Master Data Analysis with Python Solutions

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Part I

Intro to Pandas

Chapter 1

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1.1 2. The DataFrame and Series

[1]:
```
import pandas as pd
import numpy as np

pd.options.display.max_columns = 40
bikes = pd.read_csv('../data/bikes.csv')
```

Exercise 1

Select the column `events`, the type of weather that was recorded, and assign it to a variable with the same name. Output the first 10 values of it.

[2]:
```
events = bikes['events']
events.head(10)
```

[2]:
```
0    mostlycloudy
1    partlycloudy
2    mostlycloudy
3    mostlycloudy
4    partlycloudy
5    mostlycloudy
6          cloudy
7          cloudy
8          cloudy
9    mostlycloudy
Name: events, dtype: object
```

Exercise 2

What type of object is `events`?

[3]:
```
# it's a Series
type(events)
```

[3]:
```
pandas.core.series.Series
```

Exercise 3

Select the last two rows of the `bikes` DataFrame and assign it to the variable `bikes_last_2`. What type of object is `bikes_last_2`?

[4]:
```
# it's a DataFrame
bikes_last_2 = bikes.tail(2)
type(bikes_last_2)
```

[4]:
```
pandas.core.frame.DataFrame
```

Exercise 4

Use `pd.reset_option('all')` to reset the options to their default values. Test that this worked.

[5]:
```
pd.reset_option('all')
```

1.2 3. Data Types and Missing Values

Exercise 1

What type of object is returned from the `dtypes` attribute?

[6]:
```
# a Series
type(bikes.dtypes)
```

[6]:
```
pandas.core.series.Series
```

Exercise 2

What type of object is returned from the `shape` attribute?

[7]:
```
# a tuple of rows, columns
type(bikes.shape)
```

[7]:
```
tuple
```

Exercise 3

What type of object is returned from the `info` method?

The object `None` is returned. What you see is just output printed to the screen.

[8]:
```
info_return = bikes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50089 entries, 0 to 50088
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   trip_id            50089 non-null  int64
 1   gender             50089 non-null  object
 2   starttime          50089 non-null  object
 3   stoptime           50089 non-null  object
```

```
 4   tripduration       50089 non-null  int64
 5   from_station_name  50089 non-null  object
 6   dpcapacity_start   50083 non-null  float64
 7   to_station_name    50089 non-null  object
 8   dpcapacity_end     50077 non-null  float64
 9   temperature        50089 non-null  float64
 10  visibility         50089 non-null  float64
 11  wind_speed         50089 non-null  float64
 12  precipitation      50089 non-null  float64
 13  events             50089 non-null  object
dtypes: float64(6), int64(2), object(6)
memory usage: 5.4+ MB
```

[9]:
```
type(info_return)
```

[9]:
```
NoneType
```

Exercise 4

The memory usage from the `info` method isn't correct when you have objects in your DataFrame. Read the docstrings from it and get the true memory usage.

[10]:
```
bikes.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50089 entries, 0 to 50088
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   trip_id            50089 non-null  int64
 1   gender             50089 non-null  object
 2   starttime          50089 non-null  object
 3   stoptime           50089 non-null  object
 4   tripduration       50089 non-null  int64
 5   from_station_name  50089 non-null  object
 6   dpcapacity_start   50083 non-null  float64
 7   to_station_name    50089 non-null  object
 8   dpcapacity_end     50077 non-null  float64
 9   temperature        50089 non-null  float64
 10  visibility         50089 non-null  float64
 11  wind_speed         50089 non-null  float64
 12  precipitation      50089 non-null  float64
 13  events             50089 non-null  object
dtypes: float64(6), int64(2), object(6)
memory usage: 24.1 MB
```

1.3 4. Setting a meaningful index

Exercise 1

Read in the movie dataset and set the index to be something other than movie title. Are there any other good columns to use as an index?

[11]:
```
movies = pd.read_csv('../data/movie.csv', index_col='director_name')
movies.head(3)
```

director_name	title	year	color	content_rating	duration	...	plot_keywords	language	country	budget	imdb_score
James Cameron	Avatar	2009.0	Color	PG-13	178.0	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Gore Verbinski	Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Sam Mendes	Spectre	2015.0	Color	PG-13	148.0	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Director name isn't unique. There aren't any other good column names to use as an index.

Exercise 2

Use `set_index` to set the index and keep the column as part of the data. Read the docstrings to find the parameter that controls this functionality.

[12]:
```
movies = pd.read_csv('../data/movie.csv')
movies = movies.set_index('title', drop=False)
movies.head(3)
```

title	title	year	color	content_rating	duration	...	plot_keywords	language	country	budget	imdb_score
Avatar	Avatar	2009.0	Color	PG-13	178.0	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	Spectre	2015.0	Color	PG-13	148.0	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 3

Read in the movie DataFrame and set the index as the title column. Assign the index to its own variable and output the last 10 movies titles.

[13]:
```
movies = pd.read_csv('../data/movie.csv', index_col='title')
index = movies.index
index[-10:]
```

[13]:
```
Index(['Primer', 'Cavite', 'El Mariachi', 'The Mongol King', 'Newlyweds',
       'Signed Sealed Delivered', 'The Following', 'A Plague So Pleasant',
       'Shanghai Calling', 'My Date with Drew'],
      dtype='object', name='title')
```

Exercise 4

Use an integer instead of the column name for `index_col` when reading in the data using `read_csv`. What does it do?

[14]:
```
movies = pd.read_csv('../data/movie.csv', index_col=-5)
movies.head(3)
```

plot_keywords	title	year	color	content_rating	duration	...	num_voted_users	language	country	budget	imdb_score
avatar|future|marine|native|paraplegic	Avatar	2009.0	Color	PG-13	178.0	...	886204	English	USA	237000000.0	7.9
goddess|marriage ceremony|marriage proposal|pirate|singapore	Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	...	471220	English	USA	300000000.0	7.1
bomb|espionage|sequel|spy|terrorist	Spectre	2015.0	Color	PG-13	148.0	...	275868	English	UK	245000000.0	6.8

It chooses the column name with that integer location.

Part II

Selecting Subsets of Data

Chapter 2

Solutions

2.1 1. Selecting Subsets of Data from DataFrames with just the brackets

[1]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
```

Exercise 1

Select the column with the director's name as a Series

[2]:
```
movie['director_name'].head(3)
```

[2]:
```
title
Avatar                                         James Cameron
Pirates of the Caribbean: At World's End    Gore Verbinski
Spectre                                         Sam Mendes
Name: director_name, dtype: object
```

Exercise 2

Select the column with the director's name and number of Facebook likes.

[3]:
```
movie[['director_name', 'director_fb']].head(3)
```

	director_name	director_fb
title		
Avatar	James Cameron	0.0
Pirates of the Caribbean: At World's End	Gore Verbinski	563.0
Spectre	Sam Mendes	0.0

Exercise 3

Select a single column as a DataFrame and not a Series

[4]:
```
# make a one item list
col = ['director_name']
movie[col].head(3)
```

title	director_name
Avatar	James Cameron
Pirates of the Caribbean: At World's End	Gore Verbinski
Spectre	Sam Mendes

2.2 2. Selecting Subsets of Data from DataFrames with `loc`

[5]:
```
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 1

Select columns `actor1`, `actor2`, and `actor3` for the movies 'Home Alone' and 'Top Gun'.

[6]:
```
rows = ['Home Alone', 'Top Gun']
cols = ['actor1', 'actor2', 'actor3']
movie.loc[rows, cols]
```

title	actor1	actor2	actor3
Home Alone	Macaulay Culkin	Devin Ratray	Catherine O'Hara
Top Gun	Tom Cruise	Tom Skerritt	Adrian Pasdar

Exercise 2

Select columns `actor1`, `actor2`, and `actor3` for all of the movies beginning at 'Home Alone' and ending at 'Top Gun'.

[7]:
```
cols = ['actor1', 'actor2', 'actor3']
movie.loc['Home Alone':'Top Gun', cols]
```

title	actor1	actor2	actor3
Home Alone	Macaulay Culkin	Devin Ratray	Catherine O'Hara
3 Men and a Baby	Tom Selleck	Ted Danson	Steve Guttenberg
Tootsie	Bill Murray	Sydney Pollack	Teri Garr
Top Gun	Tom Cruise	Tom Skerritt	Adrian Pasdar

Exercise 3

Select just the `director_name` column for the movies 'Home Alone' and 'Top Gun'.

[8]:
```
rows = ['Home Alone', 'Top Gun']
movie.loc[rows, 'director_name']
```

[8]:
```
title
Home Alone    Chris Columbus
Top Gun           Tony Scott
Name: director_name, dtype: object
```

Exercise 4

Repeat exercise 3, but return a DataFramea instead.

[9]:
```
rows = ['Home Alone', 'Top Gun']
cols = ['director_name']
movie.loc[rows, cols]
```

title	director_name
Home Alone	Chris Columbus
Top Gun	Tony Scott

Exercise 5

Select all columns for the movie 'The Dark Knight Rises'.

[10]:
```
movie.loc['The Dark Knight Rises', :]
```

[10]:
```
year                                2012
color                              Color
content_rating                     PG-13
duration                             164
director_name          Christopher Nolan
director_fb                        22000
actor1                       Tom Hardy
actor1_fb                          27000
```

```
actor2                                                Christian Bale
actor2_fb                                                      23000
actor3                                             Joseph Gordon-Levitt
actor3_fb                                                      23000
gross                                                    4.48131e+08
genres                                                 Action|Thriller
num_reviews                                                      813
num_voted_users                                              1144337
plot_keywords      deception|imprisonment|lawlessness|police offi…
language                                                     English
country                                                          USA
budget                                                       2.5e+08
imdb_score                                                       8.5
Name: The Dark Knight Rises, dtype: object
```

Alternatively, don't include the empty slice.

[11]:
```
# movie.loc['The Dark Knight Rises']
```

Exercise 6

Repeat exercise 5 but return a DataFrame instead.

[12]:
```
movie.loc[['The Dark Knight Rises'], :]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
The Dark Knight Rises	2012.0	Color	PG-13	164.0	Christopher Nolan	...	deception|imprisonment|lawlessness|police offi...	English	USA	250000000.0	8.5

Exercise 7

Select all columns for the movies 'Tangled' and 'Avatar'.

[13]:
```
rows = ['Tangled', 'Avatar']
movie.loc[rows, :]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Tangled	2010.0	Color	PG	100.0	Nathan Greno	...	17th century|based on fairy tale|disney|flower...	English	USA	260000000.0	7.8
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9

Alternatively, omit the empty slice.

[14]:
```
# movie.loc[rows]
```

Exercise 8

What year was 'Tangled' and 'Avatar' made and what was their IMBD scores?

[15]:
```
movie.loc[['Tangled', 'Avatar'], ['year', 'imdb_score']]
```

title	year	imdb_score
Tangled	2010.0	7.8
Avatar	2009.0	7.9

Exercise 9

What is the data type of the `year` column?

[16]:
```
movie.dtypes.head() # Int64
```

[16]:
```
year              float64
color              object
content_rating     object
duration          float64
director_name      object
dtype: object
```

Exercise 10

Use a single method to output the data type and number of non-missing values of `year`. Is it missing any?

[17]:
```
# yes, it's missing many values. 4810 non-missing vs 4916 total
movie.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 4916 entries, Avatar to My Date with Drew
Data columns (total 21 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   year             4810 non-null   float64
 1   color            4897 non-null   object
 2   content_rating   4616 non-null   object
 3   duration         4901 non-null   float64
 4   director_name    4814 non-null   object
 5   director_fb      4814 non-null   float64
 6   actor1           4909 non-null   object
 7   actor1_fb        4909 non-null   float64
 8   actor2           4903 non-null   object
 9   actor2_fb        4903 non-null   float64
 10  actor3           4893 non-null   object
 11  actor3_fb        4893 non-null   float64
 12  gross            4054 non-null   float64
 13  genres           4916 non-null   object
 14  num_reviews      4867 non-null   float64
 15  num_voted_users  4916 non-null   int64
 16  plot_keywords    4764 non-null   object
```

```
 17  language          4904 non-null   object
 18  country           4911 non-null   object
 19  budget            4432 non-null   float64
 20  imdb_score        4916 non-null   float64
dtypes: float64(10), int64(1), object(10)
memory usage: 1004.9+ KB
```

Exercise 11

Select every 300th movie between 'Tangled' and 'Forrest Gump'. Why doesn't 'Forrest Gump' appear in the results?

[18]:
```
# Forrest Gump is not a multiple of 300 away from Tangled
movie.loc['Tangled':'Forrest Gump':300]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Tangled	2010.0	Color	PG	100.0	Nathan Greno	...	17th century|based on fairy tale|disney|flower...	English	USA	260000000.0	7.8
Cloud Atlas	2012.0	Color	R	172.0	Tom Tykwer	...	composer|future|letter|nonlinear timeline|nurs...	English	Germany	102000000.0	7.5
Doom	2005.0	Color	R	113.0	Andrzej Bartkowiak	...	commando unit|extra chromosome|first person sh...	English	UK	60000000.0	5.2

2.3 3. Selecting Subsets of Data from DataFrames with `iloc`

Exercise 1

Select the columns with integer location 10, 5, and 1.

[19]:
```
movie.iloc[:, [10, 5, 1]].head(3)
```

title	actor3	director_fb	color
Avatar	Wes Studi	0.0	Color
Pirates of the Caribbean: At World's End	Jack Davenport	563.0	Color
Spectre	Stephanie Sigman	0.0	Color

Exercise 2

Select the rows with integer location 10, 5, and 1.

[20]:
```
movie.iloc[[10, 5, 1], :]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Batman v Superman: Dawn of Justice	2016.0	Color	PG-13	183.0	Zack Snyder	...	based on comic book|batman|sequel to a reboot|...	English	USA	250000000.0	6.9
John Carter	2012.0	Color	PG-13	132.0	Andrew Stanton	...	alien|american civil war|male nipple|mars|prin...	English	USA	263700000.0	6.6
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1

Exercise 3

Select rows with integer location 100 to 104 along with the column integer location 5.

[21]:
```
movie.iloc[100:105, 5]
```

[21]:
```
title
The Fast and the Furious                    357.0
The Curious Case of Benjamin Button       21000.0
X-Men: First Class                          905.0
The Hunger Games: Mockingjay - Part 2       508.0
The Sorcerer's Apprentice                   226.0
Name: director_fb, dtype: float64
```

Exercise 4

Select the value at row integer location 100 and column integer location 4.

[22]:
```
movie.iloc[100, 4]
```

[22]:
```
'Rob Cohen'
```

Exercise 5

Return the result of exercise 4 as a DataFrame.

[23]:
```
movie.iloc[[100], [4]]
```

title	director_name
The Fast and the Furious	Rob Cohen

Exercise 6

Select the last 5 rows of the last 5 columns.

[24]:
```
movie.iloc[-5:, -5:]
```

title	plot_keywords	language	country	budget	imdb_score
Signed Sealed Delivered	fraud|postal worker|prison|theft|trial	English	Canada	NaN	7.7
The Following	cult|fbi|hideout|prison escape|serial killer	English	USA	NaN	7.5
A Plague So Pleasant	NaN	English	USA	1400.0	6.3
Shanghai Calling	NaN	English	USA	NaN	6.3
My Date with Drew	actress name in title|crush|date|four word tit...	English	USA	1100.0	6.6

Exercise 7

Select every 25th row between rows with integer location 100 and 200 along with every fifth column.

