set aside some data to evaluate how well your model does.

Random Forest Example in Scikit-Learn

Let's go through an example of Random Forest model.

This example is in `07_05_random_forest.py`. We'll pick up right after importing our libraries and loading our player-game data into a DataFrame named `df`.

In this example, we'll use our player-game data and try to predict position given all of our other numeric data. That is, we'll model position as a function of:

```
xvars = ['carries', 'rush_yards', 'rush_fumbles', 'rush_tds', 'targets',
         'receptions', 'rec_yards', 'raw_yac', 'rec_fumbles', 'rec_tds',
         'ac_tds', 'rec_raw_airyards', 'caught_airyards', 'attempts',
         'completions', 'pass_yards', 'pass_raw_airyards',
         'comp_airyards', 'timeshit', 'interceptions', 'pass_tds',
         'air_tds']
yvar = 'pos'
```

Because tree based models like Random Forest are so flexible, it's meaningless to evaluate them on the same data you used to build the model — they'll perform too well. Instead, it's good practice to take a **holdout** set, i.e. set aside some portion of the data where you *know* the outcome you're trying to predict (player's position here) so you can evaluate the model on data that wasn't used to train it.

Scikit-learn's `train_test_split` function automatically does that. Here we have it randomly split our data 80/20 — 80% to build the model, 20% to test it.

```
In [1]: train, test = train_test_split(df, test_size=0.20)
```

Running the model takes place on two lines. Note the `n_estimators` option. That's the number of different trees the algorithm will run.

```
In [2]:
model = RandomForestClassifier(n_estimators=100)
model.fit(train[xvars], train[yvar])
--
Out[2]: RandomForestClassifier()
```

Note how the `fit` function takes your input and output variable as separate arguments.

Unlike `statsmodels`, `scikit-learn` doesn't give us any fancy, pre-packaged results string to look at. But we can check to see how this model does on our holdout dataset with some basic Pandas.

```
In [3]: test['pos_hat'] = model.predict(test[xvars])

In [4]: test['correct'] = (test['pos_hat'] == test['pos'])

In [5]: test['correct'].mean()
Out[5]: 0.7630662020905923
```

Above 75%, not bad. Note, when you run this yourself, you'll get something different. A Random Forest model contains randomness (hence the name), so you'll get a slightly different answer every time you run it.

Another thing it's interesting to look at is how confident the model is about each prediction. Remember, this model ran 100 different trees. Each of which classified every observation into one of: QB, RB, WR, TE. If the model assigned some player RB for 51/100 trees and WR for the other 49/100, we can interpret it as relatively unsure in it's prediction.

Let's run each of our test samples through each of our 100 trees and check the frequencies. We can do this with the `predict_proba` method on `model`:

```
In [6]: model.predict_proba(test[xvars])
Out[6]:
array([[0.        , 0.        , 0.2       , 0.8       ],
       [0.        , 0.97      , 0.01      , 0.02      ],
       [0.        , 0.12      , 0.35      , 0.53      ],
       ...,
       [0.        , 0.03      , 0.40616667, 0.56383333],
       [0.        , 0.08      , 0.51      , 0.41      ],
       [0.        , 0.        , 0.23      , 0.77      ]])
```

This is just a raw, unformatted matrix. Let's put it into a DataFrame, making sure to give it the same index as `test`:

```
In [7]:
probs = DataFrame(model.predict_proba(test[xvars]),
                  index=test.index,
                  columns=model.classes_)
--

In [8]: probs.head()
Out[8]:
       QB    RB        TE        WR
249   0.0  0.00  0.200000  0.800000
677   0.0  0.97  0.010000  0.020000
1091  0.0  0.12  0.350000  0.530000
384   0.0  1.00  0.000000  0.000000
642   0.0  0.00  0.153333  0.846667
```

We're looking at the first 5 rows of our holdout dataset here. We can see the model says the first observation has a 20% of being a TE, and an 80% of being a WR.

Let's bring in the actual, known position from our test dataset.

```
In [9]:
results = pd.concat([
    test[['player_id', 'player_name', 'pos', 'pos_hat', 'correct']],
    probs], axis=1)
```

And how did the model do for these first five observations?

```
In [10]:
results[['player_name', 'pos', 'correct', 'QB', 'RB', 'TE', 'WR']].head()

Out[10]:
     player_name pos  correct   QB    RB        TE        WR
249       K.Cole  WR     True  0.0  0.00  0.200000  0.800000
677     L.Miller  RB     True  0.0  0.97  0.010000  0.020000
1091    T.Taylor  WR     True  0.0  0.12  0.350000  0.530000
384       L.Bell  RB     True  0.0  1.00  0.000000  0.000000
642    A.Jeffery  WR     True  0.0  0.00  0.153333  0.846667
```

5/5. Perfect. Let's try grouping to see how our model did by position.

```
In [11]:
results.groupby('pos')[['correct', 'QB', 'RB', 'WR', 'TE']].mean()

Out[11]:
      correct        QB        RB        WR        TE
pos
QB   1.000000  0.987647  0.011765  0.000588  0.000000
RB   0.947368  0.000263  0.911711  0.052667  0.035360
TE   0.189655  0.000000  0.056724  0.619003  0.324273
WR   0.857143  0.000756  0.058319  0.735185  0.205739
```

The model performs worst on TEs, getting them correct only 19% of the time. As we might expect, it usually misclassifies them as a WR.

Working with a holdout dataset let's us do interesting things and is conceptually easy to understand. It's also noisy, especially with small datasets. Different, random holdout sets can give widely fluctuating accuracy numbers. This isn't ideal, which is why an alternative called cross validation is more common.

Cross Validation

Cross validation reduces noise, basically by taking *multiple* holdout sets and blending them together.

How it works: you divide your data into some number of groups, say 10. Then, you run your model 10 separate times, each time using 1 of the groups as the test data, and the other 9 to train it. That gives you 10 different accuracy numbers, which you can average to get a better look at overall performance.

Besides being less noisy, cross validation lets you get more out of your data. Every observation contributes, vs only the 80% (or whatever percentage you use) with a train-test split. One disadvantage is its more computationally intensive since you're running 10x as many models.

To run cross validation, you create model like we did above. But instead of calling `fit` on it, you pass it to the `scikit-learn` function `cross_val_score`.

```
In [12]: model = RandomForestClassifier(n_estimators=100)

In [13]: scores = cross_val_score(model, df[xvars], df[yvar], cv=10)
```

With `cv=10`, we're telling scikit learn to do divide our data into 10 groups. This gives back 10 separate scores, which we can look at and average.

```
In [14]: scores
Out[14]:
array([0.8137931 , 0.84137931, 0.8137931 , 0.85416667, 0.77777778,
       0.8041958 , 0.74647887, 0.77304965, 0.73049645, 0.78014184])

In [15]: scores.mean()
Out[15]: 0.7935272582383476
```

Again, your results will vary, both due to the randomness of the Random Forest models, as well as the cross validation splits.

Finally, although we don't have anything like the coefficients we get with linear regressions, the model does output some information on which features are most important (e.g. made the biggest difference in being able to split correctly or not).

We can look at them with:

```
In [16]:
Series(model.feature_importances_, xvars).sort_values(ascending=False)

Out[16]:
rec_raw_airyards     0.170337
carries              0.158026
caught_airyards      0.126099
rush_yards           0.106618
rec_yards            0.071190
raw_yac              0.061879
targets              0.053837
receptions           0.037801
completions          0.037200
comp_airyards        0.036965
attempts             0.035756
pass_yards           0.033988
pass_raw_airyards    0.019725
rec_tds              0.012279
pass_tds             0.010109
rush_tds             0.009317
ac_tds               0.005330
air_tds              0.004494
rec_fumbles          0.004319
timeshit             0.002719
interceptions        0.001030
rush_fumbles         0.000981
```

There you go, you've run your first Random Forest model.

Random Forest Regressions

`RandomForestClassifier` is the `scikit-learn` model for modeling an output variable with discrete categories (position, touchdown or not, etc). If you're modeling a continuous valued variable (like fantasy points) you do the exact same thing, but with `RandomForestRegressor` instead.

When might you want to use `RandomForestRegressor` vs the OLS and `statsmodels` techniques we covered earlier?

Generally, if you're interested in the coefficients and understanding and interpreting your model, you should lean towards the classic linear regression. If you just want the model to be as accurate as possible and don't care about understanding how it works, try a Random Forest[5].

[5] Of course, there are other, more advanced models than Random Forest available in scikit-learn too. See the documentation for more.

End of Chapter Exercises

7.1

This problem builds off `07_01_ols.py` and assumes you have it open and run in the REPL.

a) Using `prob_of_td` and the apply function, create a new column in the data `offensive_td_hat_alt` — how does it compare to `results.predict(df)`?

b) Try adding distance to first down to the model, is it significant at the 5% level?

In our statistical significance coin flipping example, we had a variable 'guess' that was either 'H' or 'T'. We put it in our coin flipping regression with `C(guess)`.

c) Add `C(down)` to the probability of touchdown model, and look the results, what does `C()` do? Controlling for everything else in our regression, which down is most likely to lead to a touchdown?

d) Run the same model without the `C(down)` syntax, creating dummy variables for down manually instead, do you get the same thing?

7.2

This problem builds off `07_02_coinflip.py` and assumes you have it open and run in the REPL.

a) Build a function `run_sim_get_pvalue` that flips a coin n times (default to 100), runs a regression on it, and returns the P value of your guess.

Hint: the P values are available in `results.pvalues`.

b) Run your function at least 1k times and put the results in a `Series`, what's the average P value? About what do you think it'd be if you ran it a million times?

c) The function below will run your `run_sim_get_pvalue` simulation from (a) until it gets a significant result, then return the number of simulations it took.

```
def runs_till_threshold(i, p=0.05):
    pvalue = run_sim_get_pvalue()
    if pvalue < p:
        return i
    else:
        return runs_till_threshold(i+1, p)
```

You run it a single time like this: `runs_till_threshold(1)`.

Run it 100 or so times and put the results in a Series.

d) The probability distribution for what we're simulating ("how many times will it take until an event with probability p happens?") is a called the Geometric distribution, look up the median and mean of it and compare it to your results.

7.3

This problem builds off `07_03_ols2.py` and assumes you have it open and run in the REPL.

a) Using the play-by-play data, run the regression:

```
wpa ~ offensive_td + interception + yards_gained + fumble
```

What's worse for team's win probability, fumbling or throwing a pick? Why do you think this is?

b) Replace `fumble` with `fumble_lost` instead. How do you think the coefficients on `fumble_lost` and `interception` will compare now?

7.4

Explain why your prediction about the sign and significance of `b2` might depend on your opinion on the aggregate smarts and skills of your fellow fantasy players:

```
ave points = b0 + b1*adp + b2*is_rookie
```

7.5

This problem builds off of `07_05_random_forest.py` and assumes you have it open and run in the REPL.

Right now, in `07_05_random_forest.py` we're predicting position for each player-game combination. But really, we're interesting in position at the *player* level.

Try grouping the player-game data to the player-season level rerunning the random forest model. Use cross-validation to see how the models perform.

a) First try using the season average of each stat for every player.

b) Then try other (or multiple) aggregations. Use cross validation to figure out which model performs the best.

8. Intermediate Coding and Next Steps: High Level Strategies

If you've made it this far you should have all the technical skills you need to start working on your own projects.