[25]:
```
movie.iloc[100:200:25, ::5]
```

title	year	director_fb	actor3	num_voted_users	imdb_score
The Fast and the Furious	2001.0	357.0	Jordana Brewster	272223	6.7
Frozen	2013.0	69.0	Livvy Stubenrauch	421658	7.6
Armageddon	1998.0	0.0	Will Patton	322395	6.6
The Incredible Hulk	2008.0	255.0	William Hurt	326286	6.8

Exercise 8

Select the column with integer location 7 as a Series.

[26]:
```
movie.iloc[:, 7].head(3)
```

[26]:
```
title
Avatar                                         1000.0
Pirates of the Caribbean: At World's End      40000.0
Spectre                                       11000.0
Name: actor1_fb, dtype: float64
```

Exercise 9

Select the rows with integer location 999, 99, and 9 and the columns with integer location 9 and 19.

[27]:
```
rows = [999, 99, 9]
cols = [9, 19]
movie.iloc[rows, cols]
```

title	actor2_fb	budget
The Iron Giant	631.0	70000000.0
The Hobbit: An Unexpected Journey	972.0	180000000.0
Harry Potter and the Half-Blood Prince	11000.0	250000000.0

2.4 4. Selecting Subsets of Data from a Series

[28]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
duration = movie['duration']
duration.head()
```

[28]:
```
title
Avatar                                        178.0
Pirates of the Caribbean: At World's End      169.0
Spectre                                       148.0
The Dark Knight Rises                         164.0
Star Wars: Episode VII - The Force Awakens      NaN
Name: duration, dtype: float64
```

Exercise 1

How long was the movie 'Titanic'?

[29]:
```
duration.loc['Titanic']
```

[29]:
```
194.0
```

Exercise 2

How long was the movie at the 999th integer location?

[30]:
```
duration.iloc[999]
```

[30]:
```
90.0
```

Exercise 3

Select the duration for the movies 'Hulk', 'Toy Story', and 'Cars'.

[31]:
```
names = ['Hulk', 'Toy Story', 'Cars']
duration.loc[names]
```

[31]:
```
title
Hulk         138.0
Toy Story     74.0
Cars         117.0
```

```
Name: duration, dtype: float64
```

Exercise 4

Select the duration for every 100th movies from 'Hulk' to 'Cars'.

[32]:
```
duration.loc['Hulk':'Cars':100]
```

[32]:
```
title
Hulk                     138.0
Live Free or Die Hard    129.0
Valkyrie                 121.0
Yogi Bear                 80.0
Dr. Dolittle 2            87.0
Name: duration, dtype: float64
```

Exercise 5

Select the duration for every 10th movie beginning from the 100th from the end.

[33]:
```
duration.iloc[-100::10]
```

[33]:
```
title
Antarctic Edge: 70° South                72.0
A Dog's Breakfast                        88.0
Penitentiary                             99.0
Peace, Propaganda & the Promised Land    80.0
Supporting Characters                    87.0
Bending Steel                            92.0
Run, Hide, Die                           75.0
Manito                                   79.0
Breaking Upwards                         88.0
Primer                                   77.0
Name: duration, dtype: float64
```

Read in the bikes dataset

Read in the bikes dataset and select the `wind_speed` column by executing the cell below and use it for the rest of the exercises. Notice that the index labels are integers, meaning that when you use `loc` you will be using integers.

[34]:
```
bikes = pd.read_csv('../data/bikes.csv')
wind = bikes['wind_speed']
wind.head()
```

[34]:
```
0    12.7
1     6.9
2    16.1
3    16.1
4    17.3
Name: wind_speed, dtype: float64
```

Exercise 6

What kind of index does the `wind` Series have?

It has a `RangeIndex`

[35]:
```
wind.index
```

[35]:
```
RangeIndex(start=0, stop=50089, step=1)
```

Exercise 7

From the `wind` Series, select the integer locations 4 through, but not including 10.

[36]:
```
wind.iloc[4:10]
```

[36]:
```
4    17.3
5    17.3
6    15.0
7     5.8
8     0.0
9    12.7
Name: wind_speed, dtype: float64
```

Exercise 8

Copy and paste your answer to Exercise 7 below but use `loc` instead. Do you get the same result? Why not?

[37]:
```
wind.loc[4:10]
```

[37]:
```
4     17.3
5     17.3
6     15.0
7      5.8
8      0.0
9     12.7
10     9.2
Name: wind_speed, dtype: float64
```

This is tricky - the index in this case contains integers and not strings. So the labels themselves are also integers and happen to be the same integers corresponding to integer location. The reason `.iloc` and `.loc` produce different results is that `.loc` always includes the last value when slicing.

2.5 5. Boolean Selection Single Conditions

[38]:
```
bikes = pd.read_csv('../data/bikes.csv')
bikes.head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
0	7147	Male	2013-06-28 19:01:00	2013-06-28 19:17:00	993	...	73.9	10.0	12.7	-9999.0	mostlycloudy
1	7524	Male	2013-06-28 22:53:00	2013-06-28 23:03:00	623	...	69.1	10.0	6.9	-9999.0	partlycloudy
2	10927	Male	2013-06-30 14:43:00	2013-06-30 15:01:00	1040	...	73.0	10.0	16.1	-9999.0	mostlycloudy

Exercise 1

Find all the rides with temperature below 0.

[39]:
```
filt = bikes['temperature'] < 0
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
1871	1071512	Male	2013-12-12 05:13:00	2013-12-12 05:27:00	878	...	-2.0	10.0	6.9	-9999.0	mostlycloudy
2049	1142687	Female	2014-01-23 06:15:00	2014-01-23 06:29:00	828	...	-2.0	10.0	16.1	-9999.0	partlycloudy
2054	1144341	Male	2014-01-23 21:15:00	2014-01-23 21:21:00	351	...	-0.9	10.0	12.7	-9999.0	clear

Exercise 2

Find all the rides with wind speed greater than 30.

[40]:
```
filt = bikes['wind_speed'] > 30
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
2164	1193566	Male	2014-02-20 19:06:00	2014-02-20 19:07:00	66	...	46.9	10.0	31.1	-9999.0	mostlycloudy
2165	1193760	Male	2014-02-20 20:47:00	2014-02-20 21:14:00	1605	...	39.0	10.0	35.7	-9999.0	cloudy
2479	1320861	Male	2014-04-01 08:28:00	2014-04-01 08:29:00	82	...	33.1	10.0	31.1	-9999.0	mostlycloudy

Exercise 3

Find all the rides that began from station 'Millennium Park'.

[41]:
```
bikes['from_station_name'] == 'Millennium Park'
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
2164	1193566	Male	2014-02-20 19:06:00	2014-02-20 19:07:00	66	...	46.9	10.0	31.1	-9999.0	mostlycloudy
2165	1193760	Male	2014-02-20 20:47:00	2014-02-20 21:14:00	1605	...	39.0	10.0	35.7	-9999.0	cloudy
2479	1320861	Male	2014-04-01 08:28:00	2014-04-01 08:29:00	82	...	33.1	10.0	31.1	-9999.0	mostlycloudy

Exercise 4

Find all the rides with wind speed less than 0. How is this possible?

[42]:
```
# these are likely missing values.
# The dataset uses -9999 to represent missing values
filt = bikes['wind_speed'] < 0
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
22990	8976097	Male	2016-03-19 10:08:00	2016-03-19 10:20:00	702	...	42.8	10.0	-9999.0	-9999.00	mostlycloudy
27168	10412628	Female	2016-06-30 11:47:00	2016-06-30 11:51:00	240	...	-9999.0	-9999.0	-9999.0	-9999.00	unknown
28368	10863258	Female	2016-07-21 21:02:29	2016-07-21 21:20:28	1079	...	73.0	1.0	-9999.0	0.39	tstorms

Exercise 5

Find all the rides where the starting number of bikes at the station (dpcapacity_start) was more than 50.

[43]:
```
filt = bikes['dpcapacity_start'] > 50
bikes[filt].head()
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
36122	13228203	Male	2017-02-17 17:00:36	2017-02-17 17:23:27	1371	...	63.0	10.0	10.4	-9999.0	partlycloudy
37617	13648506	Male	2017-04-14 18:44:47	2017-04-14 19:00:53	966	...	63.0	10.0	4.6	-9999.0	cloudy
37920	13750060	Male	2017-04-22 12:28:51	2017-04-22 12:44:14	923	...	55.9	10.0	12.7	-9999.0	mostlycloudy
37940	13754184	Female	2017-04-22 17:12:55	2017-04-22 17:23:44	649	...	57.9	10.0	12.7	-9999.0	partlycloudy
39102	14106813	Male	2017-05-21 20:40:10	2017-05-21 20:51:29	679	...	51.1	10.0	12.7	-9999.0	cloudy

Exercise 6

Did any rides happen in temperature over 100 degrees?

[44]:
```
# no, a dataframe with no rows is returned.
filt = bikes['temperature'] > 100
bikes[filt]
```

trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events

Read in new data

Read in the movie dataset by executing the cell below and use it for the following exercises.

[45]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 7

Select all movies that have 'Tom Hanks' as `actor1`. How many of these movies has he starred in?

[46]:
```
filt = movie['actor1'] == 'Tom Hanks'
hanks_movies = movie[filt]
hanks_movies.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Toy Story 3	2010.0	Color	G	103.0	Lee Unkrich	...	college|day care|escape|teddy bear|toy	English	USA	200000000.0	8.3
The Polar Express	2004.0	Color	G	100.0	Robert Zemeckis	...	boy|christmas|christmas eve|north pole|train	English	USA	165000000.0	6.6
Angels & Demons	2009.0	Color	PG-13	146.0	Ron Howard	...	conclave|illuminati|murder|reference to bernin...	English	USA	150000000.0	6.7

He's starred in 24 movies

[47]:
```
hanks_movies.shape
```

[47]:
```
(24, 21)
```

Exercise 8

Select movies with an IMDB score greater than 9.

[48]:
```
filt = movie['imdb_score'] > 9
movie[filt]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
The Shawshank Redemption	1994.0	Color	R	142.0	Frank Darabont	...	escape from prison|first person narration|pris...	English	USA	25000000.0	9.3
Towering Inferno	NaN	Color	NaN	65.0	John Blanchard	...	NaN	English	Canada	NaN	9.5
Dekalog	NaN	Color	TV-MA	55.0	NaN	...	meaning of life|moral challenge|morality|searc...	Polish	Poland	NaN	9.1
The Godfather	1972.0	Color	R	175.0	Francis Ford Coppola	...	crime family|mafia|organized crime|patriarch|r...	English	USA	6000000.0	9.2
Kickboxer: Vengeance	2016.0	NaN	NaN	90.0	John Stockwell	...	NaN	NaN	USA	17000000.0	9.1

Exercise 9

Write a function that accepts a single parameter to find the number of movies for a given content rating. Use the function to find the number of movies for ratings 'R', 'PG-13', and 'PG'.

[49]:
```
def count_rating(rating):
    filt = movie['content_rating'] == rating
    count = len(movie[filt])
    return f'There are {count} movies rated {rating}'
```

[50]:
```
count_rating('R')
```

[50]:
```
'There are 2067 movies rated R'
```

[51]:
```
count_rating('PG-13')
```

[51]:
```
'There are 1411 movies rated PG-13'
```

[52]:
```
count_rating('PG')
```

[52]:
```
'There are 686 movies rated PG'
```

2.6 6. Boolean Selection Multiple Conditions

[53]:
```
import pandas as pd
bikes = pd.read_csv('../data/bikes.csv')
bikes.head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
0	7147	Male	2013-06-28 19:01:00	2013-06-28 19:17:00	993	...	73.9	10.0	12.7	-9999.0	mostlycloudy
1	7524	Male	2013-06-28 22:53:00	2013-06-28 23:03:00	623	...	69.1	10.0	6.9	-9999.0	partlycloudy
2	10927	Male	2013-06-30 14:43:00	2013-06-30 15:01:00	1040	...	73.0	10.0	16.1	-9999.0	mostlycloudy

Exercise 1

Find all the rides where visibility was between 0 and 2.

[54]:
```
filt1 = bikes['visibility'] >= 0
filt2 = bikes['visibility'] <= 2
filt = filt1 & filt2
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
689	528940	Male	2013-09-19 10:47:00	2013-09-19 10:53:00	364	...	69.8	1.8	6.9	0.03	tstorms
972	666814	Female	2013-10-03 06:31:00	2013-10-03 06:51:00	1241	...	64.4	0.5	3.5	-9999.00	fog
973	666837	Male	2013-10-03 06:36:00	2013-10-03 06:50:00	836	...	64.4	0.5	3.5	-9999.00	fog

Exercise 2

Find all the rides with trip duration less than 100 done by females.

[55]:
```
filt1 = bikes['tripduration'] < 100
filt2 = bikes['gender'] == 'Female'
filt = filt1 & filt2
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
2485	1322828	Female	2014-04-01 15:43:00	2014-04-01 15:44:00	67	...	46.0	10.0	23.0	-9999.0	partlycloudy
3366	1694713	Female	2014-05-17 14:55:00	2014-05-17 14:56:00	62	...	57.9	10.0	11.5	-9999.0	partlycloudy
3629	1835879	Female	2014-05-27 07:55:00	2014-05-27 07:56:00	70	...	73.0	10.0	9.2	-9999.0	cloudy

Exercise 3

Find all the rides from 'Daley Center Plaza' to 'Michigan Ave & Washington St'.

[56]:
```
filt1 = bikes['from_station_name'] == 'Daley Center Plaza'
filt2 = bikes['to_station_name'] == 'Michigan Ave & Washington St'
filt = filt1 & filt2
bikes[filt]
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
6276	2950236	Female	2014-08-04 17:18:00	2014-08-04 17:22:00	214	...	73.0	10.0	8.1	-9999.0	cloudy
31038	11751095	Female	2016-09-07 07:48:30	2016-09-07 07:53:27	297	...	79.0	10.0	10.4	-9999.0	cloudy
46116	16397748	Male	2017-09-13 16:29:00	2017-09-13 16:32:42	222	...	72.0	10.0	9.2	-9999.0	cloudy

Exercise 4

Find all the rides with temperature greater than 90 or visibility equal to 1 or wind speed greater than 20.

[57]:
```
filt1 = bikes['temperature'] > 90
filt2 = bikes['visibility'] == 1
filt3 = bikes['wind_speed'] > 20
filt = filt1 | filt2 | filt3
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
54	69250	Male	2013-07-16 15:13:00	2013-07-16 15:18:00	347	...	91.0	10.0	8.1	-9999.0	mostlycloudy
55	69320	Male	2013-07-16 15:31:00	2013-07-16 15:37:00	363	...	91.0	10.0	8.1	-9999.0	mostlycloudy
56	69613	Male	2013-07-16 16:35:00	2013-07-16 16:42:00	390	...	91.0	10.0	10.4	-9999.0	mostlycloudy

Exercise 5

Invert the condition from exercise 4.

[58]:
```
filt1 = bikes['temperature'] > 90
filt2 = bikes['visibility'] == 1
filt3 = bikes['wind_speed'] > 20
filt = filt1 | filt2 | filt3
bikes[~filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
0	7147	Male	2013-06-28 19:01:00	2013-06-28 19:17:00	993	...	73.9	10.0	12.7	-9999.0	mostlycloudy
1	7524	Male	2013-06-28 22:53:00	2013-06-28 23:03:00	623	...	69.1	10.0	6.9	-9999.0	partlycloudy
2	10927	Male	2013-06-30 14:43:00	2013-06-30 15:01:00	1040	...	73.0	10.0	16.1	-9999.0	mostlycloudy

Exercise 6

Are there any rides where the weather event was snow and the temperature was greater than 40?

[59]:
```
# no
filt1 = bikes['events'] == 'snow'
filt2 = bikes['temperature'] > 40
filt = filt1 & filt2
bikes[filt]
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events

Read in the movie dataset by executing the cell below and use it for the following exercises.

[60]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 7

Select all movies with an IMDB score between 8 and 9.

[61]:
```
filt1 = movie['imdb_score'] >= 8
filt2 = movie['imdb_score'] <= 9
filt = filt1 & filt2
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
The Dark Knight Rises	2012.0	Color	PG-13	164.0	Christopher Nolan	...	deception|imprisonment|lawlessness|police offi...	English	USA	250000000.0	8.5
The Avengers	2012.0	Color	PG-13	173.0	Joss Whedon	...	alien invasion|assassin|battle|iron man|soldier	English	USA	220000000.0	8.1
Captain America: Civil War	2016.0	Color	PG-13	147.0	Anthony Russo	...	based on comic book|knife|marvel cinematic uni...	English	USA	250000000.0	8.2

Exercise 8

Select all movies rated 'PG-13' that had IMDB scores between 8 and 9.

[62]:
```
filt1 = movie['imdb_score'] >= 8
filt2 = movie['imdb_score'] <= 9
filt3 = movie['content_rating'] == 'PG-13'
filt = filt1 & filt2 & filt3
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
The Dark Knight Rises	2012.0	Color	PG-13	164.0	Christopher Nolan	...	deception|imprisonment|lawlessness|police offi...	English	USA	250000000.0	8.5
The Avengers	2012.0	Color	PG-13	173.0	Joss Whedon	...	alien invasion|assassin|battle|iron man|soldier	English	USA	220000000.0	8.1
Captain America: Civil War	2016.0	Color	PG-13	147.0	Anthony Russo	...	based on comic book|knife|marvel cinematic uni...	English	USA	250000000.0	8.2

Exercise 9

Select movies that were rated either R, PG-13, or PG.

[63]:
```
filt = movie['content_rating'].isin(['R', 'PG-13', 'PG'])
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 10

Select movies that are either rated PG-13 or had an IMDB score greater than 7.

[64]:
```
filt1 = movie['content_rating'] == 'PG-13'
filt2 = movie['imdb_score'] > 7
filt = filt1 | filt2
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 11

Find all the movies that have at least one of the three actors with more than 10,000 Facebook likes.

[65]:
```
filt1 = movie['actor1_fb'] > 10000
filt2 = movie['actor2_fb'] > 10000
filt3 = movie['actor3_fb'] > 10000
filt = filt1 | filt2 | filt3
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8
The Dark Knight Rises	2012.0	Color	PG-13	164.0	Christopher Nolan	...	deception|imprisonment|lawlessness|police offi...	English	USA	250000000.0	8.5

Exercise 12

Invert the condition from exercise 10. In words, what have you selected?

The following selects non-PG-13 movies with IMDB score 7 or less.

[66]:
```
filt1 = movie['content_rating'] == 'PG-13'
filt2 = movie['imdb_score'] > 7
filt = filt1 | filt2
movie[~filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
The Chronicles of Narnia: Prince Caspian	2008.0	Color	PG	150.0	Andrew Adamson	...	brother brother relationship|brother sister re...	English	USA	225000000.0	6.6
Alice in Wonderland	2010.0	Color	PG	108.0	Tim Burton	...	alice in wonderland|mistaking reality for drea...	English	USA	200000000.0	6.5
Oz the Great and Powerful	2013.0	Color	PG	130.0	Sam Raimi	...	circus|magic|magician|oz|witch	English	USA	215000000.0	6.4

Exercise 13

Select all movies from the 1970's.

[67]:
```
filt1 = movie['year'] >= 1970
filt2 = movie['year'] <= 1979
filt = filt1 & filt2
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
All That Jazz	1979.0	Color	R	123.0	Bob Fosse	...	dancer|editing|stand up comedian|surgery|vomiting	English	USA	NaN	7.8
Superman	1978.0	Color	PG	188.0	Richard Donner	...	1970s|clark kent|planet|superhero|year 1978	English	USA	55000000.0	7.3
Solaris	1972.0	Black and White	PG	115.0	Andrei Tarkovsky	...	hallucination|ocean|psychologist|scientist|spa...	Russian	Soviet Union	1000000.0	8.1

2.7 7. Boolean Selection More

[68]:
```
import pandas as pd
bikes = pd.read_csv('../data/bikes.csv')
```

Exercise 1

Select the wind speed column a a Series and assign it to a variable. Are there any negative wind speeds?

[69]:
```
wind = bikes['wind_speed']
wind.head(3)
```

[69]:
```
0    12.7
1     6.9
2    16.1
Name: wind_speed, dtype: float64
```

Yes, there is really strong negative wind! Or maybe its just bad data...

[70]:
```
filt = wind < 0
wind[filt].head(3)
```

[70]:
```
22990   -9999.0
27168   -9999.0
28368   -9999.0
Name: wind_speed, dtype: float64
```

Exercise 2

Select all wind speed values between 12 and 16.

[71]:
```
filt = wind.between(12, 16)
wind[filt].head(3)
```

[71]:
```
0    12.7
6    15.0
9    12.7
Name: wind_speed, dtype: float64
```

Exercise 3

Select the events and gender columns for all trip durations longer than 1,000 seconds.

[72]:
```
filt = bikes['tripduration'] > 1000
cols = ['events', 'gender']
bikes.loc[filt, cols].head(3)
```

	events	gender
2	mostlycloudy	Male
8	cloudy	Male
10	mostlycloudy	Male

Read in the movie dataset by executing the cell below and use it for the following exercises.

[73]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 4

Select all the movies such that the Facebook likes for actor 2 are greater than those for actor 1.

There are none!

[74]:
```
filt = movie['actor2_fb'] > movie['actor2_fb']
movie[filt]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score

Exercise 5

Select the year, content rating, and IMDB score columns for movies from the year 2016 with IMDB score less than 4.

[75]:
```
filt1 = movie['year'] == 2016
filt2 = movie['imdb_score'] < 4
filt = filt1 & filt2
cols = ['year', 'content_rating', 'imdb_score']

movie.loc[filt, cols]
```

title	year	content_rating	imdb_score
Fifty Shades of Black	2016.0	R	3.5
Cabin Fever	2016.0	Not Rated	3.7
God's Not Dead 2	2016.0	PG	3.4

Exercise 6

Select all the movies that are missing values for content rating.

[76]:
```
filt = movie['content_rating'].isna()
movie[filt].head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Star Wars: Episode VII - The Force Awakens	NaN	NaN	NaN	NaN	Doug Walker	...	NaN	NaN	NaN	NaN	7.1
Godzilla Resurgence	2016.0	Color	NaN	120.0	Hideaki Anno	...	blood|godzilla|monster|sequel	Japanese	Japan	NaN	8.2
Harry Potter and the Deathly Hallows: Part II	2011.0	Color	NaN	NaN	Matt Birch	...	NaN	English	UK	NaN	7.5

Exercise 7

Select all the movies that are missing values for both the gross and budget columns. Return just those columns to verify that those values are indeed missing.

[77]:
```
filt = movie['gross'].isna() & movie['budget'].isna()
cols = ['gross', 'budget']
movie.loc[filt, cols].head(3)
```

title	gross	budget
Star Wars: Episode VII - The Force Awakens	NaN	NaN
The Lovers	NaN	NaN
Godzilla Resurgence	NaN	NaN

Exercise 8

Write a function `find_missing` that has three parameters, `df`, `col1` and `col2` where `df` is a DataFrame and `col1` and `col2` are column names. This function should return all the rows of the DataFrame where `col1` and `col2` are missing. Only return the two columns as well. Answer Exercise 7 with this function.

[78]:
```
def find_missing(df, col1, col2):
    filt = df[col1].isna() & df[col2].isna()
    cols = [col1, col2]

    return df.loc[filt, cols]
```

[79]:
```
movie_missing = find_missing(movie, 'gross', 'budget')
movie_missing.head(3)
```

title	gross	budget
Star Wars: Episode VII - The Force Awakens	NaN	NaN
The Lovers	NaN	NaN
Godzilla Resurgence	NaN	NaN

2.8 8. Filtering with the query Method

Exercise 1

Use the `query` method to select trip durations between 5,000 and 10,000.

[80]:
```
bikes.query('5000 <= tripduration <= 10000').head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
18	40924	Male	2013-07-09 13:12:00	2013-07-09 14:42:00	5396	...	79.0	10.0	13.8	0.0	cloudy
40	61401	Female	2013-07-14 14:08:00	2013-07-14 15:53:00	6274	...	87.1	10.0	8.1	-9999.0	partlycloudy
77	87005	Female	2013-07-21 11:35:00	2013-07-21 13:54:00	8299	...	82.9	10.0	5.8	-9999.0	mostlycloudy

Exercise 2

Use the `query` method to select trip durations between 5,000 and 10,000 when the weather was snow or rain. Retrieve the same data with boolean selection.

[81]:
```
bikes.query('5000 <= tripduration <= 10000 and events in ["snow", "rain"]').head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
8506	3846762	Male	2014-10-04 12:33:00	2014-10-04 14:06:00	5568	...	42.1	8.0	17.3	0.02	rain
13355	5650639	Male	2015-06-15 11:41:00	2015-06-15 13:43:00	7295	...	75.9	10.0	4.6	0.00	rain
22155	8723460	Male	2016-02-09 10:09:00	2016-02-09 12:28:00	8309	...	16.0	4.0	16.1	0.00	snow

[82]:
```
filt1 = bikes['tripduration'].between(5000, 10000)
filt2 = bikes['events'].isin(['snow', 'rain'])
filt = filt1 & filt2
bikes[filt].head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
8506	3846762	Male	2014-10-04 12:33:00	2014-10-04 14:06:00	5568	...	42.1	8.0	17.3	0.02	rain
13355	5650639	Male	2015-06-15 11:41:00	2015-06-15 13:43:00	7295	...	75.9	10.0	4.6	0.00	rain
22155	8723460	Male	2016-02-09 10:09:00	2016-02-09 12:28:00	8309	...	16.0	4.0	16.1	0.00	snow

Exercise 3

Use the `query` method to select trip durations between 5,000 and 10,000 when it was snow or rain. Create a list outside of the `query` method to hold the weather and reference that variable with `@` within `query`.

[83]:
```
weather = ["snow", "rain"]
bikes.query('5000 <= tripduration <= 10000 and events in @weather').head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
8506	3846762	Male	2014-10-04 12:33:00	2014-10-04 14:06:00	5568	...	42.1	8.0	17.3	0.02	rain
13355	5650639	Male	2015-06-15 11:41:00	2015-06-15 13:43:00	7295	...	75.9	10.0	4.6	0.00	rain
22155	8723460	Male	2016-02-09 10:09:00	2016-02-09 12:28:00	8309	...	16.0	4.0	16.1	0.00	snow

Read in the movie dataset by executing the cell below and use it for the following exercises.

[84]:
```
import pandas as pd
pd.set_option('display.max_columns', 50)
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 4

Use the `query` method to find all movies where the total number of Facebook likes for all three actors is greater than 50,000.

[85]:
```
movie.query('actor1_fb + actor2_fb + actor3_fb > 50000').head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
The Dark Knight Rises	2012.0	Color	PG-13	164.0	Christopher Nolan	...	deception|imprisonment|lawlessness|police offi...	English	USA	250000000.0	8.5
Avengers: Age of Ultron	2015.0	Color	PG-13	141.0	Joss Whedon	...	artificial intelligence|based on comic book|ca...	English	USA	250000000.0	7.5
The Avengers	2012.0	Color	PG-13	173.0	Joss Whedon	...	alien invasion|assassin|battle|iron man|soldier	English	USA	220000000.0	8.1

Exercise 5

Select all the movies where the number of user voters is less than 10 times the number of reviews.

[86]:
```
movie.query('num_voted_users < 10 * num_reviews').head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Indignation	2016.0	Color	R	110.0	James Schamus	...	based on novel	Hebrew	USA	NaN	7.8
Pete's Dragon	2016.0	Color	PG	102.0	David Lowery	...	NaN	English	USA	65000000.0	7.3
Kicks	2016.0	Color	R	80.0	Justin Tipping	...	NaN	English	USA	NaN	7.8

Exercise 6

Select all the movies made in the 1990's that were rated R with an IMDB score greater than 8.

[87]:
```
movie.query('1990 <= year <= 1999 and content_rating == "R" and imdb_score > 8').
↪head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Terminator 2: Judgment Day	1991.0	Color	R	153.0	James Cameron	...	future|liquid metal|multiple cameos|sexy woman...	English	USA	102000000.0	8.5
Braveheart	1995.0	Color	R	178.0	Mel Gibson	...	14th century|legend|revolt|scotland|tyranny	English	USA	72000000.0	8.4
Saving Private Ryan	1998.0	Color	R	169.0	Steven Spielberg	...	army|invasion|killed in action|normandy|soldier	English	USA	70000000.0	8.6

2.9 9. Miscellaneous Subset Selection

Part III

Essential Series Commands

Chapter 3

Solutions

3.1 1. Series Attributes and Statistical Methods

[1]:
```
import pandas as pd
import numpy as np
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

[2]:
```
score = movie['imdb_score']
score.head()
```

[2]:
```
title
Avatar                                        7.9
Pirates of the Caribbean: At World's End      7.1
Spectre                                       6.8
The Dark Knight Rises                         8.5
Star Wars: Episode VII - The Force Awakens    7.1
Name: imdb_score, dtype: float64
```

Exercise 1

What is the data type of `score` and how many values does it contain?

[3]:
```
score.dtype
```

[3]:
```
dtype('float64')
```

[4]:
```
score.size
```

[4]:
```
4916
```

Or use the `len` method

[5]:
```
len(score)
```

[5]:
```
4916
```

Exercise 2

What is the maximum and minimum score?

[6]:
```
score.max()
```

[6]:
```
9.5
```

[7]:
```
score.min()
```

[7]:
```
1.6
```

Exercise 3

How many movies have scores greater than 6?

[8]:
```
(score > 6).sum()
```

[8]:
```
3368
```

Exercise 4

How many movies have scores greater than 4 and less than 7?

[9]:
```
filt1 = score > 4
filt2 = score < 7
filt = filt1 & filt2
filt.sum()
```

[9]:
```
3021
```

Or in one line of code

[10]:
```
((score > 4) & (score < 7)).sum()
```

[10]:
```
3021
```

Or use the `between` method.

[11]:
```
score.between(4, 7, inclusive=False).sum()
```

[11]:
```
3021
```

Exercise 5

Find the difference between the median and mean of the scores.

[12]:
```
score.median() - score.mean()
```

[12]:
```
0.16257119609438497
```

Exercise 6

Add 1 to every value of `score` and then calculate the median.

[13]:
```
(score + 1).median()
```

[13]:
```
7.6
```

Exercise 7

Calculate the median of `score` and add 1 to this. Why is this value the same as Exercise 6?

[14]:
```
score.median() + 1
```

[14]:
```
7.6
```

Exercise 8

Return a Series that has only scores above the 99.9th percentile.