That's not to say you won't continue to learn (the opposite!). But moving beyond the basics is less "things you can do with DataFrames #6-10" and more about mindset, high level strategies and getting experience. That's why, to wrap up, I wanted to cover a few, mostly non-technical strategies that I've found useful.

These concepts are both high level (e.g. Gall's Law) and low level (get your code working then put it in a function), but all of them should help as you move beyond the self-contained examples in this book.

Gall's Law

> *"A complex system that works is invariably found to have evolved from a simple system that worked."* - John Gall

Perhaps the most important idea to keep in mind as you start working on your own projects is *Gall's Law*.

Applied to programming, it says: any complicated, working program or piece of code (and most programs that do real work are complicated) evolved from some simpler, working code.

You may look at the final version of some project or even some of the extended examples in this book and think "there's so way I could ever do that." But if I just sat down and tried to write these complete programs off the top of my head I wouldn't be able to either.

The key is building up to it, starting with simple things that work (even if they're not exactly what you want), and going from there.

I sometimes imagine writing a program as tunneling through a giant wall of rock. When starting, your job is to get a tiny hole through to the other side, even if it just lets in a small glimmer of light. Once it's there, you can enlarge and expand it

Also, Gall's law says that complex systems evolve from simpler ones, but what's "simple" and "complex" might change depending on where you're at as a programmer.

If you're just starting out, writing some code to concatenate or merge two DataFrames together might be complex enough that you'll want to examine your your outputs to make sure everything works.

As you get more experience and practice everything will seem easier. Your intuition and first attempts will gradually get better, and your initial working "simple" systems will get more complicated.

Get Quick Feedback

A related idea that will help you move faster: get quick feedback.

When writing code, you want to do it in small pieces that you run and test as soon as you can.

That's why I recommend coding in Spyder with your editor on the left and your REPL on the right, as well as getting comfortable with the shortcut keys to quickly move between them.

This is important because you'll inevitably (and often) screw up, mistyping variable names, passing incorrect function arguments, etc. Running code as you write it helps you spot and fix these errors as they happen.

Here's a question: say you need to write some small, self contained piece of code; something you've done before that is definitely in your wheelhouse — what are the chances it does what you want without any errors the first time you try it?

For me, if it's anything over three lines, it's maybe 50-50 at *best*. Less if it's something I haven't done in a while.

Coding is precise, and it's really easy to mess things up in some minor way. If you're not constantly testing and running what you write, it's going to be way more painful when you eventually do.

Use Functions

For me, the advice above (start simple + get quick feedback) usually means writing simple, working code in the "top level" (the main, regular Python file; as opposed to inside a function).

Then — after I've examined the outputs in the REPL and am confident some particular piece works — I'll usually put it inside a function.

Functions have two benefits: (1) DRY and (2) letting you set aside and abstract parts of your code.

DRY: Don't Repeat Yourself

A popular maxim among programmers is "DRY" for Don't Repeat Yourself[1].

For example: say you need to run some similar code a bunch of times. Maybe it's code that summarizes points by position, and you need to run it for all the RBs, WRs, TEs etc.

The naive approach would be to get it working for one position, then copy and paste it a bunch of times, making the necessary tweaks for the others.

But what happens if you need to modify it, either because you change something or find a mistake?

Well, if it's a bunch of copy and pasted code, you need to change it everywhere. This is tedious at best and error-prone at worst.

But if you put the code in a function, with arguments to allow for your slightly different use cases, you only have to fix it in one spot when you make inevitable changes.

Functions Help You Think Less

The other benefit of functions is they let you group related concepts and ideas together. This is nice because it gives you fewer things to think about.

For example, say we're working with some function called `win_prob` that takes information about the game — the score, who has the ball, how much time is left — and uses that to calculate each team's probability of winning.

Putting that logic in a function like `win_prob` means we no longer have to remember our win probability calculation every time we want to do it. We just use the function.

The flip side is also true. Once it's in a function, we no longer have to mentally process a bunch of Pandas code (what's that doing… multiplying time left by a number … adding it to the difference between team scores … oh, that's right — win probability!) when reading through our program.

This is another reason it's usually better to use small functions that have one-ish job vs large functions that do everything and are harder to think about.

Attitude

As you move into larger projects and "real" work, coding will go much better if you adopt a certain mindset.

[1] DRY comes from a famous (but old) book called The Pragmatic Programmer, which is good, but first came out in 1999 and is a bit out of date technically. It also takes a bit of a different (object oriented) approach that we do here

First, it's helpful to take a sort of "pride" (pride isn't exactly the right word but it's close) in your code. You should appreciate and care about well designed, functioning code and strive to write it yourself. The guys who coined DRY talk about this as a sense of *craftsmanship*.

Of course, your standards for whats well-designed will change over time, but that's OK.

Second, you should be continuously growing and improving. You'll be able to do more faster if you deliberately try to get better as a programmer — experimenting, learning and pushing yourself to write better code — especially early on.

One good sign you're doing this well is if you can go back to code you've written in the past and are able to tell approximately when you wrote it.

For example, say we want to modify this dictionary:

```
roster_dict = {'qb': 'Tom Brady', 'rb': 'Dalvin Cook', 'wr': 'DJ Chark'}
```

And turn all the player names to uppercase.

When we're first starting out, maybe we do something like:

```
In [1]: roster_dict1 = {}
In [2]: for pos in roster_dict:
            roster_dict1[pos] = roster_dict[pos].upper()

In [3]: roster_dict1
Out[3]: {'qb': 'TOM BRADY', 'rb': 'DALVIN COOK', 'wr': 'DJ CHARK'}
```

Then we learn about comprehensions and realize we could just do this on one line.

```
In [4]: roster_dict2 = {pos: roster_dict[pos].upper()
                        for pos in roster_dict}

In [5]: roster_dict2
Out[5]: {'qb': 'TOM BRADY', 'rb': 'DALVIN COOK', 'wr': 'DJ CHARK'}
```

Then later we learn about `.items` in dictionary comprehensions and realize we can write the same thing:

```
In [6]: roster_dict3 = {pos: name.upper()
                        for pos, name in roster_dict.items()}

In [7]: roster_dict3
Out[7]: {'qb': 'TOM BRADY', 'rb': 'DALVIN COOK', 'wr': 'DJ CHARK'}
```

This illustrates a few points:

First, if you go back and look at some code with `roster_dict2`, you can roughly remember, "oh I must have written this after getting the hang of comprehensions but before I started using `.items`." You definitely don't need to memorize your complete coding journey and remember when exactly when you started doing what. But noticing things like this once in a while can be a sign you're learning and getting better, and is good.

Second, does adding `.items` matter much for the functionality of the code in this case? Probably not.

But preferring the `.items` in v3 to the regular comprehension in v2 is an example of what I mean about taking pride in your code and wanting it to be well designed. Over time these things will accumulate and eventually you'll be able to do things that people who don't care about their code and "just want it to work" can't.

Finally, taking pride in your code doesn't always mean you have to use the fanciest techniques. Maybe you think the code is easier to understand and reason about without `.items`. That's fine.

The point is that you should be consciously thinking about these decisions and be *deliberate*; have reasons for what you do. And what you do should be changing over time as you learn and get better.

I think most programmers have this mindset to some degree. If you've made it this far, you probably do too. I'd encourage you to cultivate it.

Review

Combined with the fundamentals, this high and medium level advice:

- Start with a working simple program then make more complex.
- Get quick feedback about what you're coding by running it.
- Don't repeat yourself and think more clearly by putting common code in functions.
- Care about the design your code and keep trying to get better at.

Will get you a long way.

9. Conclusion

Congratulations! If you've made it this far you are well on your way to doing data analysis on *any* topic, not just fantasy football. We've covered a lot of material, and there many ways you could go from here.

I'd recommend starting on your own analysis ASAP (see the appendix for a few ideas on places to look for data). Especially if you're self-taught, diving in and working on your own projects is by far the fastest and most fun way to learn.

When I started building the website that became www.fantasymath.com I knew nothing about Python, Pandas, SQL, web scraping, or machine learning. I learned all of it because I wanted to beat my friends in fantasy football.

The goal of this book has been to make things easier for people who feel the same way. Judging by the response so far, there are a lot of you. I hope I've been successful, but if you have any questions, errata, or other feedback, don't hesitate to get in touch — nate@nathanbraun.com

Appendix A: Places to Get Data

This appendix lists a few places to get fantasy related data.

Ready-made Datasets

RScraper

The play-by-play and player-game data we use in this book is a modified subset of the data now available via:

https://www.nflfastr.com

`nflfastR` is an R package written by Sebastian Carl and Ben Baldwin that scrapes play-by-play data.

Note on R

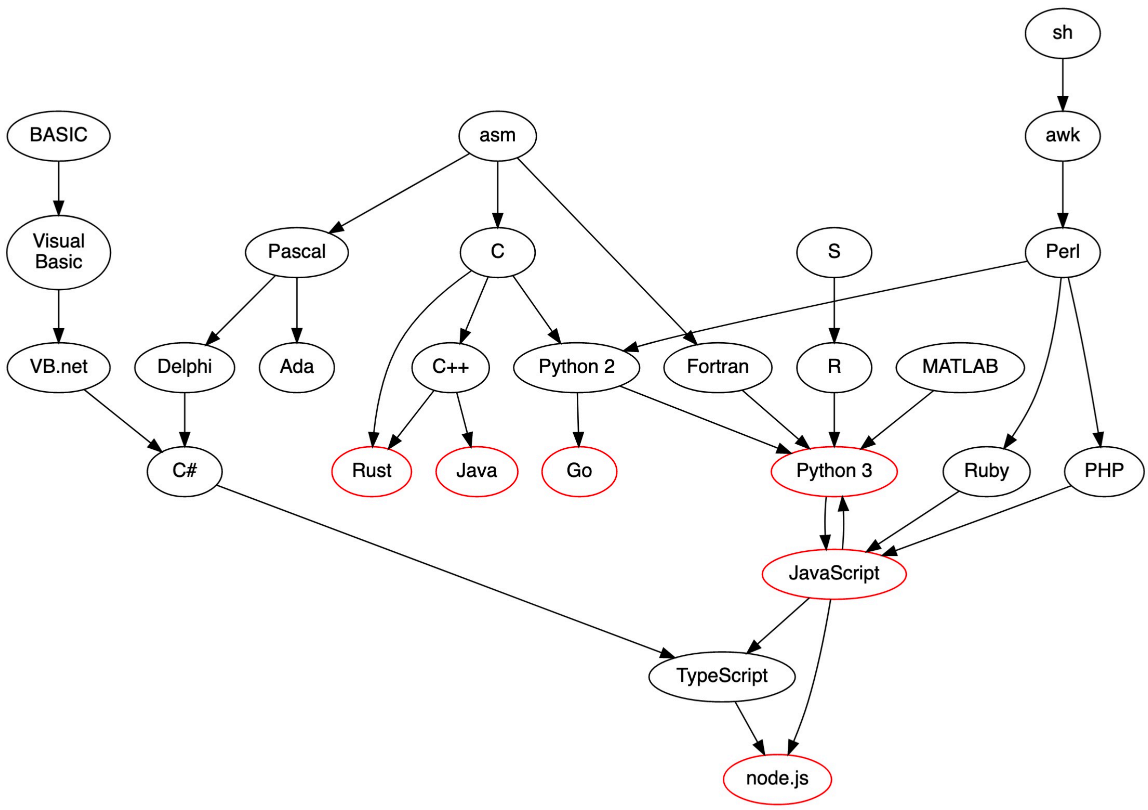
R is a programming language and an alternative to Python. You can basically think of it as Pandas + a few other statistical libraries. It's been around longer and has a solid NFL analytics following, as evidence by the guys from `nflfastR`, among others.