[15]:
```
filt = score > score.quantile(.999)
score[filt]
```

[15]:
```
title
The Shawshank Redemption    9.3
Towering Inferno            9.5
Dekalog                     9.1
The Godfather               9.2
Kickboxer: Vengeance        9.1
Name: imdb_score, dtype: float64
```

Exercise 9

Assign the gross column of the movie dataset to its own variable name as a Series. Round it to the nearest million.

[16]:
```
gross = movie['gross']
gross.head()
```

[16]:
```
title
Avatar                                         760505847.0
Pirates of the Caribbean: At World's End       309404152.0
Spectre                                        200074175.0
The Dark Knight Rises                          448130642.0
Star Wars: Episode VII - The Force Awakens             NaN
Name: gross, dtype: float64
```

[17]:
```
gross.round(-6).head()
```

[17]:
```
title
Avatar                                        761000000.0
Pirates of the Caribbean: At World's End      309000000.0
Spectre                                       200000000.0
The Dark Knight Rises                         448000000.0
Star Wars: Episode VII - The Force Awakens            NaN
Name: gross, dtype: float64
```

Exercise 10

Calculate the cumulative sum of the gross Series and then select the 99th integer location.

[18]:
```
gross.cumsum().iloc[99]
```

[18]:
```
23119723385.0
```

Exercise 11

Select the first 100 values of the gross Series and then calculate the sum. Does the result match exercise 10?

[19]:
```
gross.iloc[:100].sum()
```

[19]:
```
23119723385.0
```

3.2 2. Series Missing Value Methods

[20]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
duration = movie['duration']
actor1_fb = movie['actor1_fb']
actor2_fb = movie['actor2_fb']
actor1_fb.head()
```

[20]:
```
title
Avatar                                        1000.0
Pirates of the Caribbean: At World's End     40000.0
Spectre                                      11000.0
The Dark Knight Rises                        27000.0
Star Wars: Episode VII - The Force Awakens     131.0
Name: actor1_fb, dtype: float64
```

[21]:
```
actor2_fb.head()
```

[21]:
```
title
Avatar                                         936.0
Pirates of the Caribbean: At World's End      5000.0
Spectre                                        393.0
The Dark Knight Rises                        23000.0
Star Wars: Episode VII - The Force Awakens      12.0
Name: actor2_fb, dtype: float64
```

Exercise 1

What percentage of actor 1 Facebook likes are missing?

[22]:
```
actor1_fb.isna().mean() * 100
```

[22]:
```
0.14239218877135884
```

Exercise 2

Use the `notna` method to find the number of non-missing values in the actor 1 Facebook like column. Verify this number is the same as the `count` method.

[23]:
```
actor2_fb.notna().sum()
```

[23]:
```
4903
```

[24]:
```
actor2_fb.count()
```

[24]:
```
4903
```

Exercise 3

Fill the missing values of `actor1_fb` with the maximum of `actor2_fb`. Save this result to variable `actor1_fb_full`.

[25]:
```
max_fb2 = actor2_fb.max()
max_fb2
```

[25]:
```
137000.0
```

[26]:
```
actor1_fb_full = actor1_fb.fillna(max_fb2)
actor1_fb_full.head()
```

[26]:
```
title
Avatar                                         1000.0
Pirates of the Caribbean: At World's End      40000.0
Spectre                                       11000.0
The Dark Knight Rises                         27000.0
Star Wars: Episode VII - The Force Awakens      131.0
Name: actor1_fb, dtype: float64
```

Exercise 4

Verify the results of Exercise 3 by selecting just the values of `actor1_fb_full` that were filled by `actor2_fb`.

[27]:
```
filt = actor1_fb.isna()
actor1_fb_full[filt]
```

[27]:
```
title
Pink Ribbons, Inc.          137000.0
Sex with Strangers          137000.0
The Harvest/La Cosecha      137000.0
```

```
Ayurveda: Art of Being     137000.0
The Brain That Sings       137000.0
The Blood of My Brother    137000.0
Counting                   137000.0
Name: actor1_fb, dtype: float64
```

[28]:
```
actor2_fb.max()
```

[28]:
```
137000.0
```

Exercise 5

Use the `duration` Series and test whether each movie is greater than 100. Assign the resulting Series to `filt`. Then test whether the `duration` Series is less than or equal to 100 and assign it to `filt2`. Call the `sum` method on both of these new Series and add their results together. Why doesn't this result equal the total length of the Series? Shouldn't a value be either greater than 100 or less than or equal to 100?

[29]:
```
filt = duration > 100
filt2 = duration <= 100
```

[30]:
```
filt.sum() + filt2.sum()
```

[30]:
```
4901
```

Missing values always get evaluated as `False` for comparisons. You need to add in the missing values to get the total length of the Series.

[31]:
```
filt.sum() + filt2.sum() + duration.isna().sum()
```

[31]:
```
4916
```

[32]:
```
len(duration)
```

[32]:
```
4916
```

Exercise 6

How many missing values are there in the `year` column?

[33]:
```
movie['year'].isna().sum()
```

[33]:
```
106
```

Exercise 7

Select the language column as a Series and assign it to a variable with the same name. Create a variable `filt` that determines whether a language is missing. Create a new Series that fills in all missing languages with 'English' and assign it to the variable `language2`. Output both `language` and `language2` for the movies that originally had missing values.

[34]:
```
language = movie['language']
filt = language.isna()
```

```
language2 = language.fillna('English')
```

[35]:
```
language[filt]
```

[35]:
```
title
Star Wars: Episode VII - The Force Awakens                NaN
10,000 B.C.                                               NaN
Unforgettable                                             NaN
September Dawn                                            NaN
Alpha and Omega 4: The Legend of the Saw Toothed Cave     NaN
Silent Movie                                              NaN
Love's Abiding Joy                                        NaN
Kickboxer: Vengeance                                      NaN
A Fine Step                                               NaN
Intolerance: Love's Struggle Throughout the Ages          NaN
The Big Parade                                            NaN
Over the Hill to the Poorhouse                            NaN
Name: language, dtype: object
```

[36]:
```
language2[filt]
```

[36]:
```
title
Star Wars: Episode VII - The Force Awakens                English
10,000 B.C.                                               English
Unforgettable                                             English
September Dawn                                            English
Alpha and Omega 4: The Legend of the Saw Toothed Cave     English
Silent Movie                                              English
Love's Abiding Joy                                        English
Kickboxer: Vengeance                                      English
A Fine Step                                               English
Intolerance: Love's Struggle Throughout the Ages          English
The Big Parade                                            English
Over the Hill to the Poorhouse                            English
Name: language, dtype: object
```

Exercise 8

Repeat exercise 7 without first assigning the language column to a variable. Reference it by using *just the brackets*. Still make a variable `language2` to verify the results.

[37]:
```
filt = movie['language'].isna()
language2 = movie['language'].fillna('English')
language2[filt]
```

[37]:
```
title
Star Wars: Episode VII - The Force Awakens                English
10,000 B.C.                                               English
Unforgettable                                             English
September Dawn                                            English
Alpha and Omega 4: The Legend of the Saw Toothed Cave     English
```

```
Silent Movie                                                English
Love's Abiding Joy                                          English
Kickboxer: Vengeance                                        English
A Fine Step                                                 English
Intolerance: Love's Struggle Throughout the Ages            English
The Big Parade                                              English
Over the Hill to the Poorhouse                              English
Name: language, dtype: object
```

Exercise 9

Select the `gross` column, and drop all missing values from it. Confirm that the new length of the resulting Series is correct.

[38]:
```
gd = movie['gross'].dropna()
len(gd)
```

[38]:
```
4054
```

[39]:
```
movie['gross'].isna().sum()
```

[39]:
```
862
```

[40]:
```
movie['gross'].isna().sum() + len(gd)
```

[40]:
```
4916
```

Exercise 10

Read in `girl_height.csv` as a DataFrame and output all of the data. The average height for each age is found in the `height` column. Assign the `height_na` Series to a variable. Notice that all ages from 2 through 12 are missing, but all other ages have the same value as the `height` column. Use the `interpolate` method to fill in the missing values with method 'linear', 'quadratic', and 'cubic'. Save each interpolated Series to a variable with the same name as its method.

[41]:
```
girl_height = pd.read_csv('../data/girl_height.csv')
girl_height
```

	age	height	height_na
0	0	19.00	19.00
1	1	29.00	29.00
2	2	34.00	NaN
3	3	37.00	NaN
4	4	39.50	NaN
5	5	42.00	NaN
6	6	45.50	NaN
7	7	48.00	NaN
8	8	50.00	NaN
9	9	52.50	NaN
10	10	54.00	NaN
11	11	56.00	NaN
12	12	59.50	NaN
13	13	61.50	61.50
14	14	63.50	63.50
15	15	64.00	64.00
16	16	64.25	64.25
17	17	64.25	64.25
18	18	64.25	64.25

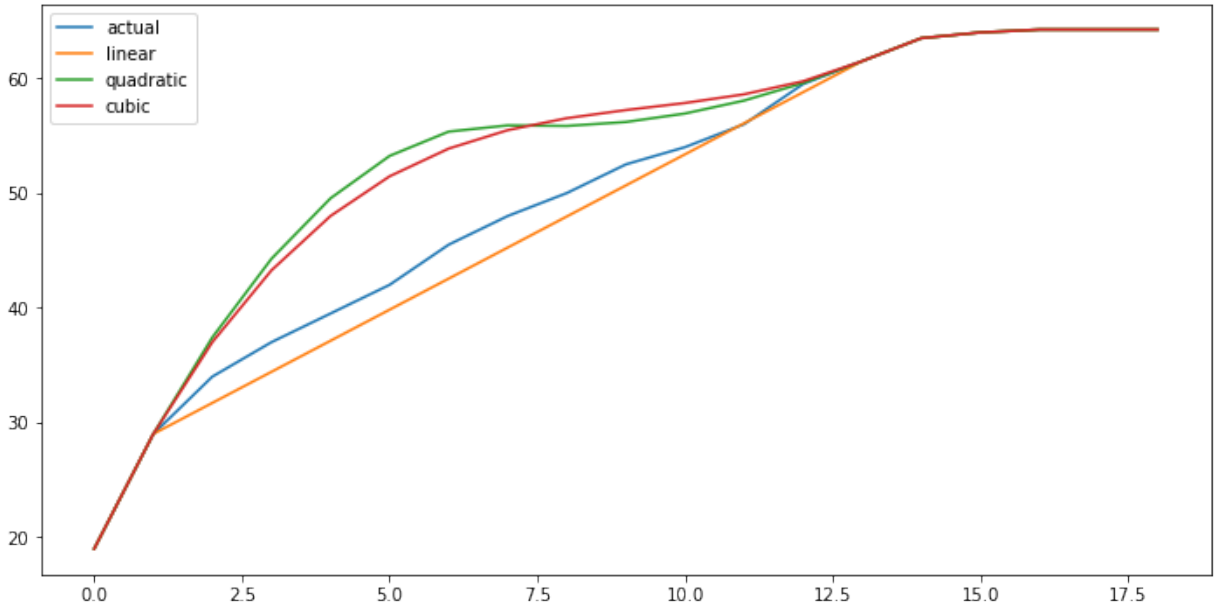
[42]:
```
hna = girl_height['height_na']
linear = hna.interpolate('linear')
quadratic = hna.interpolate('quadratic')
cubic = hna.interpolate('cubic')
```

Exercise 11

Uncomment and run the commands below to plot each interpolated Series. Which one provides the best estimate for height?

[43]:
```
%matplotlib inline
girl_height['height'].plot(figsize=(12, 6), label='actual', legend=True)
linear.plot(label='linear', legend=True)
quadratic.plot(label='quadratic', legend=True)
cubic.plot(label='cubic', legend=True)
```

[43]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x125525750>
```



3.3 3. Series Sorting, Ranking, and Uniqueness

[44]:
```
movie = pd.read_csv('../data/movie.csv', index_col='title')
movie.head(3)
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Avatar	2009.0	Color	PG-13	178.0	James Cameron	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	...	bomb|espionage|sequel|spy|terrorist	English	UK	245000000.0	6.8

Exercise 1

Select the column holding the number of reviews as a Series and sort if from greatest to least.

[45]:
```
movie['num_reviews'].sort_values(ascending=False).head()
```

[45]:
```
title
The Dark Knight Rises    813.0
Prometheus               775.0
Django Unchained         765.0
Skyfall                  750.0
Mad Max: Fury Road       739.0
Name: num_reviews, dtype: float64
```

Exercise 2

Find the number of unique actors in each of the actor columns. Do not count missing values. Use three separate calls to `nunique`.

[46]:
```
movie['actor1'].nunique()
```

[46]:
```
2095
```

[47]:
```
movie['actor2'].nunique()
```

[47]:
```
3030
```

[48]:
```
movie['actor3'].nunique()
```

[48]:
```
3519
```

Exercise 3

Select the `year` column, sort it, and drop any duplicates.

[49]:
```
movie['year'].sort_values().drop_duplicates().head()
```

[49]:
```
title
Intolerance: Love's Struggle Throughout the Ages    1916.0
Over the Hill to the Poorhouse                      1920.0
The Big Parade                                      1925.0
Metropolis                                          1927.0
The Broadway Melody                                 1929.0
Name: year, dtype: float64
```

Exercise 4

Get the same result as Exercise 3 by dropping duplicates first and then sort. Which method is faster?

[50]:
```
movie['year'].drop_duplicates().sort_values().head()
```

[50]:
```
title
Intolerance: Love's Struggle Throughout the Ages    1916.0
Over the Hill to the Poorhouse                      1920.0
The Big Parade                                      1925.0
Metropolis                                          1927.0
Pandora's Box                                       1929.0
Name: year, dtype: float64
```

It's faster to drop duplicates first and then sort.

[51]:
```
%timeit -n 5 movie['year'].sort_values().drop_duplicates().head()
```

```
1.8 ms ± 194 µs per loop (mean ± std. dev. of 7 runs, 5 loops each)
```

[52]:
```
%timeit -n 5 movie['year'].drop_duplicates().sort_values().head()
```

```
1.15 ms ± 79.7 µs per loop (mean ± std. dev. of 7 runs, 5 loops each)
```

Exercise 5

Rank each movie by duration from greatest to least and then sort this ranking from least to greatest. Output the top 10 values. Do you get the same result by sorting the duration from greatest to least?

[53]:
```
# yes, they are the same
movie['duration'].rank(ascending=False).sort_values().head(10)
```

[53]:
```
title
Trapped                      1.0
Carlos                       2.0
Blood In, Blood Out          3.0
Heaven's Gate                4.0
The Legend of Suriyothai     5.0
Das Boot                     6.0
Apocalypse Now               7.0
The Company                  8.0
Gods and Generals            9.0
Gettysburg                  10.0
Name: duration, dtype: float64
```

[54]:
```
movie['duration'].sort_values(ascending=False).head(10)
```

[54]:
```
title
Trapped                     511.0
Carlos                      334.0
Blood In, Blood Out         330.0
Heaven's Gate               325.0
The Legend of Suriyothai    300.0
Das Boot                    293.0
Apocalypse Now              289.0
The Company                 286.0
Gods and Generals           280.0
Gettysburg                  271.0
Name: duration, dtype: float64
```

Exercise 6

Select actor1 as a Series and sort it from least to greatest, but have missing values appear first. Output the first 10 values.

[55]:
```
movie['actor1'].sort_values(na_position='first').head(10)
```

[55]:
```
title
Pink Ribbons, Inc.                 NaN
Sex with Strangers                 NaN
The Harvest/La Cosecha             NaN
Ayurveda: Art of Being             NaN
The Brain That Sings               NaN
The Blood of My Brother            NaN
Counting                           NaN
Get Rich or Die Tryin'          50 Cent
The Good Dinosaur          A.J. Buckley
```

```
Queen of the Damned             Aaliyah
Name: actor1, dtype: object
```

3.4 4. Series Methods More

[56]:
```
import pandas as pd
emp = pd.read_csv('../data/employee.csv')
movie = pd.read_csv('../data/movie.csv', index_col='title')
emp.head()
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black
3	Police	SENIOR POLICE OFFICER	1997-05-27	75942.10	Male	Hispanic
4	Police	SENIOR POLICE OFFICER	2006-01-23	69355.26	Male	White

Exercise 1

Find the minimum, maximum, mean, median, and standard deviation of the salary column. Return the result as a Series.