If this gives you a case of FOLTWPR (fear of learning the wrong programming language), relax. Until about 5 years ago the R/Python split was about 50/50, but since then Python is the much more popular option, as a quick search for "R vs Python market share" shows.

Also interesting is this study of programmer migration patterns by programmer blogger apenwarr. He found that R users are much more likely to go from R -> Python than the other way around.

As apenwarr explains, nodes in red below are "currently the most common 'terminal nodes' — where people stop because they can't find anything better".

Python 3 (what we've been learning) is a terminal node. It's not only R users that tend to flow to it, but MATLAB and Fortran (and in my case Stata and SAS) users too.



Programmer migration patterns (apenwarr)

Figure 0.1: Programmer Migration Pattersn

Anyway, just because we've decided to learn Python instead of R doesn't mean we can't recognize good work and useful tools when we see them.

In this case it's even easier (we don't even have to do anything in R) because the authors have helpfully put up all their historical data (as zipped csv files, among others) here:

https://github.com/guga31bb/nflfastR-data

See the `data`, `legacy-data` and `roster-data` directories.

Google Dataset Search

Google has a dataset search engine with some interesting datasets:

https://toolbox.google.com/datasetsearch

Kaggle.com

Kaggle.com is best known for its modeling and machine learning competitions, but it also has a dataset search engine with some football related datasets.

Data Available via Public APIs

myfantasyleague.com

My Fantasy League is one of the oldest league hosting websites, and has always been very developer friendly. They have a public API available:

http://home.myfantasyleague.com/features/developers-api/

The nice thing about MFL is the amount detail they have. A few years ago, for example, I used the API to get detailed draft data for more than 6,000 leagues to build a draft pick trade value chart.

fantasyfootballcalculator.com

In chapter 5 we connected to Fantasy Football Calculator, which is one of the most popular places for mock drafts. It might be one of the only sites where people are doing mock drafts in March. As a result, their ADP is generally pretty good and up to date when it comes to late breaking, preseason news.

https://fantasyfootballcalculator.com/resources/average-draft-position-api/

sportsdata.io

It isn't free, but sportsdata.io, the company that provides data to some of the big name sites, has a nice hobbyist focused API with a ton of data available.

Appendix B: Anki

Remembering What You Learn

A problem with reading technical books is remembering everything you read. To help with that, this book comes with more than 300 flashcards covering the material. These cards are designed for **Anki**, a (mostly) free, open source *spaced repetition* flashcard program.

> "The single biggest change that Anki brings about is that it means memory is no longer a haphazard event, to be left to chance. Rather, it guarantees I will remember something, with minimal effort. That is, Anki makes memory a choice." — Michael Nielsen

With normal flashcards, you have to decide when and how often to review them. When you use Anki, it takes care of this for you.

Take a card that comes with this book, "What does REPL stand for?" Initially, you'll see it often — daily, or even more frequently. Each time you do, you tell Anki whether or not you remembered the answer. If you got it right ("Read Eval Print Loop") Anki will wait longer before showing it to you again — 3, 5, 15 days, then weeks, then months, years etc. If you get a question wrong, Anki will show it to you sooner.

By gradually working towards longer and longer intervals, Anki makes it straightforward to remember things long term. I'm at the point where I'll go for a year or longer in between seeing some Anki cards. To me, a few moments every few months or years is a reasonable trade off in return for the ability to remember something indefinitely.

Remembering things with Anki is not costless — the process of learning and processing information and turning that into your own Anki cards takes time (though you don't have to worry about making cards on this material since I've created them for you) — and so does actually going through Anki cards for a few minutes every day.

Also, Anki is a tool for *remembering*, not for learning. Trying to "Ankify" something you don't understand is a waste of time. Therefore, I strongly recommend you read the book and go through the code *first*, then start using Anki after that. To make the process easier, I've divided the Anki cards into "decks" corresponding with the major sections of this book. Once you read and understand the material in a chapter, you can add the deck to Anki to make sure you'll remember it.

Anki is optional — all the material in the cards is also in the book — but I strongly recommend at least trying it out.

If you're on the fence, here's a good essay by YCombinator's Michael Nielson for inspiration:

http://augmentingcognition.com/ltm.html

Like Nielsen, I personally have hundreds of Anki cards covering anything I want to remember long term — programming languages (including some on Python and Pandas), machine learning concepts, book notes, optimal blackjack strategy, etc.

Anki should be useful to everyone reading this book — after all, you bought this book because you want to remember it — but it'll be particularly helpful for readers who don't have the opportunity to program in Python or Pandas regularly. When I learned how to code, I found it didn't necessarily "stick" until I was able to do it often — first as part of a sports related side project, then at my day job. I still think working on your own project is a great way to learn, but not everyone is able to do this immediately. Anki will help.

Installing Anki

Anki is available as desktop and mobile software. I almost always use the desktop software for making cards, and the mobile client for reviewing them.

You can download the desktop client here:

https://apps.ankiweb.net/

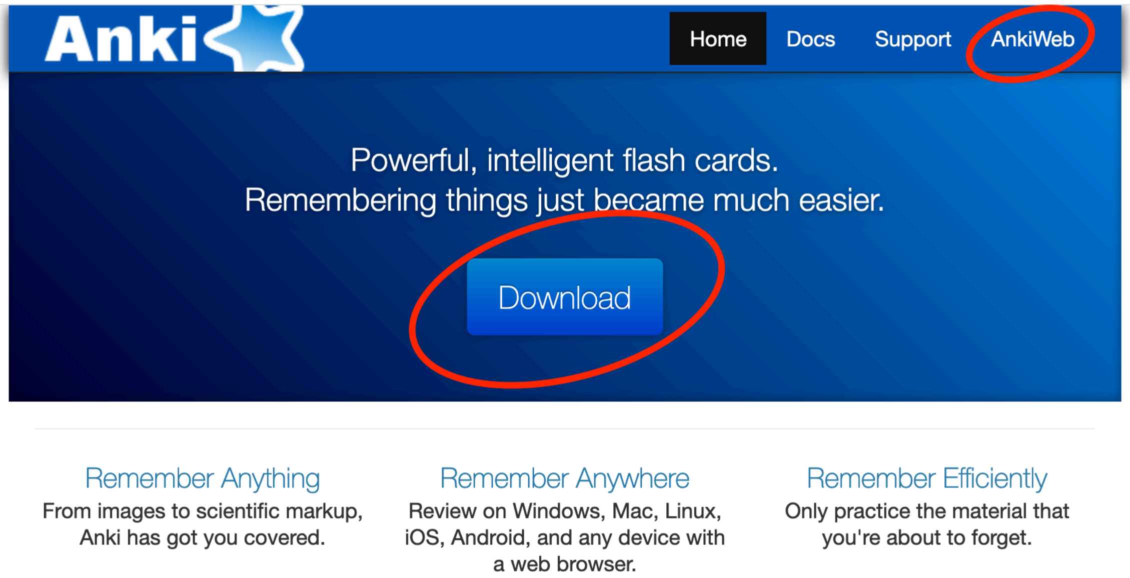


Figure 0.1: Anki Website

You should also make a free AnkiWeb account (in the upper right hand corner) and login with it on the desktop version so that you can save your progress and sync it with the mobile app.

Then install the mobile app. I use AnkiDroid, which is free and works well, but is only for Android.

The official IPhone version costs $25. It would be well worth it to me personally and goes towards supporting the creator of Anki, but if you don't want to pay for it you can either use the computer version or go to https://ankiweb.net on your phone's browser and review your flash cards there. I've also included text versions of the cards if you want to use another flashcard program.

Once you have the mobile app installed, go to settings and set it up to sync with your AnkiWeb account.

Using Anki with this Book

Anki has a ton of settings, which can be a bit overwhelming. You can ignore nearly all of them to start. By default, Anki makes one giant deck (called Default), which you can just add everything to. This is how I use it and it's worked well for me.

Once you've read and understand a section of the book and want to add the Anki cards for it, open up the desktop version of Anki, go to File -> Import… and then find the name of the apkg file (included with the book) you're importing.

For instance, after you're done with the prerequisite Tooling section of the book, you can import 00_tooling.apkg.

Importing automatically add them to your Default deck. Once they're added, you'll see some cards under New. If you click on the name of your deck 'Default' and then the 'Study Now' button, you can get started.

You'll see a question come up — "What does REPL stand for?" — and mentally recite, "Read Eval Print Loop".

Then click 'Show Answer'. If you got the question right click 'Good', if not click 'Again'. If it was really easy and you don't want to see it for a few days, press 'Easy'. How soon you'll see this question again depends on whether you got it right. Like I said, I usually review cards on my phone, but you can do it wherever works for you.

As you progress through sections of this book, you can keep adding more cards. By default, they'll get added to this main deck.

If you like Anki and want to apply it elsewhere, you can add other cards too. If you want to edit or make changes on the fly to any of the cards included here, that's encouraged too.

Appendix C: Answers to End of Chapter Exercises

All of the 2-7 chapter solutions are also available as (working) Python files in the `./solutions-to-exercises` directory of the files that came with this book.

1. Introduction

1.1

a) team-quarter (and game)
b) player-game
c) player-season
d) player-season with games as columns
e) position

1.2

This is somewhat subjective, but:

- 40 time
- longest (touchdown) reception
- number of touchdowns
- total or average air yards

might work.

1.3

a) Wind speed and temperature at kickoff.

b) Total combined points for both teams.

c) This model is at the game level.

d) The main limitation has to be it includes no information about the teams playing (e.g. how good their offenses are, how many points they typically score or let up). The over under for KC-NO is going to be very different from MIA-CHI.

1.4

a) manipulating data
b) analyzing data
c) manipulating data
d) loading data
e) collecting data
f) analyzing data
g) collecting data
h) usually manipulating your data, though sometimes loading or analyzing too
i) analyzing data
j) loading or manipulating data

2. Python

2.1

a) Valid. Python programmers often start variables with _ if they're throwaway or temporary, short term variables.
b) Valid.
c) Not valid. Can't start with a number.
d) Valid, though convention is to split words with _, not camelCase.
e) `rb1_name`. Valid. Numbers OK as long as they're not in the first spot
f) `flex spot name`. Not valid. No spaces
g) `@home_or_away`. Not valid. Only non alphanumeric character allowed is _
h) `'pts_per_rec_yd'`. Not valid. A string (wrapped in quotes), not a variable name. Again, only non alphanumeric character allowed is _

2.2

```
In [3]:
weekly_points = 100
weekly_points = weekly_points + 28
weekly_points = weekly_points + 5

In [4]: weekly_points # 133
Out[4]: 133
```

2.3

```
In [5]:
def for_the_td(player1, player2):
    return f'{player1} to {player2} for the td!'

In [6]: for_the_td('Dak', 'Zeke')
Out[6]: 'Dak to Zeke for the td!'
```

2.4

It's a string method, so what might `islower()` in the context of a string? How about whether or not the string is lowercase.

A function "is *something*" usually returns a yes or no answer (is it something or not), which would mean it returns a boolean.