[57]:
```
emp['salary'].agg(['min', 'max', 'mean', 'median', 'std'])
```

[57]:
```
min         9912.000000
max       342784.000000
mean       58206.761571
median     56956.640000
std        23322.315285
Name: salary, dtype: float64
```

Exercise 2

Use the `idxmax` and `idxmin` methods to find the index where the maximum and minimum salaries are located in the DataFrame. Then use the `loc` indexer to select both of those rows as a DataFrame.

[58]:
```
imax = emp['salary'].idxmax()
imin = emp['salary'].idxmin()
rows = [imax, imin]
rows
```

[58]:
```
[1732, 1183]
```

[59]:
```
emp.loc[rows, :]
```

	dept	title	hire_date	salary	sex	race
1732	Fire	PHYSICIAN,MD	2014-09-27	342784.0	Male	White
1183	Library	CUSTOMER SERVICE CLERK	2016-01-19	9912.0	Female	Hispanic

Exercise 3

Repeat exercise 3, but do so on the `imdb_score` column from the movie dataset.

[60]:
```
score = movie['imdb_score']
rows = [score.idxmax(), score.idxmin()]
rows
```

[60]:
```
['Towering Inferno', 'Justin Bieber: Never Say Never']
```

[61]:
```
movie.loc[rows, :]
```

title	year	color	content_rating	duration	director_name	...	plot_keywords	language	country	budget	imdb_score
Towering Inferno	NaN	Color	NaN	65.0	John Blanchard	...	NaN	English	Canada	NaN	9.5
Justin Bieber: Never Say Never	2011.0	Color	G	115.0	Jon M. Chu	...	boyhood friend|manager|plasma tv|prodigy|star	English	USA	13000000.0	1.6

Exercise 4

The `idxmax` and `idxmin` methods are aggregations as they return a single value. Use the `agg` method to return the min/max `imdb_score` and the label for each score.

[62]:
```
score = movie['imdb_score']
score.agg(['min', 'idxmin', 'max', 'idxmax'])
```

[62]:
```
min                                   1.6
idxmin    Justin Bieber: Never Say Never
max                                   9.5
idxmax                  Towering Inferno
Name: imdb_score, dtype: object
```

Exercise 5

Read in 20 years of Microsoft stock data, setting the 'timestamp' column as the index. Find the top 5 largest one-day percentage gains in the `adjusted_close` column.

[63]:
```
msft = pd.read_csv('../data/stocks/msft20.csv')
msft.head(3)
```

	date	open	high	low	close	adjusted_close	volume	dividend_amount
0	1999-10-19	88.250	89.250	85.25	86.313	27.8594	69945600	0.0
1	1999-10-20	91.563	92.375	90.25	92.250	29.7758	88090600	0.0
2	1999-10-21	90.563	93.125	90.50	93.063	30.0381	60801200	0.0

[64]:
```
ac = msft['adjusted_close']
ac.pct_change().nlargest()
```

[64]:
```
254     0.195654
2259    0.186043
2288    0.122646
639     0.111181
305     0.105183
Name: adjusted_close, dtype: float64
```

Exercise 6

Randomly sample the `actor1` column as a Series with replacement to select three values. Use random state 12345. Setting a random state ensures that the same random sample is chosen regardless of which machine or version of numpy is being used.

[65]:
```
movie['actor1'].sample(n=3, random_state=12345)
```

[65]:
```
title
Windtalkers                      Nicolas Cage
Mission: Impossible                Tom Cruise
Saw 3D: The Final Chapter     Costas Mandylor
Name: actor1, dtype: object
```

Exercise 7

Select the title column from the employee dataset as a Series. Replace all occurrences of 'POLICE OFFICER' and 'SENIOR POLICE OFFICER' with 'POLICE'. You can use a list as the first argument passed to the `replace` method.

[66]:
```
emp['title'].head()
```

[66]:
```
0               POLICE SERGEANT
1    ASSISTANT CITY ATTORNEY II
2       SENIOR SLUDGE PROCESSOR
3         SENIOR POLICE OFFICER
4         SENIOR POLICE OFFICER
Name: title, dtype: object
```

[67]:
```
vals = ['POLICE OFFICER', 'SENIOR POLICE OFFICER']
emp['title'].replace(vals, 'POLICE').head()
```

[67]:
```
0               POLICE SERGEANT
1    ASSISTANT CITY ATTORNEY II
```

```
2       SENIOR SLUDGE PROCESSOR
3                        POLICE
4                        POLICE
Name: title, dtype: object
```

3.5 5. String Series Methods

[68]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
actor1 = movie['actor1'].dropna()
actor1.head(3)
```

[68]:
```
title
Avatar                                         CCH Pounder
Pirates of the Caribbean: At World's End        Johnny Depp
Spectre                                      Christoph Waltz
Name: actor1, dtype: object
```

Exercise 1

Which actor 1 has appeared in the most movies? Can you write an expression that returns this actors name as a string?

[69]:
```
actor1.value_counts().head()
```

[69]:
```
Robert De Niro       48
Johnny Depp          36
Nicolas Cage         32
Denzel Washington    29
Matt Damon           29
Name: actor1, dtype: int64
```

[70]:
```
actor1.value_counts().index[0]
```

[70]:
```
'Robert De Niro'
```

Exercise 2

What percent of movies have the top 100 most frequent actor 1's appeared in?

[71]:
```
actor1.value_counts(normalize=True).iloc[:100].sum()
```

[71]:
```
0.325117131798737
```

Exercise 3

How many actor 1's have appeared in exactly one movie?

[72]:
```
(actor1.value_counts() == 1).sum()
```

[72]:
```
1379
```

Exercise 4

How many actor 1's have more than 3 e's in their name? Output a unique array of just these actor names so we can manually verify them.

[73]:
```
filt = actor1.str.count('e') > 3
unique_e = actor1[filt].unique()
unique_e
```

[73]:
```
array(['Jennifer Lawrence', 'Keanu Reeves', 'Seychelle Gabriel',
       'Jeremy Renner', 'Amber Stevens West', 'Peter Greene',
       'Steven Anthony Lawrence', 'Cedric the Entertainer',
       'Sean Pertwee', 'Xander Berkeley', 'Kathleen Freeman',
       'Pierre Perrier', 'Catherine Deneuve', 'George Kennedy',
       'Leighton Meester', 'Steve Guttenberg', 'Emmanuelle Seigner',
       'Jurnee Smollett-Bell', 'Steve Oedekerk',
       'Johannes Silberschneider', 'Bernadette Peters',
       'Jacqueline McKenzie', 'Dee Bradley Baker', 'Jennifer Freeman',
       'Gene Tierney', 'Roscoe Lee Browne', 'Phoebe Legere',
       'Eric Sheffer Stevens', 'Michael Greyeyes', 'Steven Weber',
       'George Newbern', 'Florence Henderson', 'Michelle Simone Miller',
       'Chemeeka Walker', 'Fereshteh Sadre Orafaiy'], dtype=object)
```

[74]:
```
len(unique_e)
```

[74]:
```
35
```

To be more exact and account for both upper and lowercase letters, use the regular expression, `[eE]`.

[75]:
```
filt = actor1.str.count('[eE]') > 3
unique_eE = actor1[filt].unique()
unique_eE
```

[75]:
```
array(['Jennifer Lawrence', 'Keanu Reeves', 'Seychelle Gabriel',
       'Jeremy Renner', 'Amber Stevens West', 'Rupert Everett',
       'Peter Greene', 'Eileen Brennan', 'Steven Anthony Lawrence',
       'Cedric the Entertainer', 'Sean Pertwee', 'Xander Berkeley',
       'Eddie Redmayne', 'Jennifer Ehle', 'Kathleen Freeman',
       'Alden Ehrenreich', 'Pierre Perrier', 'Catherine Deneuve',
       'George Kennedy', 'Leighton Meester', 'Steve Guttenberg',
       'Ernie Reyes Jr.', 'Emmanuelle Vaugier', 'Emmanuelle Seigner',
       'Jurnee Smollett-Bell', 'Steve Oedekerk',
       'Johannes Silberschneider', 'Bernadette Peters',
       'Jacqueline McKenzie', 'Dee Bradley Baker', 'Jennifer Freeman',
       'Eugenio Derbez', 'Gene Tierney', 'Roscoe Lee Browne',
       'Ed Speleers', 'Joe Estevez', 'Phoebe Legere',
       'Eric Sheffer Stevens', 'Michael Greyeyes', 'Steven Weber',
       'George Newbern', 'Florence Henderson', 'Michelle Simone Miller',
       'Chemeeka Walker', 'Fereshteh Sadre Orafaiy'], dtype=object)
```

[76]:
```
len(unique_eE)
```

[76]:
```
45
```

Exercise 5

Get a unique list of all actors that have the name 'Johnson' as part of their name.

[77]:
```
filt = actor1.str.contains('Johnson')
actor1[filt].drop_duplicates()
```

[77]:
```
title
Miami Vice                                  Don Johnson
San Andreas                               Dwayne Johnson
The Boy in the Striped Pajamas          Richard Johnson
The Work and the Glory                     Eric Johnson
The Texas Chainsaw Massacre 2              Bill Johnson
Jimmy and Judy                    Nicole Randall Johnson
Fabled                                R. Brandon Johnson
Name: actor1, dtype: object
```

Exercise 6

How many unique actor 1 names end in 'x'?

[78]:
```
filt = actor1.str.endswith('x')
act_endx = actor1[filt].drop_duplicates()
act_endx
```

[78]:
```
title
Independence Day: Resurgence                    Vivica A. Fox
Total Recall                                        Ronny Cox
The Warrior's Way                                    Tony Cox
Sex Tape                                          James Wilcox
Duplex                                           Justin Theroux
The Pianist                                         Emilia Fox
Suspect Zero                                      Harry Lennix
Jeepers Creepers II                                Nicki Aycox
Molly                                            Elaine Hendrix
City of Ghosts                                         Kirk Fox
Dickie Roberts: Former Child Star                Kevin Grevioux
Alien Zone                                         Bernard Fox
A Nightmare on Elm Street 5: The Dream Child       Lisa Wilcox
The Perfect Wave                                 Rachel Hendrix
Cotton Comes to Harlem                               Redd Foxx
Name: actor1, dtype: object
```

[79]:
```
len(act_endx)
```

[79]:
```
15
```

Exercise 7

The pandas string methods overlap with the built-in Python string methods. Find all the public method names that are in-common to both. Then find the public methods that are unique to each.

[80]:
```
python_str = {method for method in dir(str) if method[0] != '_'}
pandas_str = {method for method in dir(actor1.str) if method[0] != '_'}
```

[81]:
```
python_str & pandas_str
```

[81]:
```
{'capitalize',
 'casefold',
 'center',
 'count',
 'encode',
 'endswith',
 'find',
 'index',
 'isalnum',
 'isalpha',
 'isdecimal',
 'isdigit',
 'islower',
 'isnumeric',
 'isspace',
 'istitle',
 'isupper',
 'join',
 'ljust',
 'lower',
 'lstrip',
 'partition',
 'replace',
 'rfind',
 'rindex',
 'rjust',
 'rpartition',
 'rsplit',
 'rstrip',
 'split',
 'startswith',
 'strip',
 'swapcase',
 'title',
 'translate',
 'upper',
 'zfill'}
```

[82]:
```
python_str - pandas_str
```

[82]:
```
{'expandtabs',
 'format',
 'format_map',
 'isascii',
 'isidentifier',
 'isprintable',
```

```
 'maketrans',
 'splitlines'}
```

[83]:
```
pandas_str - python_str
```

[83]:
```
{'cat',
 'contains',
 'decode',
 'extract',
 'extractall',
 'findall',
 'get',
 'get_dummies',
 'len',
 'match',
 'normalize',
 'pad',
 'repeat',
 'slice',
 'slice_replace',
 'wrap'}
```

3.6 6. Datetime Series Methods

[84]:
```
bikes = pd.read_csv('../data/bikes.csv', parse_dates=['starttime', 'stoptime'])
start = bikes['starttime']
```

Exercise 1

What percentage of bike rides happen in January?

[85]:
```
# 2.7%
start.dt.month_name().value_counts(normalize=True).round(3)
```

[85]:
```
August       0.137
July         0.132
September    0.130
June         0.121
October      0.111
May          0.086
November     0.071
April        0.064
December     0.045
March        0.044
February     0.030
January      0.027
Name: starttime, dtype: float64
```

[86]:
```
# or
(start.dt.month == 1).mean() * 100
```

[86]:
```
2.7191598953862126
```

Exercise 2

What percentage of bike rides happen on the weekend?

[87]:
```
start.dt.weekday.isin([5, 6]).mean()
```

[87]:
```
0.19692946555131866
```

Or like this:

[88]:
```
(start.dt.weekday > 4).mean()
```

[88]:
```
0.19692946555131866
```

Exercise 3

What percentage of bike rides happen on the last day of the month?

[89]:
```
start.dt.is_month_end.mean()
```

[89]:
```
0.031563816406795904
```

Exercise 4

We would expect that the value of the minutes recorded for each starting ride is approximately random. Can you show some data that confirms or rejects this?

The distribution looks quite uniform:

[90]:
```
start.dt.minute.value_counts(normalize=True)
```

[90]:
```
12    0.017968
6     0.017928
8     0.017868
18    0.017808
43    0.017629
21    0.017549
10    0.017529
48    0.017509
44    0.017449
15    0.017409
53    0.017349
17    0.017329
37    0.017309
13    0.017289
19    0.017269
33    0.017229
42    0.017229
39    0.017189
24    0.017189
22    0.017110
```