We can test it like:

```
In [6]: 'tom brady'.islower()  # should return True
Out[5]: True

In [7]: 'Tom Brady'.islower()  # should return False
Out[7]: False
```

2.5

```
In [7]
def is_leveon(player):
    return player.replace("'", '').lower() == 'leveon bell'

In [8]: is_leveon('tom brady')
Out[8]: False

In [9]: is_leveon("Le'Veon Bell")
Out[9]: True

In [10]: is_leveon("LEVEON BELL")
Out[10]: True
```

2.6

```
In [11]
def commentary(score):
    if score >= 100:
        return f'{score} is a good score'
    else:
        return f"{score}'s not that good"

In [14]: commentary(90)
Out[14]: "90's not that good"

In [15]: commentary(200)
Out[15]: '200 is a good score'
```

2.7

Here's what I came up with. The last two use list comprehensions.

```
giants_roster[0:3]
giants_roster[:3]
giants_roster[:-1]
[x for x in giants_roster if x != 'OBJ']
[x for x in giants_roster if x in ['Daniel Jones', 'Saquon Barkley',
                                   'Evan Engram']]
```

2.8a

```
In [26]: league_settings['number_of_teams'] = 10

In [27]: league_settings
Out[27]: {'number_of_teams': 10, 'ppr': True}
```

2.8b

```
In [29]:
def toggle_ppr(settings):
    settings['ppr'] = not settings['ppr']
    return settings

In [30]: league_settings
Out[30]: {'number_of_teams': 10, 'ppr': False}

In [31]: toggle_ppr(league_settings)
Out[31]: {'number_of_teams': 10, 'ppr': True}
```

2.9

a) No. `'has_a_flex'` hasn't been defined.
b) No, `number_of_teams` is a variable that hasn't been defined, the key is `'number_of_teams'`.
c) Yes.

2.10a

```
In [34]:
for x in my_roster_list:
  print(x.split(' ')[-1])
--
brady
peterson
brown
```

2.10b

```
In [35]: {player: len(player) for player in my_roster_list}
Out[35]: {'tom brady': 9, 'adrian peterson': 15, 'antonio brown': 13}
```

2.11a

```
In [37]: [pos for pos in my_roster_dict]
Out[37]: ['qb', 'rb1', 'wr1', 'wr2']
```

2.11b

```
In [38]:
[player for _, player in my_roster_dict.items()
    if player.split(' ')[-1][0] in ['a', 'b']]
--
Out[38]: ['tom brady', 'davante adams', 'john brown']
```

2.12a

```
def mapper(my_list, my_function):
  return [my_function(x) for x in my_list]
```

2.12b

```
In [41]: mapper(list_of_rushing_yds, lambda x: x*0.1)
Out[41]: [0.1, 11.0, 6.0, 0.4, 0.0, 0.0, 0.0]
```

3.0 Pandas Basics

3.0.1

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
adp = pd.read_csv(path.join(DATA_DIR, 'adp_2017.csv'))
```

3.0.2

```
# works because data is sorted by adp already
In [2]: adp50 = adp.head(50)

# this is better if don't want to assume data is sorted
In [3]: adp50 = adp.sort_values('adp').head(50)
```

3.0.3

```
In [4]: adp.sort_values('name', ascending=False, inplace=True)

In [5]: adp.head()
Out[5]:
       adp  ...              name  ...  stdev team  times_drafted
125  122.0  ...         Zay Jones  ...   10.4  BUF             94
72    72.8  ...        Zach Ertz  ...    7.8  PHI            148
86    83.8  ...     Willie Snead  ...    9.2   NO            122
173  161.0  ...          Wil Lutz  ...    6.7   NO             42
151  146.1  ...  Wendell Smallwood  ...   14.4  PHI            157
```

Note: if this didn't work when you printed it on a new line in the REPL you probably forgot the `inplace=True` argument.

3.0.4

```
In [8]: type(adp.sort_values('adp'))  # it's a DataFrame
Out[8]: pandas.core.frame.DataFrame
```

3.0.5a

```
In [10]: adp_simple = adp[['name', 'position', 'adp']]
```

3.0.5b

```
In [11]: adp_simple = adp_simple[['position', 'name', 'adp']]
```

3.0.5c

```
In [12]: adp_simple['team'] = adp['team']
```

3.0.5d

```
In [13]: adp.to_csv(path.join(DATA_DIR, 'adp.txt'), sep='|')
```

3.1 Columns

3.1.1

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
pg = pd.read_csv(path.join(DATA_DIR, 'player_game_2017_sample.csv'))
```

3.1.2

```
In [15]: pg['rec_pts_ppr'] = (0.1*pg['rec_yards'] + 6*pg['rec_tds']
            + pg['receptions' ])

In [16]: pg['rec_pts_ppr'].head()
Out[16]:
0      0.0
1      0.0
2     16.0
3      1.8
4      9.0
```

3.1.3

```
In [17]: (pg['player_desc'] = pg['player_name'] + ' is the ' + pg['team']
    +
            ' ' + pg[ 'pos'])

In [18]: pg['player_desc'].head()
Out[18]:
0        T.Brady is the NE QB
1        A.Smith is the KC QB
2     D.Amendola is the NE WR
3     R.Burkhead is the NE RB
4        T.Kelce is the KC TE
```

3.1.4

```
In [25]: pg['is_possession_rec'] = pg['caught_airyards'] > pg['raw_yac']

In [26]: pg['is_possession_rec'].head()
Out[26]:
0    False
1    False
2     True
3    False
4    False
```

3.1.5

```
In [27]:
pg['len_last_name'] = (pg['player_name']
                       .apply(lambda x: len(x.split('.')[-1])))
--

In [28]: pg['len_last_name'].head()
Out[28]:
0    5
1    5
2    8
3    8
4    5
```

3.1.6

```
In [29]: pg['gameid'] = pg['gameid'].astype(str)
```

3.1.7a

```
In [31]: pg.columns = [x.replace('_', ' ') for x in pg.columns]

In [32]: pg.head()
Out[32]:
  player name  ...              player desc is possession rec  len last
     name
0     T.Brady  ...     T.Brady is the NE QB            False
    5
1     A.Smith  ...     A.Smith is the KC QB            False
    5
2  D.Amendola  ...  D.Amendola is the NE WR             True
    8
3  R.Burkhead  ...  R.Burkhead is the NE RB            False
    8
4     T.Kelce  ...     T.Kelce is the KC TE            False
    5
```

3.1.7b

```
In [33]: pg.columns = [x.replace(' ', '_') for x in pg.columns]

In [34]: pg.head()
Out[34]:
  player_name  ...              player_desc is_possession_rec
     len_last_name
0     T.Brady  ...     T.Brady is the NE QB            False
    5
1     A.Smith  ...     A.Smith is the KC QB            False
    5
2  D.Amendola  ...  D.Amendola is the NE WR             True
    8
3  R.Burkhead  ...  R.Burkhead is the NE RB            False
    8
4     T.Kelce  ...     T.Kelce is the KC TE            False
    5
```

3.1.8a

```
In [35]: pg['rush_td_percentage'] = pg['rush_tds']/pg['carries']
```

3.1.8b

`'rush_td_percentage'` is rushing tds divided by carries. Since you can't divide by 0, rush td percentage is missing whenever carries are missing.

To replace all the missing values with `-99`:

```
In [37]: pg['rush_td_percentage'].fillna(-99, inplace=True)

In [38]: pg['rush_td_percentage'].head()
Out[38]:
0   -99.0
1     0.0
2   -99.0
3     0.0
4     0.0
```

3.1.9

```
In [39]: pg.drop('rush_td_percentage', axis=1, inplace=True)
```

If you forget the `axis=1` Pandas will try to drop the *row* with the index value `'rush_td_percentage'`. Since that doesn't exist, it'll throw an error.

Without the `inplace=True`, Pandas just returns a new copy of `pg` without the `'rush_td_percentage'` column. Nothing happens to the original `pg`, though we could reassign it if we wanted like this:

```
pg = pg.drop('rush_td_percentage', axis=1)  # alt to inplace
```

3.2 Built-in Functions

3.2.1

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
pg = pd.read_csv(path.join(DATA_DIR, 'player_game_2017_sample.csv'))
```

3.2.2

```
In [42]:
pg['total_yards1'] = pg['rush_yards'] + pg['rec_yards'] + pg['pass_yards']

pg['total_yards2'] = pg[['rush_yards', 'rec_yards', 'pass_yards']].sum(
    axis=1)

(pg['total_yards1'] == pg['total_yards2']).all()
--
Out[42]: True
```

3.2.3a

```
In [43]: pg[['rush_yards', 'rec_yards']].mean()
Out[43]:
rush_yards     14.909154
rec_yards      32.761705
```

3.2.3b

```
In [44]: ((pg['pass_yards'] >= 300) & (pg['pass_tds'] >= 3)).sum()
Out[44]: 15
```

3.2.3c

```
[ins] In [48]:
(((pg['pass_yards'] >= 300) & (pg['pass_tds'] >= 3)).sum()
 / (pg['pos'] == 'QB').sum())
--
Out[48]: 0.10204081632653061
```

3.2.3d

```
In [49]: pg['rush_tds'].sum()
Out[49]: 141.0
```

3.2.3e

Most: 14, least: 8

```
In [50]: pg['week'].value_counts()
Out[50]:
14    92
4     91
13    89
12    89
3     89
2     86
7     86
10    85
11    84
5     84
15    82
16    82
17    79
9     79
6     79
1     79
8     76
```

3.3 Filtering

3.3.1

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
adp = pd.read_csv(path.join(DATA_DIR, 'adp_2017.csv'))
```

3.3.2a

```
In [52]: adp_cb1 = adp.loc[adp['team'] == 'DAL', ['name', 'position', 'adp
    ']]

In [53]: adp_cb1.head()
Out[53]:
                 name position    adp
4     Ezekiel Elliott       RB    6.2
20         Dez Bryant       WR   20.5
76    Darren McFadden       RB   75.3
115      Dak Prescott       QB  112.8
142      Cole Beasley       WR  136.2
```

3.3.2b

```
In [54]: adp_cb2 = adp.query("team == 'DAL'")[['name', 'position', 'adp']]
```

3.3.3

```
In [56]: adp_nocb = adp.loc[adp['team'] != 'DAL',
            ['name', 'position', 'adp', 'team']]

In [57]: adp_nocb.head()
Out[57]:
                name position  adp team
0      David Johnson       RB  1.3  ARI
1        LeVeon Bell       RB  2.3  PIT
2     Antonio Brown       WR  3.7  PIT
3        Julio Jones       WR  5.7  ATL
5   Odell Beckham Jr       WR  6.4  NYG
```

3.3.4a

Yes.

```
In [58]: adp['last_name'] = adp['name'].apply(lambda x: x.split(' ')[1])

In [59]: adp[['last_name', 'position']].duplicated().any()
Out[59]: True
```

3.3.4b

```
In [60]: dups = adp[['last_name', 'position']].duplicated(keep=False)

In [61]: adp_dups = adp.loc[dups]

In [62]: adp_no_dups = adp.loc[~dups]
```

3.3.5

```
In [78]:
import numpy as np

adp['adp_description'] = np.nan
adp.loc[adp['adp'] < 40, 'adp_description'] = 'stud'
adp.loc[adp['adp'] > 120, 'adp_description'] = 'scrub'

In [79]: adp[['adp', 'adp_description']].sample(5)
Out[79]:
       adp adp_description
43    42.5             NaN
5      6.4            stud
16    17.1            stud
77    76.5             NaN
139  134.5           scrub
```

3.3.6a

```
In [80]: adp_no_desc1 = adp.loc[adp['adp_description'].isnull()]
```

3.3.6b

```
In [81]: adp_no_desc2 = adp.query("adp_description.isnull()")
```

3.4 Granularity

3.4.1

Usually you can only shift your data from more (play-by-play) to less (game) granular, which necessarily results in a loss of information. If I go from knowing what Kareem Hunt rushed for on every particular play to just knowing how many yards he rushed for *total*, that's a loss of information.