```
34    0.017070
29    0.017070
45    0.016950
5     0.016890
36    0.016870
11    0.016870
14    0.016870
49    0.016850
47    0.016830
30    0.016810
16    0.016710
32    0.016670
38    0.016630
1     0.016630
40    0.016531
7     0.016491
2     0.016471
46    0.016471
4     0.016391
23    0.016331
54    0.016311
57    0.016291
3     0.016251
28    0.016091
35    0.016071
59    0.016071
56    0.016031
0     0.015932
58    0.015912
50    0.015872
31    0.015872
55    0.015852
9     0.015812
27    0.015812
41    0.015712
20    0.015612
25    0.015512
52    0.015253
51    0.015213
26    0.014973
Name: starttime, dtype: float64
```

Exercise 5

Assign the length of the ride to `ride_length`. Then find the percentage of rides that lasted longer than 30 minutes.

[91]:
```
stop = bikes['stoptime']
ride_length = stop - start
```

[92]:
```
(ride_length.dt.total_seconds() > (60 * 30)).mean()
```

[92]:
```
0.019625067380063487
```

3.7 Project - Testing Normality of Stock Market Returns

Execute the cells below to read in 20 years of Apple (AAPL) data as a Series and answer the exercises below with it.

[93]:
```
stocks = pd.read_csv('../data/stocks/stocks10.csv', index_col='date',␣
↪parse_dates=['date'])
stocks.head(3)
```

date	MSFT	AAPL	SLB	AMZN	TSLA	XOM	WMT	T	FB	V
1999-10-25	29.84	2.32	17.02	82.75	NaN	21.45	38.99	16.78	NaN	NaN
1999-10-26	29.82	2.34	16.65	81.25	NaN	20.89	37.11	17.28	NaN	NaN
1999-10-27	29.33	2.38	16.52	75.94	NaN	20.80	36.94	18.27	NaN	NaN

[94]:
```
aapl = stocks['AAPL']
aapl.head()
```

[94]:
```
date
1999-10-25    2.32
1999-10-26    2.34
1999-10-27    2.38
1999-10-28    2.43
1999-10-29    2.50
Name: AAPL, dtype: float64
```

Exercise 1

Use one line of code to find the daily percentage returns of AAPL and drop any missing values. Save the result to `aapl_change`.

[95]:
```
aapl_change = aapl.pct_change().dropna()
aapl_change.head(3)
```

[95]:
```
date
1999-10-26    0.008621
1999-10-27    0.017094
1999-10-28    0.021008
Name: AAPL, dtype: float64
```

Exercise 2

Find the mean daily return for Apple, the first and last closing prices, and the number of trading days. Store all four of these values into separate variables.

[96]:
```
mean = aapl_change.mean()
first = aapl.iloc[0]
last = aapl.iloc[-1]
n = aapl_change.size
mean, first, last, n
```

[96]:
```
(0.0012692984527780723, 2.32, 242.46, 5032)
```

[97]:
```
aapl_change.agg(['mean'])
```

[97]:
```
mean    0.001269
Name: AAPL, dtype: float64
```

Exercise 3

If Apple returned its mean percentage return every single day since the first day you have data, what would its last closing price be? Is it the same as the actual last closing price? You need to use all the variables calculated from Exercise 2.

[98]:
```
first * (mean + 1) ** n
```

[98]:
```
1372.8262535261679
```

[99]:
```
last
```

[99]:
```
242.46
```

Exercise 4

Find the z-score for the Apple daily returns. Save this to a variable `z_score_raw`. What is the max and minimum score?

[100]:
```
std = aapl_change.std()
z_score_raw = (aapl_change - mean) / std
z_score_raw.head()
```

[100]:
```
date
1999-10-26    0.286300
1999-10-27    0.616294
1999-10-28    0.768740
1999-10-29    1.072441
1999-11-01   -1.295674
Name: AAPL, dtype: float64
```

[101]:
```
z_score_raw.max(), z_score_raw.min()
```

[101]:
```
(5.3712520859138, -20.221564477921486)
```

Or with agg.

[102]:
```
z_score_raw.agg(['min', 'max']).round(3)
```

[102]:
```
min   -20.222
max     5.371
Name: AAPL, dtype: float64
```

Exercise 5

What percentage did Apple's stock increase when it had its highest maximum raw z-score?

[103]:
```
aapl_change[z_score_raw == z_score_raw.max()]
```

[103]:
```
date
2008-10-13    0.139188
Name: AAPL, dtype: float64
```

[104]:
```
aapl_change.agg(['max', 'idxmax'])
```

[104]:
```
max                  0.139188
idxmax    2008-10-13 00:00:00
Name: AAPL, dtype: object
```

Exercise 6

Create a function that accepts a Series of stock closing prices. Have it return the percentage of prices within 1, 2, and 3 standard deviations from the mean. Use your function to return results for different stocks found in the `stocks` DataFrame.

[105]:
```
def stock_pct_finder(close):
    close_change = close.pct_change().dropna()
    mean = close_change.mean()
    std = close_change.std()
    z_score_abs = (close_change - mean).abs() / std

    pct_within1 = round((z_score_abs < 1).mean(), 3)
    pct_within2 = round((z_score_abs < 2).mean().round(3), 3)
    pct_within3 = round((z_score_abs < 3).mean().round(3), 3)

    return pct_within1, pct_within2, pct_within3
```

[106]:
```
stock_pct_finder(stocks['AMZN'])
```

[106]:
```
(0.833, 0.95, 0.98)
```

[107]:
```
stock_pct_finder(stocks['FB'])
```

[107]:
```
(0.804, 0.956, 0.988)
```

[108]:
```
stock_pct_finder(stocks['SLB'])
```

[108]:
```
(0.763, 0.948, 0.988)
```

Exercise 7

How many days did Apple close above 100 and below 120?

[109]:
```
filt = (aapl > 100) & (aapl < 120)
filt.sum()
```

[109]:
```
401
```

Exercise 8

How many days did Apple close below 50 or above 150?

[110]:
```
((aapl < 50) | (aapl > 150)).sum()
```

[110]:
```
3596
```

Exercise 9

Look up the definition for interquartile range and select all Apple closing prices that are within this range. There are multiple ways to do this. Check the `quantile` method.

[111]:
```
# using the quantile method
q1 = aapl.quantile(.25)
q3 = aapl.quantile(.75)

criteria = (aapl >= q1) & (aapl <= q3)

aapl[criteria].head()
```

[111]:
```
date
2000-03-01    4.06
2000-03-03    3.99
2000-03-06    3.92
2000-03-10    3.92
2000-03-21    4.21
Name: AAPL, dtype: float64
```

[112]:
```
# a few ways to do this
n = aapl.size
first_q = n // 4
third_q = n // 4 * 3

aapl.sort_values().iloc[first_q:third_q].head()
```

[112]:
```
date
2004-12-03    3.91
2000-03-06    3.92
2000-03-10    3.92
2004-12-07    3.92
2000-03-30    3.92
Name: AAPL, dtype: float64
```

Exercise 10

Find the date of the highest closing price. Find out how many trading days it has been since Apple recorded it highest closing price.

[113]:
```
max_close_date = aapl.idxmax()
max_close_date
```

[113]:
```
Timestamp('2019-10-23 00:00:00')
```

Number of trading days

[114]:
```
aapl.loc[max_close_date:].size
```

[114]:
```
2
```

Part IV

Essential DataFrame Commands

Chapter 4

Solutions

[1]:
```
import pandas as pd
college = pd.read_csv('../data/college.csv', index_col='instnm')
```

4.1 1. DataFrame Attributes and Methods

Exercise 1

Select only the 64-bit float columns from the `college` DataFrame. How many are there?

[2]:
```
college.select_dtypes('float64').shape
```

[2]:
```
(7535, 20)
```

There are 20 float columns

Exercise 2

When you call the `info` method on a DataFrame, one of the very last items that gets outputted is the count of columns for each data type. Can you think of a different combination of pandas operations that would return this as a Series.

[3]:
```
college.dtypes.value_counts()
```

[3]:
```
float64    20
object      4
int64       2
dtype: int64
```

4.2 2. DataFrame Statistical Methods

[4]:
```
import pandas as pd
movie = pd.read_csv('../data/movie.csv', index_col='title')
cols = ['actor1_fb', 'actor2_fb', 'actor3_fb']
actor_fb = movie[cols]
actor_fb.head(3)
```

title	actor1_fb	actor2_fb	actor3_fb
Avatar	1000.0	936.0	855.0
Pirates of the Caribbean: At World's End	40000.0	5000.0	1000.0
Spectre	11000.0	393.0	161.0

Exercise 1

Calculate the mean of each actor Facebook like column. Which actor (1, 2, or 3) has the highest mean?

actor 1 has the highest mean.

[5]:
```
actor_fb.mean()
```

[5]:
```
actor1_fb    6494.488491
actor2_fb    1621.923516
actor3_fb     631.276313
dtype: float64
```

Exercise 2

The result of exercise 1 is a Series of three values. Can you call a method on this Series to choose the column name with the highest mean Facebook likes.

[6]:
```
actor_fb.mean().idxmax()
```

[6]:
```
'actor1_fb'
```

Exercise 3

Calculate the total Facebook likes of all three actors for each movie

[7]:
```
actor_fb.sum(axis=1).head()
```

[7]:
```
title
Avatar                                        2791.0
Pirates of the Caribbean: At World's End     46000.0
Spectre                                      11554.0
The Dark Knight Rises                        73000.0
Star Wars: Episode VII - The Force Awakens      143.0
dtype: float64
```

Exercise 4

What percentage of movies have more than 10,000 total actor FB likes?

About 30%

[8]:
```
(actor_fb.sum(axis='columns') > 10000).mean()
```

[8]:
```
0.2982099267697315
```

Exercise 5

Find the median gross revenue in millions of dollars for the movies that have more than 10,000 total actor FB likes. Do the same for movies with 10,000 or less total actor FB likes.

[9]:
```
filt = actor_fb.sum(axis='columns') > 10000
movie.loc[filt, 'gross'].median() / 1e6
```

[9]:
```
42.3919155
```

[10]:
```
movie.loc[~filt, 'gross'].median() / 1e6
```

[10]:
```
16.8157525
```

Exercise 6

From exercise 5, it appears that movies with more than 10,000 total actor FB likes gross 2.5 times as much. This may be due to the fact that newer movies have more actors that are recognized by FB users. Find the median year produced for both groups.

[11]:
```
movie.loc[filt, 'year'].median()
```

[11]:
```
2006.0
```

[12]:
```
movie.loc[~filt, 'year'].median()
```

[12]:
```
2005.0
```

Exercise 7

For each movie made in the year 2016, what is the median of the total actor FB likes?

[13]:
```
filt = movie['year'] == 2016
actor_fb[filt].sum(axis=1).median()
```

[13]:
```
3571.5
```

If the above is too complex, here it is one step at a time.

[14]:
```
actor_fb_2016 = actor_fb[filt]
actor_fb_2016.head()
```

title	actor1_fb	actor2_fb	actor3_fb
Batman v Superman: Dawn of Justice	15000.0	4000.0	2000.0
Captain America: Civil War	21000.0	19000.0	11000.0
Star Trek Beyond	998.0	119.0	105.0
The Legend of Tarzan	11000.0	10000.0	103.0
X-Men: Apocalypse	34000.0	13000.0	1000.0

[15]:
```
actor_fb_2016_total = actor_fb_2016.sum(axis=1)
actor_fb_2016_total.head()
```

[15]:
```
title
Batman v Superman: Dawn of Justice    21000.0
Captain America: Civil War            51000.0
Star Trek Beyond                       1222.0
The Legend of Tarzan                  21103.0
X-Men: Apocalypse                     48000.0
dtype: float64
```

[16]:
```
actor_fb_2016_total.median()
```

[16]:
```
3571.5
```

Exercise 8

Write a function that has a single parameter, `year`. Have it return the median of the total actor FB likes for the given year. Test your function with the year 2016 and verify the result with Exercise 6.

[17]:
```
def median_fb_likes(year):
    filt = movie['year'] == year
    return actor_fb.loc[filt].sum(axis='columns').median()
```

[18]:
```
median_fb_likes(2016)
```

[18]:
```
3571.5
```

Exercise 9

Write a loop to print out the year and median total actor FB likes for that year from 1990 to 2016

[19]:
```
for year in range(1990, 2017):
    print(year, median_fb_likes(year))
```

```
1990 2017.0
1991 2436.0
1992 2147.5
1993 2018.0
1994 2368.5
```

```
1995 2612.0
1996 2692.5
1997 1964.0
1998 2482.0
1999 2595.0
2000 2378.0
2001 2424.0
2002 2146.0
2003 2019.0
2004 2298.0
2005 2072.0
2006 2359.0
2007 2002.5
2008 2400.0
2009 2145.0
2010 2411.0
2011 2818.5
2012 2426.0
2013 2420.0
2014 2084.0
2015 2063.0
2016 3571.5
```

Use the college dataset with the institution name as the index for the remaining exercises.

[20]:
```
college = pd.read_csv('../data/college.csv', index_col='instnm')
```

Exercise 10

Find the number of non-missing values in each column and again for each row.

non-missing for each column

[21]:
```
college.count()
```

[21]:
```
city                7535
stabbr              7535
hbcu                7164
menonly             7164
womenonly           7164
relaffil            7535
satvrmid            1185
satmtmid            1196
distanceonly        7164
ugds                6874
ugds_white          6874
ugds_black          6874
ugds_hisp           6874
ugds_asian          6874
ugds_aian           6874
ugds_nhpi           6874
ugds_2mor           6874
ugds_nra            6874
```

```
ugds_unkn             6874
pptug_ef              6853
curroper              7535
pctpell               6849
pctfloan              6849
ug25abv               6718
md_earn_wne_p10       6413
grad_debt_mdn_supp    7503
dtype: int64
```

non-missing count for the rows

[22]:
```
college.count(axis='columns').head()
```

[22]:
```
instnm
Alabama A & M University               26
University of Alabama at Birmingham    26
Amridge University                     24
University of Alabama in Huntsville    26
Alabama State University               26
dtype: int64
```

Exercise 11

What is the average number of non-missing values for each row?

[23]:
```
college.count(axis=1).mean()
```

[23]:
```
22.70763105507631
```

Exercise 12

The ugds column of the college dataset contains the total undergraduate population. What is the least number of colleges it would take to have have a total of more than 5 million students?

[24]:
```
ugds_cumsum = college['ugds'].sort_values(ascending=False).cumsum()
ugds_cumsum.head(10)
```

[24]:
```
instnm
University of Phoenix-Arizona             151558.0
Ivy Tech Community College                229215.0
Miami Dade College                        290685.0
Lone Star College System                  350605.0
Houston Community College                 408689.0
University of Central Florida             460969.0
Liberty University                        510309.0
Texas A & M University-College Station    557250.0
American Public University System         602174.0
Ashford University                        646918.0
Name: ugds, dtype: float64
```

[25]:
```
(ugds_cumsum < 5000000).sum() + 1
```

[25]:
```
185
```

It takes the top 185 colleges (by population) to total more than 5 million students. Let's verify the results:

[26]:
```
ugds_sort = college['ugds'].sort_values(ascending=False)
```

[27]:
```
ugds_sort.iloc[:184].sum()
```

[27]:
```
4989478.0
```

[28]:
```
ugds_sort.iloc[:185].sum()
```

[28]:
```
5007289.0
```

Exercise 13

Call the `describe` method, but make it work only for the string columns.

[29]:
```
college.describe(include='object')
```

	city	stabbr	md_earn_wne_p10	grad_debt_mdn_supp
count	7535	7535	6413	7503
unique	2514	59	598	2038
top	New York	CA	PrivacySuppressed	PrivacySuppressed
freq	87	773	822	1510

Exercise 14

Call the `max` method, but only return columns that are numeric.

[30]:
```
college.max(numeric_only=True)
```

[30]:
```
hbcu               1.0000
menonly            1.0000
womenonly          1.0000
relaffil           1.0000
satvrmid         765.0000
satmtmid         785.0000
distanceonly       1.0000
ugds          151558.0000
ugds_white         1.0000
ugds_black         1.0000
ugds_hisp          1.0000
ugds_asian         0.9727
ugds_aian          1.0000
ugds_nhpi          0.9983
ugds_2mor          0.5333
ugds_nra           0.9286
ugds_unkn          0.9027
```