3.4.2a

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
pbp = pd.read_csv(path.join(DATA_DIR, 'play_data_sample.csv'))
```

3.4.2b

Looks like it was Sony Michel with 106 yards in game `2018101412` and Kareem Hunt with 70 yards in game `2018111900`.

```
In [83]:
(pbp
.query("play_type == 'run'")
.groupby(['game_id', 'rusher_player_name'])['yards_gained'].sum())
--
Out[83]:
game_id     rusher_player_name
2018101412  C.Patterson             3
            Dam. Williams           1
            J.Edelman               7
            J.White                39
            K.Barner               16
            K.Hunt                 80
            P.Mahomes               9
            S.Michel              106
            S.Ware                  5
            S.Watkins              -1
            T.Brady                 3
            T.Hill                  0
2018111900  B.Cooks                 0
            J.Goff                  8
            K.Hunt                 70
            M.Brown                15
            P.Mahomes              28
            T.Gurley               55
```

3.4.2c

Just change `sum` of `'yards_gained'` to `mean`:

```
In [86]:
(pbp
.query("play_type == 'run'")
.groupby(['game_id', 'rusher_player_name'])['yards_gained'].mean())
--
Out[86]:
game_id     rusher_player_name
2018101412  C.Patterson           3.000000
            Dam. Williams         1.000000
            J.Edelman             7.000000
            J.White               6.500000
            K.Barner              5.333333
            K.Hunt                8.000000
            P.Mahomes             4.500000
            S.Michel              4.416667
            S.Ware                2.500000
            S.Watkins            -1.000000
            T.Brady               1.500000
            T.Hill                0.000000
2018111900  B.Cooks               0.000000
            J.Goff                4.000000
            K.Hunt                5.000000
            M.Brown               3.750000
            P.Mahomes             4.666667
            T.Gurley              4.583333
```

3.4.2d

```
In [87]:
pbp['lte_0_yards'] = pbp['yards_gained'] <= 0

(pbp
.query("play_type == 'run'")
.groupby(['game_id', 'rusher_player_name'])['lte_0_yards'].mean())
--
Out[87]:
game_id     rusher_player_name
2018101412  C.Patterson           0.000000
            Dam. Williams         0.000000
            J.Edelman             0.000000
            J.White               0.166667
            K.Barner              0.000000
            K.Hunt                0.100000
            P.Mahomes             0.000000
            S.Michel              0.125000
            S.Ware                0.000000
            S.Watkins             1.000000
            T.Brady               0.500000
            T.Hill                1.000000
2018111900  B.Cooks               1.000000
            J.Goff                0.000000
            K.Hunt                0.071429
            M.Brown               0.000000
            P.Mahomes             0.000000
            T.Gurley              0.250000
```

3.4.3

Count counts the number of non missing (non `np.nan`) values. This is different than `sum` which adds up the values in all of the columns. The only time `count` and `sum` would return the same thing is if you had a column filled with 1s without any missing values.

3.4.4

Pats (31.25%) and Chiefs vs LA (6.85%).

```
In [89]: pbp.groupby(['posteam', 'game_id'])['turnover', 'first_down'].
    mean()
Out[89]:
                        turnover  first_down
posteam game_id
KC      2018101412  0.034483    0.241379
        2018111900  0.068493    0.287671
LA      2018111900  0.024691    0.246914
NE      2018101412  0.012500    0.312500
```

3.4.5

Stacking is when you change the granularity in your data, but shift information from rows to columns (or vis versa) so it doesn't result in any loss on information.

An example would be going from the player-game level to the player level. If we stacked it, we'd go from rows being:

```
     player_name  week  pass_tds
214     T.Taylor    10       0.0
339       M.Ryan    14       1.0
220     T.Taylor    11       1.0
70       T.Brady    15       1.0
1192    C.Newton     1       2.0
```

To:

```
                 pass_tds      ...
week                    1    2 ...   12   13   14   15   16   17
player_name                    ...
A.Smith               4.0  1.0 ...  1.0  4.0  1.0  2.0  1.0  NaN
B.Bortles             1.0  1.0 ...  0.0  2.0  2.0  3.0  3.0  0.0
B.Hundley             NaN  NaN ...  3.0  0.0  3.0  NaN  0.0  1.0
B.Roethlisberger      2.0  2.0 ...  5.0  2.0  2.0  3.0  2.0  NaN
C.Newton              2.0  0.0 ...  0.0  2.0  1.0  4.0  0.0  1.0
```

3.5 Combining DataFrames

3.5.1a

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
df_touch = pd.read_csv(path.join(DATA_DIR, 'problems/combine1', 'touch.csv
    '))
df_yard = pd.read_csv(path.join(DATA_DIR, 'problems/combine1', 'yard.csv')
    )
df_td = pd.read_csv(path.join(DATA_DIR, 'problems/combine1', 'td.csv'))
```

3.5.1b

```
In [4]:
df_comb1 = pd.merge(df_touch, df_yard)
df_comb1 = pd.merge(df_comb1, df_td, how='left')

df_comb1[['rush_tds', 'rec_tds']] = df_comb1[['rush_tds', 'rec_tds']].
    fillna(0)
```

3.5.1c

```
In [5]:
df_comb2 = pd.concat([df_touch.set_index('id'), df_yard.set_index('id'),
                      df_td.set_index('id')], axis=1)
df_comb2[['rush_tds', 'rec_tds']] = df_comb2[['rush_tds', 'rec_tds']].
    fillna(0)
```

3.5.1d

Which is better is somewhat subjective, but I generally prefer `concat` when combining three or more DataFrames because you can do it all in one step.

Note `merge` gives a little more fine grained control over how you merge (left, or outer) vs `concat`, which just gives you inner vs outer.

3.5.2a

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
qb = pd.read_csv(path.join(DATA_DIR, 'problems/combine2', 'qb.csv'))
rb = pd.read_csv(path.join(DATA_DIR, 'problems/combine2', 'rb.csv'))
wr = pd.read_csv(path.join(DATA_DIR, 'problems/combine2', 'wr.csv'))
te = pd.read_csv(path.join(DATA_DIR, 'problems/combine2', 'te.csv'))
```

3.5.2b

```
In [7]: df = pd.concat([qb, rb, wr, te])
```

3.5.3a

```
import pandas as pd
from os import path

DATA_DIR = '/Users/nathan/ltcwff-files/data'
adp = pd.read_csv(path.join(DATA_DIR, 'adp_2017.csv'))
```

3.5.3b

```
In [12]:
for pos in ['QB', 'RB', 'WR', 'TE', 'PK', 'DEF']:
    (adp
     .query(f"position == '{pos}'")
     .to_csv(path.join(DATA_DIR, f'adp_{pos}.csv'), index=False))
```

Write a two line for loop to save subsets of the ADP data frame for each position.

3.5.3c

```
In [13]:
df = pd.concat([pd.read_csv(path.join(DATA_DIR, f'adp_{pos}.csv'))
    for pos in ['QB', 'RB', 'WR', 'TE', 'PK', 'DEF']], ignore_index=True)
```

4. SQL

Note: like the book, I'm just showing the SQL, be sure to call it inside `pd.read_sql` and pass it your sqlite connection to try these. See `04_sql.py` file for more.

4.1a

```
SELECT
    game.season, week, player_name, player_game.team, attempts,
    completions, pass_yards AS yards, pass_tds AS tds, interceptions
FROM player_game, team, game
WHERE
    player_game.team = team.team AND
    game.gameid = player_game.gameid AND
    team.conference = 'AFC' AND
    player_game.pos = 'QB'
```

4.1b

```
SELECT
    g.season, week, p.player_name, t.team, attempts, completions,
       pass_yards AS
    yards, pass_tds AS tds, interceptions
FROM player_game AS pg, team AS t, game AS g, player AS p
WHERE
    pg.player_id = p.player_id AND
    g.gameid = pg.gameid AND
    t.team = p.team AND
    t.conference = 'AFC' AND
    p.pos = 'QB'
```

4.2

```
SELECT g.*, th.mascot as home_mascot, ta.mascot as away_mascot
FROM game as g, team as th, team as ta
WHERE
    g.home = th.team AND
    g.away = ta.team
```

5.1 Scraping

5.1.1

```
from bs4 import BeautifulSoup as Soup
import requests
from pandas import DataFrame

ffc_base_url = 'https://fantasyfootballcalculator.com'

def scrape_ffc(scoring, nteams, year):
    # build URL based on arguments
    ffc_url = (ffc_base_url + '/adp' + _scoring_helper(scoring) +
               f'/{nteams}-team/all/{year}')
    ffc_response = requests.get(ffc_url)

    # all same as 05_01_scraping.py file
    adp_soup = Soup(ffc_response.text)
    tables = adp_soup.find_all('table')
    adp_table = tables[0]
    rows = adp_table.find_all('tr')

    # move parse_row to own helper function
    list_of_parsed_rows = [_parse_row(row) for row in rows[1:]]

    # put it in a dataframe
    df = DataFrame(list_of_parsed_rows)

    # clean up formatting
    df.columns = ['ovr', 'pick', 'name', 'pos', 'team', 'adp', 'std_dev',
                  'high', 'low', 'drafted', 'graph']

    float_cols =['adp', 'std_dev']
    int_cols =['ovr', 'drafted']

    df[float_cols] = df[float_cols].astype(float)
    df[int_cols] = df[int_cols].astype(int)

    df.drop('graph', axis=1, inplace=True)

    return df

# helper functions - just moving some logic to own section
def _scoring_helper(scoring):
    """
    Take a scoring system (either 'ppr', 'half', 'std') and return the
       correct
    FFC URL fragment.

    Note: helper functions are often prefixed with _, but it's not
       required.
    """
    if scoring == 'ppr':
        return '/ppr'
    elif scoring == 'half':
        return '/half-ppr'
    elif scoring == 'std':
        return '/standard'

def _parse_row(row):
```

5.1.2

The solution for this is the same as the previous, with two changes. First, `_parse_row` becomes:

```
def _parse_row_with_link(row):
    """
    Take in a tr tag and get the data out of it in the form of a list of
    strings, also get link.
    """
    # parse the row like before and save it into a list
    parsed_row = [str(x.string) for x in row.find_all('td')]

    # now get the link, which is the href attribute of the first 'a' tag
    link = ffc_base_url + str(row.find_all('a')[0].get('href'))

    # add link onto the end of the list and return
    return parsed_row + [link]
```

And then inside `scrape_ffc` we need to add `'link'` when renaming our columns.