```
pptug_ef            1.0000
curroper            1.0000
pctpell             1.0000
pctfloan            1.0000
ug25abv             1.0000
dtype: float64
```

4.3 3. DataFrame Missing Value Methods

[31]:
```
import pandas as pd
college = pd.read_csv('../data/college.csv', index_col='instnm')
```

Exercise 1

Find the number of missing values for each row.

[32]:
```
college.isna().sum(axis='columns').head(10)
```

[32]:
```
instnm
Alabama A & M University               0
University of Alabama at Birmingham    0
Amridge University                     2
University of Alabama in Huntsville    0
Alabama State University               0
The University of Alabama              0
Central Alabama Community College      2
Athens State University                2
Auburn University at Montgomery        0
Auburn University                      0
dtype: int64
```

Exercise 2

What percentage of rows have more than 5 missing values?

[33]:
```
(college.isna().sum(axis='columns') > 5).mean()
```

[33]:
```
0.09011280690112806
```

Exercise 3

How many total missing values are there in the entire DataFrame?

[34]:
```
college.isna().sum().sum()
```

[34]:
```
24808
```

Exercise 4

How many total non-missing values are there in the entire DataFrame?

[35]:
```
college.count().sum()
```

[35]:
```
171102
```

Exercise 5

How many rows will be dropped when the `dropna` method is called with its defaults. Calculate this number without calling the `dropna` method.

[36]:
```
# calculate the number of rows with at least one missing value
(college.isna().sum(axis=1) > 0).sum()
```

[36]:
```
6364
```

Exercise 6

Verify the result from exercise 5 by calling the `dropna` method.

[37]:
```
len(college) - len(college.dropna())
```

[37]:
```
6364
```

Exercise 7

Drop all the rows that are missing the `ugds` column.

[38]:
```
college.dropna(subset=['ugds']).head(3)
```

instnm	city	stabbr	hbcu	menonly	womenonly	...	pctpell	pctfloan	ug25abv	md_earn_wne_p10	grad_debt_mdn_supp
Alabama A & M University	Normal	AL	1.0	0.0	0.0	...	0.7356	0.8284	0.1049	30300	33888
University of Alabama at Birmingham	Birmingham	AL	0.0	0.0	0.0	...	0.3460	0.5214	0.2422	39700	21941.5
Amridge University	Montgomery	AL	0.0	0.0	0.0	...	0.6801	0.7795	0.8540	40100	23370

Exercise 8

Drop all columns that have more than 5% of their values missing.

[39]:
```
thresh = int(.95 * len(college))
thresh
```

[39]:
```
7158
```

[40]:
```
college.dropna(axis=1, thresh=thresh).shape
```

[40]:
```
(7535, 9)
```

17 columns were dropped.

[41]:
```
college.shape
```

[41]:
```
(7535, 26)
```

Exercise 9

Fill in the missing values with the maximum value of each column.

[42]:
```
max_vals = college.max()
max_vals.head()
```

[42]:
```
city          Zanesville
stabbr                WY
hbcu                   1
menonly                1
womenonly              1
dtype: object
```

[43]:
```
college.fillna(max_vals).head(3)
```

instnm	city	stabbr	hbcu	menonly	womenonly	...	pctpell	pctfloan	ug25abv	md_earn_wne_p10	grad_debt_mdn_supp
Alabama A & M University	Normal	AL	1.0	0.0	0.0	...	0.7356	0.8284	0.1049	30300	33888
University of Alabama at Birmingham	Birmingham	AL	0.0	0.0	0.0	...	0.3460	0.5214	0.2422	39700	21941.5
Amridge University	Montgomery	AL	0.0	0.0	0.0	...	0.6801	0.7795	0.8540	40100	23370

4.4 4. DataFrame Sorting, Ranking, and Uniqueness

[44]:
```
import pandas as pd
emp = pd.read_csv('../data/employee.csv')
```

Exercise 1

Sort department, race, sex ascending along with salary descending.

[45]:
```
emp.sort_values(['dept', 'race', 'sex', 'salary'], ascending=[True, True, True,␣
↪False]).head()
```

	dept	title	hire_date	salary	sex	race
19946	Fire	PHYSICIAN,MD	2015-06-22	342784.0	Female	Asian
514	Fire	ASSISTANT EMS PHYSICIAN DIRECTOR	2017-08-28	141669.0	Female	Asian
8642	Fire	STAFF PSYCHOLOGIST	2014-12-22	103805.0	Female	Asian
7199	Fire	SENIOR STAFF ANALYST	2003-01-14	97850.0	Female	Asian
430	Fire	ADMINISTRATIVE ASSISTANT	1985-08-19	55432.0	Female	Asian

Exercise 2

How many unique combinations of department and title exist?

[46]:
```
len(emp.drop_duplicates(subset=['dept', 'title']))
```

[46]:
```
1312
```

Exercise 3

Since only Series methods have a `unique` method, can you think of a creative way of getting the same result as exercise 2 with the `unique` method?

[47]:
```
# concatenate the two columns together to create a Series
dept_title = emp['dept'] + emp['title']
dept_title.head()
```

[47]:
```
0                         PolicePOLICE SERGEANT
1                 OtherASSISTANT CITY ATTORNEY II
2    Houston Public WorksSENIOR SLUDGE PROCESSOR
3                     PoliceSENIOR POLICE OFFICER
4                     PoliceSENIOR POLICE OFFICER
dtype: object
```

[48]:
```
# Now, use the `unique` method.
len(dept_title.unique())
```

[48]:
```
1312
```

[49]:
```
# in one line
len((emp['dept'] + emp['title']).unique())
```

[49]:
```
1312
```

Exercise 4

Find the frequency of occurrence of all race and sex combinations using the trick from exercise 3. For instance, you would return an object that contains the number of 'Hispanic Males', 'Black Females', etc...

[50]:
```
race_sex = emp['race'] + ' - ' + emp['sex']
race_sex.head()
```

[50]:
```
0       White - Male
1    Hispanic - Male
2       Black - Male
3    Hispanic - Male
4       White - Male
dtype: object
```

[51]:
```
race_sex.value_counts()
```

[51]:
```
White - Male                6488
Black - Male                5074
Hispanic - Male             4208
Black - Female              3587
Hispanic - Female           1940
White - Female              1291
Asian - Male                1059
Asian - Female               488
Native American - Male       107
Native American - Female      39
dtype: int64
```

[52]:
```
# in one line
# normalized to get relative frequency
(emp['race'] + ' - ' + emp['sex']).value_counts(normalize=True).round(3)
```

[52]:
```
White - Male                0.267
Black - Male                0.209
Hispanic - Male             0.173
Black - Female              0.148
Hispanic - Female           0.080
White - Female              0.053
Asian - Male                0.044
Asian - Female              0.020
Native American - Male      0.004
Native American - Female    0.002
dtype: float64
```

Use the college dataset for the remaining exercises

Execute the following cell to read in the college dataset which sets the institution name (`instnm`) as the index.

[53]:
```
college = pd.read_csv('../data/college.csv', index_col='instnm')
college.head(3)
```

instnm	city	stabbr	hbcu	menonly	womenonly	...	pctpell	pctfloan	ug25abv	md_earn_wne_p10	grad_debt_mdn_supp
Alabama A & M University	Normal	AL	1.0	0.0	0.0	...	0.7356	0.8284	0.1049	30300	33888
University of Alabama at Birmingham	Birmingham	AL	0.0	0.0	0.0	...	0.3460	0.5214	0.2422	39700	21941.5
Amridge University	Montgomery	AL	0.0	0.0	0.0	...	0.6801	0.7795	0.8540	40100	23370

Exercise 5

Select the columns `stabbr`, `satvrmid`, `satmtmid` and `ugds` columns for the state of Texas ('TX') that have an undergraduate student population of more than 20,000. Drop any rows with missing values and assign the result to the variable name `college_tx`.

[54]:
```
cols = ['stabbr', 'satvrmid', 'satmtmid', 'ugds']
college_tx = college[cols].query('stabbr == "TX" and ugds > 20000').dropna()
college_tx
```

instnm	stabbr	satvrmid	satmtmid	ugds
University of Houston	TX	555.0	590.0	31643.0
University of North Texas	TX	545.0	555.0	29758.0
Texas State University	TX	510.0	515.0	32177.0
Texas A & M University-College Station	TX	580.0	615.0	46941.0
The University of Texas at Arlington	TX	494.0	550.0	29616.0
The University of Texas at Austin	TX	630.0	660.0	38914.0
The University of Texas at San Antonio	TX	505.0	535.0	23815.0
Texas Tech University	TX	540.0	560.0	28278.0

Exercise 6

Rank each column from the `college_tx` DataFrame from greatest to least.

[55]:
```
college_tx.rank(ascending=False)
```

instnm	stabbr	satvrmid	satmtmid	ugds
University of Houston	4.5	3.0	3.0	4.0
University of North Texas	4.5	4.0	5.0	5.0
Texas State University	4.5	6.0	8.0	3.0
Texas A & M University-College Station	4.5	2.0	2.0	1.0
The University of Texas at Arlington	4.5	8.0	6.0	6.0
The University of Texas at Austin	4.5	1.0	1.0	2.0
The University of Texas at San Antonio	4.5	7.0	7.0	8.0
Texas Tech University	4.5	5.0	4.0	7.0

Exercise 7

Using the full college dataset, find the largest school by population for each state. Return only the `stabbr` and `ugds` columns sorting by `ugds`.

[56]:
```
college[['stabbr', 'ugds']].sort_values('ugds', ascending=False) \
       .drop_duplicates(subset='stabbr').head(10)
```

instnm	stabbr	ugds
University of Phoenix-Arizona	AZ	151558.0
Ivy Tech Community College	IN	77657.0
Miami Dade College	FL	61470.0
Lone Star College System	TX	59920.0
Liberty University	VA	49340.0
American Public University System	WV	44924.0
Ashford University	CA	44744.0
Western Governors University	UT	44499.0
Ohio State University-Main Campus	OH	43733.0
Kaplan University-Davenport Campus	IA	40335.0

Exercise 8

Several of the columns from the college dataset contain binary data (are either 0 or 1). Can you identify the names of these columns?

Start by finding the number of unique values of each column.

[57]:
```
col_unique = college.nunique()
col_unique
```

[57]:
```
city                 2514
stabbr                 59
hbcu                    2
menonly                 2
womenonly               2
relaffil                2
satvrmid              163
satmtmid              167
distanceonly            2
ugds                 2932
ugds_white           4397
ugds_black           3242
ugds_hisp            2809
ugds_asian           1254
ugds_aian             601
ugds_nhpi             363
ugds_2mor             957
ugds_nra              920
ugds_unkn            1517
pptug_ef             3420
curroper                2
pctpell              4422
pctfloan             4155
ug25abv              4285
md_earn_wne_p10       598
grad_debt_mdn_supp   2038
dtype: int64
```

Do boolean indexing to select just those that are binary.

[58]:
```
col_unique[col_unique == 2]
```

[58]:
```
hbcu           2
menonly        2
womenonly      2
relaffil       2
distanceonly   2
curroper       2
dtype: int64
```

Can extract the index to get just the names.

[59]:
```
col_unique[col_unique == 2].index
```

[59]:
```
Index(['hbcu', 'menonly', 'womenonly', 'relaffil', 'distanceonly', 'curroper'],
dtype='object')
```

4.5 5. DataFrame Structure Methods

[60]:
```
import pandas as pd
cols = ['instnm', 'city', 'stabbr', 'relaffil', 'satvrmid', 'satmtmid', 'ugds']
college_all = pd.read_csv('../data/college.csv', index_col='instnm', usecols=cols)
college_all.head(3)
```

instnm	city	stabbr	relaffil	satvrmid	satmtmid	ugds
Alabama A & M University	Normal	AL	0	424.0	420.0	4206.0
University of Alabama at Birmingham	Birmingham	AL	0	570.0	565.0	11383.0
Amridge University	Montgomery	AL	1	NaN	NaN	291.0

Exercise 1

Create a new boolean column in the `college_all` DataFrame named 'Verbal Higher' that is True for every college that has a higher verbal than math SAT score. Find the mean of this new column. Why does this number look suspiciously low?

[61]:
```
college_all['Verbal Higher'] = college_all['satvrmid'] > college_all['satmtmid']
```

[62]:
```
college_all['Verbal Higher'].mean()
```

[62]:
```
0.048042468480424684
```

One reason it is so low is that there are mostly missing values for the SAT columns and the comparison operators return False when comparing missing values. Notice that 84% of the values are missing for both SAT columns.

[63]:
```
cols = ['satvrmid', 'satmtmid']
college_all[cols].isna().mean()
```

[63]:
```
satvrmid    0.842734
satmtmid    0.841274
dtype: float64
```

Exercise 2

Find the real percentage of schools with higher verbal than math SAT scores.

Drop the rows with missing SAT values first.

[64]:
```
cols = ['satvrmid', 'satmtmid']
sat = college_all[cols].dropna()
sat.head()
```

instnm	satvrmid	satmtmid
Alabama A & M University	424.0	420.0
University of Alabama at Birmingham	570.0	565.0
University of Alabama in Huntsville	595.0	590.0
Alabama State University	425.0	430.0
The University of Alabama	555.0	565.0

[65]:
```
(sat['satvrmid'] > sat['satmtmid']).mean()
```

[65]:
```
0.30574324324324326
```

Can also find all those school with equal scores in both subjects.

[66]:
```
(sat['satvrmid'] == sat['satmtmid']).mean()
```

[66]:
```
0.08699324324324324
```

Exercise 3

Create a new column called 'median all' that has every value set to the median population of all the schools.

[67]:
```
college_all['median all'] = college_all['ugds'].median()
college_all.head()
```

instnm	city	stabbr	relaffil	satvrmid	satmtmid	ugds	Verbal Higher	median all
Alabama A & M University	Normal	AL	0	424.0	420.0	4206.0	True	412.5
University of Alabama at Birmingham	Birmingham	AL	0	570.0	565.0	11383.0	True	412.5
Amridge University	Montgomery	AL	1	NaN	NaN	291.0	False	412.5
University of Alabama in Huntsville	Huntsville	AL	0	595.0	590.0	5451.0	True	412.5
Alabama State University	Montgomery	AL	0	425.0	430.0	4811.0	False	412.5

Exercise 4

Rename the row label 'Texas A & M University-College Station' to 'TAMU'. Reassign the result back to `college_all` and then select this row as a Series.

[68]:
```
college_all = college_all.rename(index={'Texas A & M University-College Station':
 ↪'TAMU'})
college_all.loc['TAMU']
```

[68]:
```
city             College Station
stabbr                        TX
relaffil                       0
satvrmid                     580
satmtmid                     615
ugds                       46941
Verbal Higher              False
median all                 412.5
Name: TAMU, dtype: object
```

Use the City of Houston employee dataset

Execute the following cell to read in the City of Houston employee dataset and use it for the remaining problems.

[69]:
```
emp = pd.read_csv('../data/employee.csv')
emp.head(3)
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black

Exercise 5

Create a new column named `bonus` and insert it right after the salary column equal. Have its value equal to 10% of the salary. Round the bonus to the nearest thousand.