```
df.columns = ['ovr', 'pick', 'name', 'pos', 'team', 'adp', 'std_dev', '
    high',
              'low', 'drafted', 'graph', 'link']
```

5.1.3

```
def ffc_player_info(url):
    ffc_response = requests.get(url)
    player_soup = Soup(ffc_response.text)

    # info is in multiple tables, but can get all rows with shortcut
    rows = player_soup.find_all('tr')

    list_of_parsed_rows = [_parse_player_row(row) for row in rows]

    # this is a list of two item lists [[key1, value1], [key2, value2],
        ...],
    # so we're unpacking each key, value pair with for key, value in ...
    dict_of_parsed_rows = {key: value for key, value in
        list_of_parsed_rows}

    # now modify slightly to return what we want, which (per problem
    # instructions) is team, height, weight, birthday, and draft info
    return_dict = {}
    return_dict['team'] = dict_of_parsed_rows['Team:']
    return_dict['height'] = dict_of_parsed_rows['Ht / Wt:'].split('/')[0]
    return_dict['weight'] = dict_of_parsed_rows['Ht / Wt:'].split('/')[1]
    return_dict['birthday'] = dict_of_parsed_rows['Born:']
    return_dict['drafted'] = dict_of_parsed_rows['Drafted:']
    return_dict['draft_team'] = dict_of_parsed_rows['Draft Team:']

    return return_dict

def _parse_player_row(row):
    return [str(x.string) for x in row.find_all('td')]
```

5.2 APIs

5.2.1

```
import requests
from pandas import DataFrame
import pandas as pd

# given urls
url_adp = 'https://api.myfantasyleague.com/2019/export?TYPE=adp&JSON=1'
url_player = 'https://api.myfantasyleague.com/2019/export?TYPE=players&
    JSON=1'

# call w/ requests
resp_adp = requests.get(url_adp)
resp_player = requests.get(url_player)

# need to inspect the .json() results in the REPL to see what we want/can
    turn
# into a DataFrame — usually list of dicts
df_adp = DataFrame(resp_adp.json()['adp']['player'])
df_player = DataFrame(resp_player.json()['players']['player'])

# now combine
df = pd.merge(df_adp, df_player)

# get rid of IDP players, take top 200
df = df.query("position in ('WR', 'RB', 'TE', 'QB', 'Def', 'PK')")
df = df.head(200)
```

6. Summary and Data Visualization

Assuming you've loaded the play-by-play data into a DataFrame named pbp and imported seaborn as sns.

6.1a

```
g = (sns.FacetGrid(pbp)
     .map(sns.kdeplot, 'yards_gained', shade=True))
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Distribution of Yards Gained Per Play, LTCWFF Sample')
```

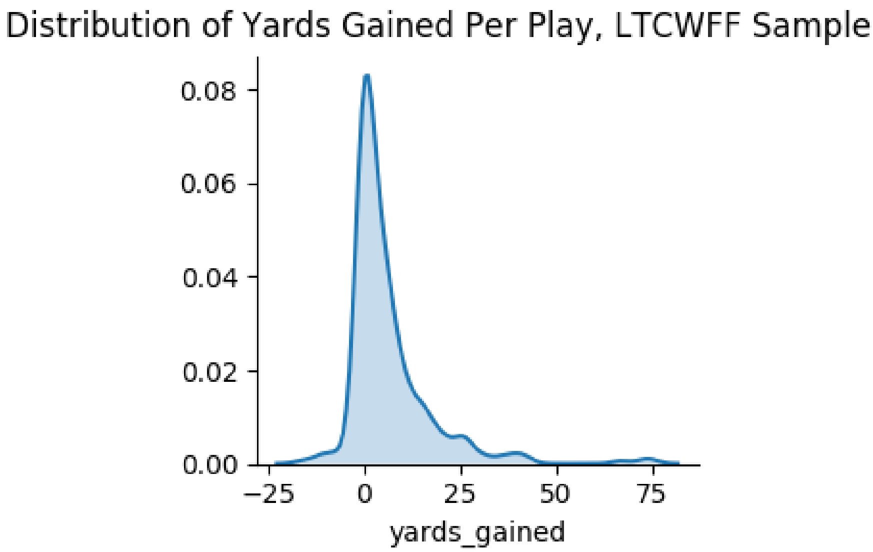


Figure 0.1: Solution 6-1a

6.1b

```
g = (sns.FacetGrid(pbp.query("down <= 3"), hue='down')
     .map(sns.kdeplot, 'yards_gained', shade=True))
g.add_legend()
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Distribution of Yards Gained Per Play by Down, LTCWFF
    Sample')
```

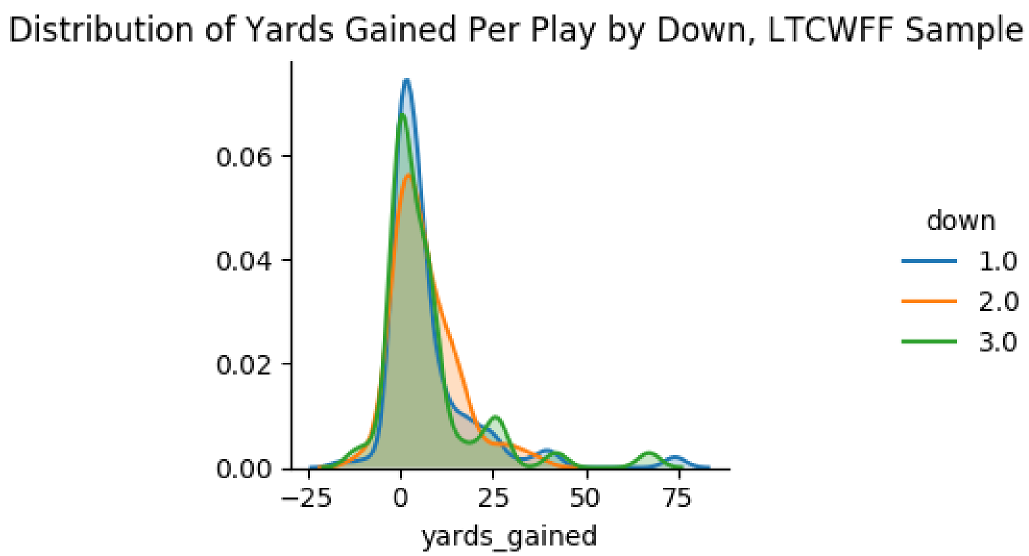


Figure 0.2: Solution 6-1b

6.1c

```
g = (sns.FacetGrid(pbp.query("down <= 3"), col='down')
     .map(sns.kdeplot, 'yards_gained', shade=True))
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Distribution of Yards Gained Per Play by Down, LTCWFF
    Sample')
```

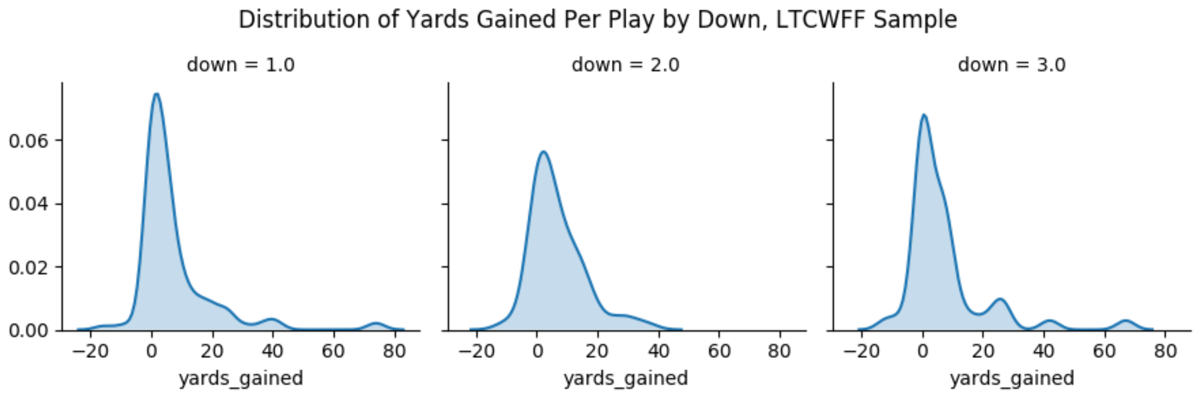


Figure 0.3: Solution 6-1c

6.1d

```
g = (sns.FacetGrid(pbp.query("down <= 3"), col='down', row='posteam')
     .map(sns.kdeplot, 'yards_gained', shade=True))
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Distribution of Yards Gained Per Play by Down, Team,
    LTCWFF Sample')
```

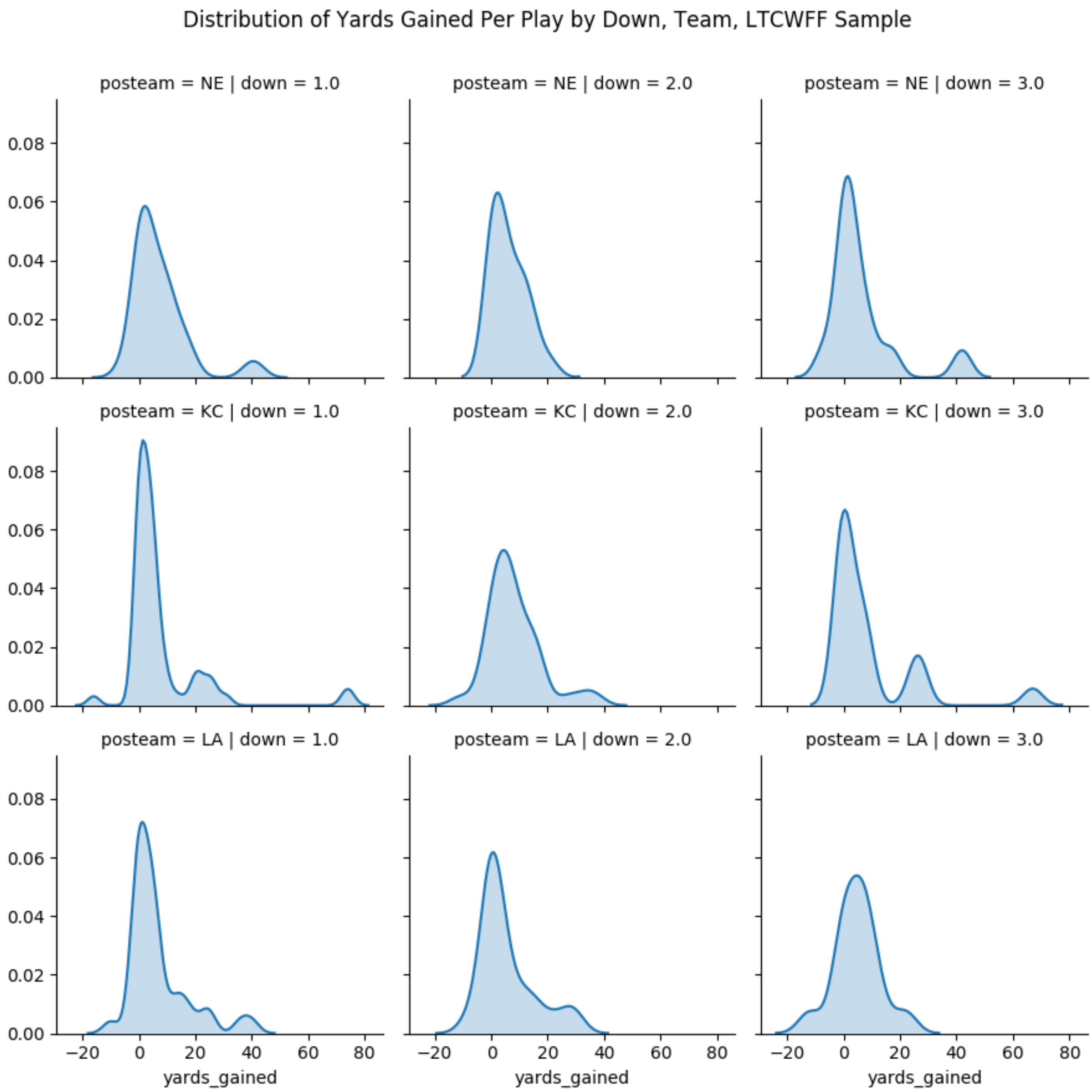


Figure 0.4: Solution 6-1d

6.1e

```
g = (sns.FacetGrid(pbp.query("down <= 3"), col='down', row='posteam',
                   hue='posteam')
     .map(sns.kdeplot, 'yards_gained', shade=True))
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Distribution of Yards Gained Per Play by Down, Team,
   LTCWFF Sample')
```

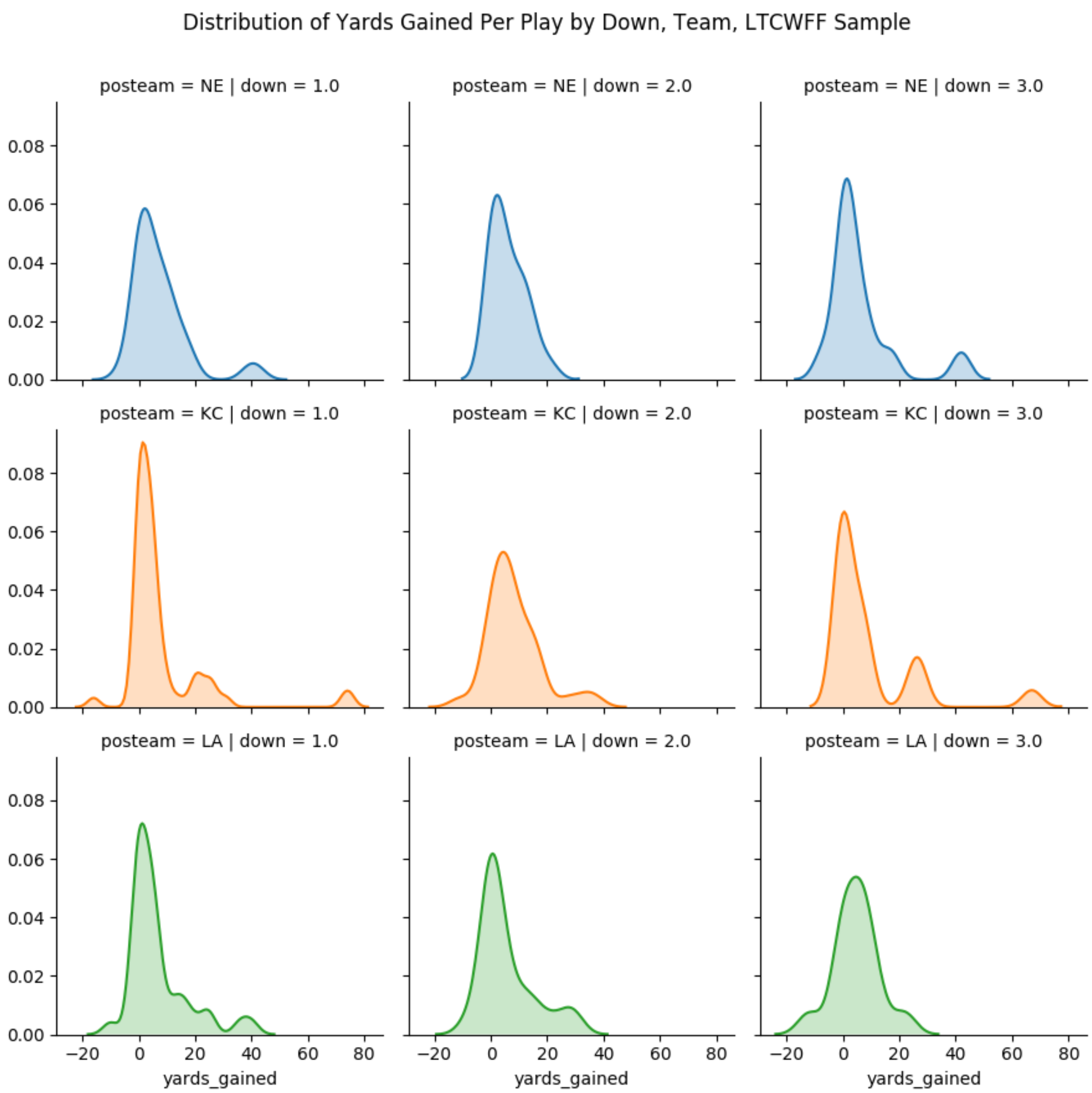


Figure 0.5: Solution 6-1e

6.2a

```
pg = pd.read_csv(path.join(DATA_DIR, 'player_game_2017_sample.csv'))
g = sns.relplot(x='carries', y='rush_yards', hue='pos', data=pg)
g.fig.subplots_adjust(top=0.9)
g.fig.suptitle('Carries vs Rush Yards by Position, LTCWFF Sample')
```

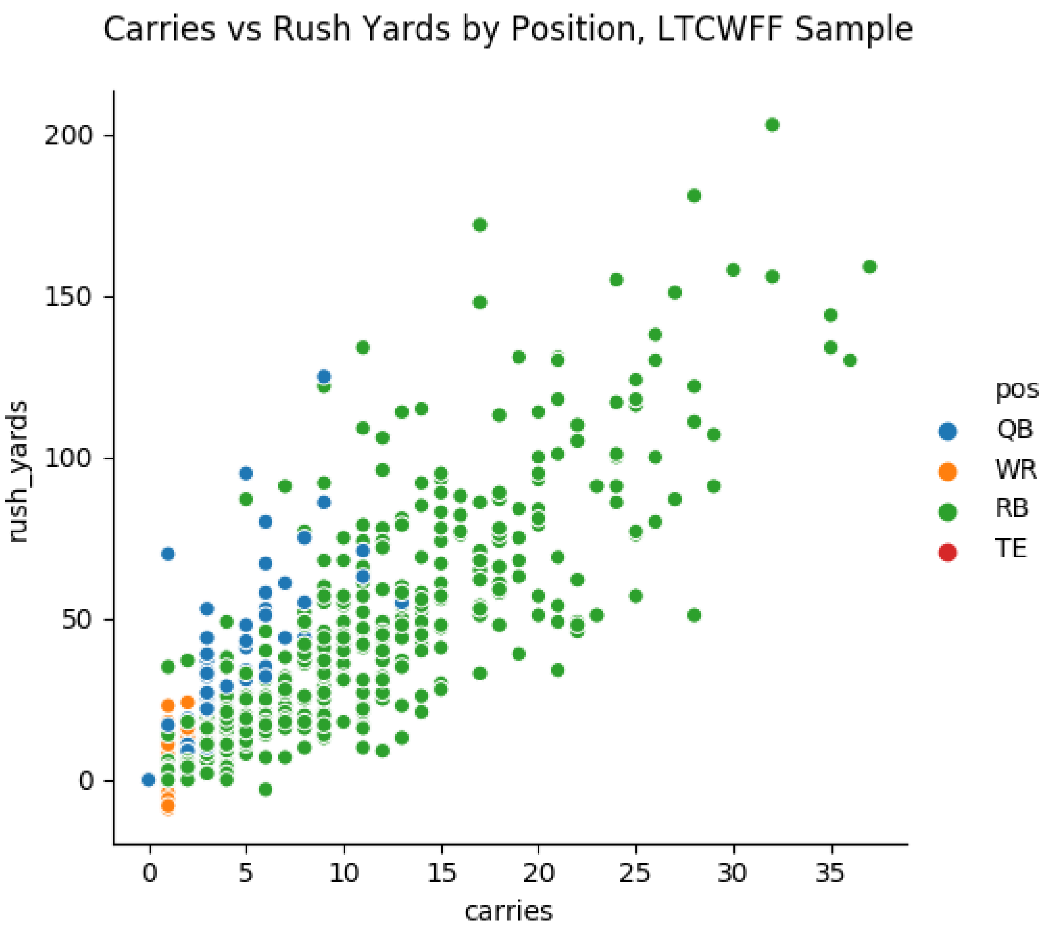


Figure 0.6: Solution 6-2

6.2b

To me, it looks like QBs have the highest yards per carry, but it's easy to verify:

```
pg['ypc'] = pg['rush_yards']/pg['carries']

# easy way to check
pg.groupby('pos')['ypc'].mean()

# more advanced (not seen before), but Pandas often is intuitive
pg.groupby('pos')['ypc'].describe()
```

7. Modeling

7.1a

To apply `prob_of_td` to our yardage data.

```
In [2]:
def prob_of_td(yds):
    b0, b1, b2 = results.params
    return (b0 + b1*yds + b2*(yds**2))

df['offensive_td_hat_alt'] = df['yardline_100'].apply(prob_of_td)
```

The two should be the same. With `'offensive_td_hat_alt'` we're just doing manually what `results.predict(df)` is doing behind the scenes. To verify:

```
In [3]: df[['offensive_td_hat', 'offensive_td_hat_alt']].head()
Out[3]:
   offensive_td_hat  offensive_td_hat_alt
0          0.017521              0.017521
1         -0.005010             -0.005010
2         -0.006370             -0.006370
3          0.007263              0.007263
4          0.007263              0.007263

In [4]: (results.predict(df) == df['offensive_td_hat_alt']).all()
Out[4]: True
```

7.1b

```
In [5]:
model_b = smf.ols(
    formula='offensive_td ~ yardline_100 + yardline_100_sq +ydstogo', data
        =df)
results_b = model_b.fit()
results_b.summary2()
--
Out[5]:
<class 'statsmodels.iolib.summary2.Summary'>
"""
                 Results: Ordinary least squares
=================================================================
Model:              OLS              Adj. R-squared:     0.118
Dependent Variable: offensive_td     AIC:                2.1081
Date:               2020-03-05 11:39 BIC:                16.4869
No. Observations:   269              Log-Likelihood:     2.9460
Df Model:           3                F-statistic:        12.89
Df Residuals:       265              Prob (F-statistic): 6.88e-08
R-squared:          0.127            Scale:              0.058146
-----------------------------------------------------------------
                   Coef.  Std.Err.    t    P>|t|   [0.025  0.975]
-----------------------------------------------------------------
Intercept          0.3273   0.0485  6.7430 0.0000  0.2317  0.4229
yardline_100      -0.0110   0.0024 -4.6646 0.0000 -0.0157 -0.0064
yardline_100_sq    0.0001   0.0000  3.6585 0.0003  0.0000  0.0001
ydstogo           -0.0009   0.0040 -0.2144 0.8304 -0.0088  0.0071
-----------------------------------------------------------------
Omnibus:             170.817      Durbin-Watson:         2.086
Prob(Omnibus):       0.000        Jarque-Bera (JB):      963.480
Skew:                2.729        Prob(JB):              0.000
Kurtosis:            10.495       Condition No.:         12455
=================================================================
"""
```

Looking at the results in `results_b.summary2()` we can see the P value on `ydstogo` is 0.8304, which means the coefficient is not statistically significant.

7.1c

Wrapping a variable in `C()` turns it into a categorical variable (that' what the C stands for) and puts it in the model via fixed effects. Remember, including dummy variables for all four downs would be redundant, so statsmodels automatically drops first down.

```
In [6]:
model_c = smf.ols(formula='offensive_td ~ yardline_100 + yardline_100_sq +
    C(down)', data=df)
results_c = model_c.fit()
results_c.summary2()
--
Out[6]:
<class 'statsmodels.iolib.summary2.Summary'>
"""
                 Results: Ordinary least squares
=================================================================
Model:              OLS              Adj. R-squared:     0.134
Dependent Variable: offensive_td     AIC:                -0.9816
Date:               2020-03-05 11:39 BIC:                20.5866
No. Observations:   269              Log-Likelihood:     6.4908
Df Model:           5                F-statistic:        9.288
Df Residuals:       263              Prob (F-statistic): 3.68e-08
R-squared:          0.150            Scale:              0.057064
-----------------------------------------------------------------
                   Coef.  Std.Err.    t    P>|t|   [0.025  0.975]
-----------------------------------------------------------------
Intercept          0.3082   0.0475  6.4858 0.0000  0.2146  0.4018
C(down)[T.2.0]    -0.0321   0.0332 -0.9680 0.3339 -0.0975  0.0332
C(down)[T.3.0]     0.0830   0.0408  2.0330 0.0431  0.0026  0.1633
C(down)[T.4.0]    -0.0137   0.1221 -0.1123 0.9107 -0.2542  0.2267
yardline_100      -0.0106   0.0023 -4.5806 0.0000 -0.0151 -0.0060
yardline_100_sq    0.0001   0.0000  3.5085 0.0005  0.0000  0.0001
-----------------------------------------------------------------
Omnibus:              166.240      Durbin-Watson:         2.076
Prob(Omnibus):        0.000        Jarque-Bera (JB):      909.736
Skew:                 2.647        Prob(JB):              0.000
Kurtosis:             10.289       Condition No.:         31623
=================================================================
"""
```

The coefficient on third down (C(down)[T.3.0]) is highest at 0.0830 (since first down was dropped, we can interpret the coefficient on it as 0).

7.1d

Yes, the coefficients are the same. To see:

```
In [7]:
df['is2'] = df['down'] == 2
df['is3'] = df['down'] == 3
df['is4'] = df['down'] == 4

model_d = smf.ols(formula='offensive_td ~ yardline_100 + yardline_100_sq +
     is2 + is3 + is4', data=df)
results_d = model_d.fit()
results_d.summary2()

--
Out[7]:
<class 'statsmodels.iolib.summary2.Summary'>
"""
                 Results: Ordinary least squares
=================================================================
Model:              OLS              Adj. R-squared:     0.134
Dependent Variable: offensive_td     AIC:                -0.9816
Date:               2020-03-05 11:42 BIC:                20.5866
No. Observations:   269              Log-Likelihood:     6.4908
Df Model:           5                F-statistic:        9.288
Df Residuals:       263              Prob (F-statistic): 3.68e-08
R-squared:          0.150            Scale:              0.057064
-----------------------------------------------------------------
                  Coef.  Std.Err.    t    P>|t|   [0.025  0.975]
-----------------------------------------------------------------
Intercept         0.3082   0.0475  6.4858 0.0000  0.2146  0.4018
is2[T.True]      -0.0321   0.0332 -0.9680 0.3339 -0.0975  0.0332
is3[T.True]       0.0830   0.0408  2.0330 0.0431  0.0026  0.1633
is4[T.True]      -0.0137   0.1221 -0.1123 0.9107 -0.2542  0.2267
yardline_100     -0.0106   0.0023 -4.5806 0.0000 -0.0151 -0.0060
yardline_100_sq   0.0001   0.0000  3.5085 0.0005  0.0000  0.0001
-----------------------------------------------------------------
Omnibus:            166.240      Durbin-Watson:         2.076
Prob(Omnibus):      0.000        Jarque-Bera (JB):      909.736
Skew:               2.647        Prob(JB):              0.000
Kurtosis:           10.289       Condition No.:         31623
=================================================================
* The condition number is large (3e+04). This might indicate
strong multicollinearity or other numerical problems.
"
```

7.2a

```
def run_sim_get_pvalue():
    coin = ['H', 'T']

    # make empty DataFrame
    df = DataFrame(index=range(100))

    # now fill it with a "guess"
    df['guess'] = [random.choice(coin) for _ in range(100)]

    # and flip
    df['result'] = [random.choice(coin) for _ in range(100)]

    # did we get it right or not?
    df['right'] = (df['guess'] == df['result']).astype(int)

    model = smf.ols(formula='right ~ C(guess)', data=df)
    results = model.fit()

    return results.pvalues['C(guess)[T.T]']
```

7.2b

When I ran it, I got an average P value of 0.4935 (it's random, so you're numbers will be different). The more you run it, the closer it will get to 0.50. In the language of calculus, the P value *approaches* 0.5 as the number of simulations approaches infinity.

```
In [13]:
sims_1k = Series([run_sim_get_pvalue() for _ in range(1000)])
sims_1k.mean()
--
Out[13]: 0.4934848731037103
```

7.2c

```
def runs_till_threshold(i, p=0.05):
    pvalue = run_sim_get_pvalue()
    if pvalue < p:
        return i
    else:
        return runs_till_threshold(i+1, p)

sim_time_till_sig_100 = Series([runs_till_threshold(1) for _ in range(100)
    ])
```

7.2d

According to Wikipedia, the mean and median of the Geometric distribution are 1/p and -1/log_2(1-p). Since we're working with a p of 0.05, that'd give us:

```
[ins] In [19]:
from math import log
p = 0.05
g_mean = 1/p
g_median = -1/log(1-p, 2)

g_mean, g_median
Out[19]: (20.0, 13.513407333964873)
```

After simulating 100 times and looking at the summary stats, I got 19.3 and 15 (again, your numbers will be different since we're dealing with random numbers), which are close.

```
In [20]: sim_time_till_sig_100.mean()
Out[20]: 19.3

In [21]: sim_time_till_sig_100.median()
Out[21]: 15.0
```

7.3a

```
[ins] In [33]:
model_a = smf.ols(formula=
    """
    wpa ~ offensive_td + interception + yards_gained + fumble
    """, data=df)
results_a = model_a.fit()
results_a.summary2()
--
Out[33]:
<class 'statsmodels.iolib.summary2.Summary'>
"""
                  Results: Ordinary least squares
===================================================================
Model:              OLS              Adj. R-squared:     0.733
Dependent Variable: wpa              AIC:                -1041.8797
Date:               2020-03-05 11:54 BIC:                -1023.9062
No. Observations:   269              Log-Likelihood:     525.94
Df Model:           4                F-statistic:        184.8
Df Residuals:       264              Prob (F-statistic): 2.93e-75
R-squared:          0.737            Scale:              0.0011952
--------------------------------------------------------------------
                Coef.   Std.Err.     t      P>|t|    [0.025   0.975]
--------------------------------------------------------------------
Intercept      -0.0178    0.0026   -6.8153  0.0000  -0.0229  -0.0127
offensive_td    0.0663    0.0087    7.6368  0.0000   0.0492   0.0834
interception   -0.1850    0.0157  -11.7993  0.0000  -0.2159  -0.1541
yards_gained    0.0034    0.0002   17.2176  0.0000   0.0030   0.0038
fumble         -0.0560    0.0135   -4.1536  0.0000  -0.0826  -0.0295
-------------------------------------------------------------------
Omnibus:              71.070       Durbin-Watson:          2.161
Prob(Omnibus):        0.000        Jarque-Bera (JB):       1185.810
Skew:                 0.505        Prob(JB):               0.000
Kurtosis:             13.236       Condition No.:          101
===================================================================
"
```

An interception (-0.1850) is worse for win probability than a fumble (-0.0560). This is almost certainly because fumbles can be recovered by the offense, while interceptions are always turnovers.

7.3b

I'd expect the coefficient on `fumble_lost` to be a lot closer to the coefficient on `interception` than just `fumble` since now both are turnovers. In theory, it's hard for me to think why they wouldn't the same.

If you run the regression:

```
In [34]:
model_b = smf.ols(formula=
    """
    wpa ~ offensive_td + interception + yards_gained + fumble_lost
    """, data=df)
results_b = model_b.fit()
results_b.summary2()
--
Out[34]:
<class 'statsmodels.iolib.summary2.Summary'>
"""
                  Results: Ordinary least squares
===================================================================
Model:              OLS              Adj. R-squared:     0.752
Dependent Variable: wpa              AIC:                -1061.9489
Date:               2020-03-05 11:56 BIC:                -1043.9753
No. Observations:   269              Log-Likelihood:     535.97
Df Model:           4                F-statistic:        204.2
Df Residuals:       264              Prob (F-statistic): 1.59e-79
R-squared:          0.756            Scale:              0.0011093
--------------------------------------------------------------------
                Coef.   Std.Err.     t      P>|t|    [0.025   0.975]
--------------------------------------------------------------------
Intercept      -0.0169    0.0025   -6.7305  0.0000  -0.0218  -0.0119
offensive_td    0.0672    0.0084    8.0317  0.0000   0.0507   0.0837
interception   -0.1859    0.0151  -12.3101  0.0000  -0.2157  -0.1562
yards_gained    0.0033    0.0002   17.3536  0.0000   0.0030   0.0037
fumble_lost    -0.0960    0.0154   -6.2480  0.0000  -0.1263  -0.0657
-------------------------------------------------------------------
Omnibus:              75.209       Durbin-Watson:          2.175
Prob(Omnibus):        0.000        Jarque-Bera (JB):       1457.539
Skew:                 0.520        Prob(JB):               0.000
Kurtosis:             14.356       Condition No.:          104
===================================================================

"
```

and compare the results you'll see that — while `fumble_lost` is worse for win probability than just `fumble` — the coefficient on interception is still larger. I would guess this is due to small sample sizes (we're only dealing with play-by-play data from two games). I'd be interested in seeing the regression on more games.

7.4

Because ADP is also in the regression, b2 can be interpreted as "the impact of being a rookie on average fantasy points, *controlling for draft position*."

If you think ADP is generally efficient, and players go where they're supposed to, you might think the b2 is close to 0 and statistically insignificant. On the other hand, if you're more dubious about the crowd, you might expect them to under (b2 > 0) or over value (b2 < 0) rookies.

7.5a

Aggregating down to the player level and taking the mean of all the x variables:

```
In [37]:
df_mean = df.groupby('player_id')[xvars].mean()
df_mean['pos'] = df.groupby('player_id')[yvar].first()

model_a = RandomForestClassifier(n_estimators=100)
scores_a = cross_val_score(model_a, df_mean[xvars], df_mean[yvar], cv=10)

scores_a.mean()  # 0.8807, which is better than player-game level model
--
Out[37]: 0.8525252525252526
```

7.5b

Aggregating down to the player level and taking the mean AND median, min and max, chucking them all into the model, and seeing how it does.

```
In [38]:
df_med = df.groupby('player_id')[xvars].median()
df_max = df.groupby('player_id')[xvars].max()
df_min = df.groupby('player_id')[xvars].min()
df_mean = df.groupby('player_id')[xvars].mean()

df_med.columns = [f'{x}_med' for x in df_med.columns]
df_max.columns = [f'{x}_max' for x in df_max.columns]
df_min.columns = [f'{x}_min' for x in df_min.columns]
df_mean.columns = [f'{x}_mean' for x in df_mean.columns]

df_mult = pd.concat([df_med, df_mean, df_min, df_max], axis=1)
xvars_mult = list(df_mult.columns)

df_mult['pos'] = df.groupby('player_id')[yvar].first()

model_b = RandomForestClassifier(n_estimators=100)
scores_b = cross_val_score(model_b, df_mult[xvars_mult], df_mult[yvar], cv
    =10)

scores_b.mean()

--
Out[38]: 0.8699494949494495
```