[70]:
```
bonus = (emp['salary'] * .1).round(-3)
emp.insert(4, 'bonus', bonus)
emp.head()
```

	dept	title	hire_date	salary	bonus	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	9000.0	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	8000.0	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	5000.0	Male	Black
3	Police	SENIOR POLICE OFFICER	1997-05-27	75942.10	8000.0	Male	Hispanic
4	Police	SENIOR POLICE OFFICER	2006-01-23	69355.26	7000.0	Male	White

4.6 6. DataFrame Methods More

[71]:
```
import pandas as pd
emp = pd.read_csv('../data/employee.csv')
emp.head(3)
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black

Exercise 1

Find the relative frequency of departments for all employees and then find the relative frequency of departments for the top 100 salaries. Compare the differences.

[72]:
```
dept_freq = emp['dept'].value_counts(normalize=True)
dept_freq.round(2)
```

[72]:
```
Police                    0.31
Fire                      0.18
Houston Public Works      0.17
Other                     0.14
Health & Human Services   0.06
Houston Airport System    0.05
Parks & Recreation        0.05
Library                   0.02
Solid Waste Management    0.02
Name: dept, dtype: float64
```

[73]:
```
emp_top100 = emp.nlargest(100, 'salary')
emp_top100.head()
```

	dept	title	hire_date	salary	sex	race
1732	Fire	PHYSICIAN,MD	2014-09-27	342784.0	Male	White
1975	Fire	PHYSICIAN,MD	2014-09-27	342784.0	Male	Asian
4680	Fire	PHYSICIAN,MD	2015-11-23	342784.0	Male	White
4882	Fire	PHYSICIAN,MD	2017-01-09	342784.0	Male	White
6501	Fire	PHYSICIAN,MD	2016-05-31	342784.0	Male	White

[74]:
```
dept_freq_top100 = emp_top100['dept'].value_counts(normalize=True)
dept_freq_top100
```

[74]:
```
Other     0.36
Fire      0.22
Police    0.15
```

```
Houston Airport System     0.09
Houston Public Works       0.09
Health & Human Services    0.07
Solid Waste Management     0.01
Library                    0.01
Name: dept, dtype: float64
```

[75]:
```
# The police dept makes up 31% of employees
# but only 16% of the top 100 salaries
dept_freq_top100 - dept_freq
```

[75]:
```
Fire                        0.039977
Health & Human Services     0.014339
Houston Airport System      0.039975
Houston Public Works       -0.082371
Library                    -0.013161
Other                       0.221239
Parks & Recreation               NaN
Police                     -0.161544
Solid Waste Management     -0.011063
Name: dept, dtype: float64
```

Exercise 2

Find the day that each stock had its largest percentage one-day drop in price.

[76]:
```
stocks = pd.read_csv('../data/stocks/stocks10.csv', index_col='date',␣
 ↪parse_dates=['date'])
stocks.head(3)
```

date	MSFT	AAPL	SLB	AMZN	TSLA	XOM	WMT	T	FB	V
1999-10-25	29.84	2.32	17.02	82.75	NaN	21.45	38.99	16.78	NaN	NaN
1999-10-26	29.82	2.34	16.65	81.25	NaN	20.89	37.11	17.28	NaN	NaN
1999-10-27	29.33	2.38	16.52	75.94	NaN	20.80	36.94	18.27	NaN	NaN

[77]:
```
stocks.pct_change().idxmin()
```

[77]:
```
MSFT   2000-04-24
AAPL   2000-09-29
SLB    2008-10-15
AMZN   2001-07-24
TSLA   2012-01-13
XOM    2008-10-15
WMT    2018-02-20
T      2000-12-19
FB     2018-07-26
V      2008-10-15
```

```
dtype: datetime64[ns]
```

4.7 7. Assigning Subsets of Data

Use the bikes dataset for all of the following exercises.

[78]:
```
import pandas as pd
bikes = pd.read_csv('../data/bikes.csv')
```

Exercise 1

Change the values of `events` to 'HEAT WAVE' for all rides where `temperature` is above 95. Verify this by outputting just the `events` and `temperature` columns that meet the condition.

[79]:
```
filt = bikes['temperature'] > 95
bikes.loc[filt, 'events'] = 'HEAT WAVE'
bikes.loc[filt, ['temperature', 'events']]
```

	temperature	events
395	96.1	HEAT WAVE
396	96.1	HEAT WAVE
397	96.1	HEAT WAVE

Exercise 2

Increase the trip duration by 50% for all the rides that took place with a wind speed above 40. Output just the trip duration and wind speed columns both before and after the assignment.

[80]:
```
filt = bikes['wind_speed'] > 40
cols = ['tripduration', 'wind_speed']
bikes.loc[filt, cols]
```

	tripduration	wind_speed
22306	130	42.6
22307	528	42.6
22308	358	42.6
22309	221	41.4

[81]:
```
bikes.loc[filt, 'tripduration'] *= 1.5
bikes.loc[filt, cols]
```

	tripduration	wind_speed
22306	195.0	42.6
22307	792.0	42.6
22308	537.0	42.6
22309	331.5	41.4

[82]:
```
bikes.loc[filt, 'tripduration'] =  bikes['tripduration'] * 1.5
```

[83]:
```
bikes.loc[filt, 'tripduration']
```

[83]:
```
22306     292.50
22307    1188.00
22308     805.50
22309     497.25
Name: tripduration, dtype: float64
```

[84]:
```
bikes['tripduration']
```

[84]:
```
0          993.0
1          623.0
2         1040.0
3          667.0
4          130.0
           ...
50084     1625.0
50085      585.0
50086      824.0
50087      178.0
50088      214.0
Name: tripduration, Length: 50089, dtype: float64
```

Exercise 3

Change the trip duration for the first two rows to 0.

[85]:
```
bikes.iloc[:2, 5] = 0
bikes.head(2)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
0	7147	Male	2013-06-28 19:01:00	2013-06-28 19:17:00	993.0	...	73.9	10.0	12.7	-9999.0	mostlycloudy
1	7524	Male	2013-06-28 22:53:00	2013-06-28 23:03:00	623.0	...	69.1	10.0	6.9	-9999.0	partlycloudy

Part V

Data Types

Chapter 5

Solutions

5.1 1. Integer, Float, and Boolean Data types

[1]:
```
import pandas as pd
import numpy as np
```

Exercise 1

Find the maximum number of a 16-bit integer using arithmetic operations. Then verify it with numpy's `iinfo` function.

[2]:
```
2 ** 15 - 1
```

[2]:
```
32767
```

[3]:
```
np.iinfo('int16')
```

[3]:
```
iinfo(min=-32768, max=32767, dtype=int16)
```

Exercise 2

Construct a Series that has the nullable integer data type. Make sure it has a mix of integers and missing values.

[4]:
```
s = pd.Series([pd.NA, np.nan, 5, -999], dtype='Int16')
s
```

[4]:
```
0    <NA>
1    <NA>
2       5
3    -999
dtype: Int16
```

Exercise 3

Take a look at the Series below. Change it's data type such that it uses the least amount of memory and preserves the numbers as they are.

[5]:
```
s = pd.Series([1_000, 60_000])
s
```

[5]:
```
0     1000
1    60000
dtype: int64
```

[6]:
```
s.astype('uint16')
```

[6]:
```
0     1000
1    60000
dtype: uint16
```

Exercise 4

Find the precision of a 32-bit float and then create a numpy array with values that have decimal places past that precision.

[7]:
```
np.finfo('float32')
```

[7]:
```
finfo(resolution=1e-06, min=-3.4028235e+38, max=3.4028235e+38, dtype=float32)
```

[8]:
```
np.array([1.00000001, 1.123456789], dtype='float32')
```

[8]:
```
array([1.       , 1.1234568], dtype=float32)
```

Exercise 5

Create a Series of numbers that have decimal places. Use the `astype` method to convert it to an integer and then back to a float. Are the decimals from the original Series preserved?

[9]:
```
# no
s = pd.Series([4.98, -23.123])
s
```

[9]:
```
0     4.980
1   -23.123
dtype: float64
```

[10]:
```
s.astype('int64')
```

[10]:
```
0     4
1   -23
dtype: int64
```

[11]:
```
s.astype('int64').astype('float64')
```

[11]:
```
0     4.0
1   -23.0
dtype: float64
```

Exercise 6

Create a numpy array with 8-bit unsigned integers. Use negative numbers in the construction along with numbers greater than 255. Does the output make sense?

[12]:
```
np.array([-1, 0, 1, 2, 255, 256], dtype='uint8')
```

[12]:
```
array([255,   0,   1,   2, 255,   0], dtype=uint8)
```

Exercise 7

Create a numpy array that has the values 50 and 100 in it, but do so without actually using those two values (or any operations that create them).

[13]:
```
# use the ability of numpy to wrap numbers around to the start of the range.
# there are 256 numbers in the range beginning at 0
np.array([306, 356], dtype='uint8')
```

[13]:
```
array([ 50, 100], dtype=uint8)
```

Exercise 8

Create a numpy array that contains two integers and the numpy nan missing value. Assign it to a variable name and output it to the screen. What data type is it?

[14]:
```
# notice the decimals in the output
a = np.array([99, -88, np.nan])
a
```

[14]:
```
array([ 99., -88.,  nan])
```

[15]:
```
a.dtype
```

[15]:
```
dtype('float64')
```

Exercise 9

Construct a Series from the array created in exercise 8. What data type is it? Construct a new Series with the same array forcing it to be a nullable integer.

[16]:
```
pd.Series(a)
```

[16]:
```
0    99.0
1   -88.0
2     NaN
dtype: float64
```

[17]:
```
pd.Series(a, dtype='Int64')
```

[17]:
```
0      99
1     -88
2    <NA>
dtype: Int64
```

Exercise 10

Construct a Series of 32-bit nullable integers using the data type object itself (and not the string).

[18]:
```
pd.Series([1, 5, pd.NA], dtype=pd.Int32Dtype())
```

[18]:
```
0       1
1       5
2    <NA>
dtype: Int32
```

5.2 2. Object, String, and Categorical Data Types

[19]:
```
import pandas as pd
import numpy as np
```

Exercise 1

Using its constructor, create a Series containing three two-item lists of integers. Then call the `sum` method on the Series. What is returned?

[20]:
```
s = pd.Series([[3, 4], [-9, 99], [5, 59]])
s
```

[20]:
```
0      [3, 4]
1    [-9, 99]
2     [5, 59]
dtype: object
```

A single list with all values together.

[21]:
```
s.sum()
```

[21]:
```
[3, 4, -9, 99, 5, 59]
```

Exercise 2

Use the constructor to create a Series of integers, floats, and booleans. Do not set the `dtype` parameter. What data type is your Series?

[22]:
```
# object
pd.Series([1, 3.2, True])
```

[22]:
```
0       1
1     3.2
2    True
dtype: object
```

Exercise 3

Construct a Series with the same values but force the data type to be a float. Does it work? What happens to the non-float values?

[23]:
```
# Yes, it works. other values become floats. True becomes 1.0
pd.Series([1, 3.2, True], dtype='float64')
```

[23]:
```
0    1.0
1    3.2
2    1.0
dtype: float64
```

Exercise 4

Construct a Series containing three strings and the four missing values `None`, `np.nan`, `pd.NA`, and `pd.NaT` assigning the result to a variable.

[24]:
```
s = pd.Series(['Houston', 'Rockets', 'Basketball', None, np.nan, pd.NA, pd.NaT])
s
```

[24]:
```
0       Houston
1       Rockets
2    Basketball
3          None
4           NaN
5          <NA>
6           NaT
dtype: object
```

[25]:
```
s.astype('string')
```

[25]:
```
0       Houston
1       Rockets
2    Basketball
3          <NA>
4          <NA>
5          <NA>
6          <NA>
dtype: string
```

Exercise 5

Using pandas, count the number of missing values in exercise 4.

[26]:
```
# pandas treats each one as a missing value
s.isna().sum()
```

[26]:
```
4
```

Exercise 6

Convert the Series from exercise 4 to the new string data type. Notice what happens to the missing values.

[27]:
```
# pandas only uses pd.NA for missing values in string columns
# object columns
s.astype('string')
```

[27]:
```
0       Houston
1       Rockets
2    Basketball
3          <NA>
4          <NA>
5          <NA>
6          <NA>
dtype: string
```

Read in the movie dataset

Execute the cell below to read in the first 10 columns of the movie dataset setting the index to be the title.

[28]:
```
pd.set_option('display.max_columns', 100)
movie = pd.read_csv('../data/movie.csv', index_col='title', usecols=range(10))
movie.head(3)
```

title	year	color	content_rating	duration	director_name	director_fb	actor1	actor1_fb	actor2
Avatar	2009.0	Color	PG-13	178.0	James Cameron	0.0	CCH Pounder	1000.0	Joel David Moore
Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	Gore Verbinski	563.0	Johnny Depp	40000.0	Orlando Bloom
Spectre	2015.0	Color	PG-13	148.0	Sam Mendes	0.0	Christoph Waltz	11000.0	Rory Kinnear

Exercise 8

Which of the columns above are good candidates for the categorical data type?

It can be helpful to use the `value_counts` or `nunique` methods to get more information on the columns.

[29]:
```
movie['color'].value_counts()
```

[29]:
```
Color             4693
Black and White    204
Name: color, dtype: int64
```

[30]:
```
movie['content_rating'].nunique()
```

[30]:
```
18
```

[31]:
```
movie['director_name'].nunique()
```

[31]:
```
2397
```

[32]:
```
movie['actor1'].nunique()
```

[32]:
```
2095
```

[33]:
```
movie['actor2'].nunique()
```

[33]:
```
3030
```

I would make color and content_rating categorical as two have known, limited, and discrete values. Although the year column is discrete, it's not exactly limited as more years of data will come in the future. The director_name, actor1, and actor2 columns are discrete and do repeat, but the number of unique values is quite substantial and a large percentage of the overall values. I would leave those as objects.

Exercise 9

Select the `content_rating` column as a Series and convert it to categorical. Assign the result to the variable `rating`.

[34]:
```
rating = movie['content_rating'].astype('category')
rating.head(3)
```

[34]:
```
title
Avatar                                         PG-13
Pirates of the Caribbean: At World's End       PG-13
Spectre                                        PG-13
Name: content_rating, dtype: category
Categories (18, object): [Approved, G, GP, M, …, TV-Y, TV-Y7, Unrated, X]
```

Exercise 10

Write an expression that returns the number of categories.

[35]:
```
len(rating.cat.categories)
```

[35]:
```
18
```

Exercise 11

Prove that the `str` accessor still works with categorical columns by making the ratings lowercase.

[36]:
```
rating.str.lower().head()
```

[36]:
```
title
Avatar                                         pg-13
Pirates of the Caribbean: At World's End       pg-13
Spectre                                        pg-13
The Dark Knight Rises                          pg-13
Star Wars: Episode VII - The Force Awakens       NaN
Name: content_rating, dtype: object
```

Exercise 12

Assign the rating 'GGG' as the first value.

[37]:
```
rating = rating.cat.add_categories('GGG')
rating.loc['Avatar'] = 'GGG'
rating.head(3)
```

[37]:
```
title
Avatar                                         GGG
Pirates of the Caribbean: At World's End     PG-13
Spectre                                       PG-13
Name: content_rating, dtype: category
Categories (19, object): [Approved, G, GP, M, …, TV-Y7, Unrated, X, GGG]
```

Exercise 13

Convert the following Series to integer.

[38]:
```
s = pd.Series(['1', '2'])
```

[39]:
```
s.astype('int64')
```

[39]:
```
0    1
1    2
dtype: int64
```

Exercise 14

Convert the following Series to integer.

[40]:
```
s = pd.Series(['1', '2', 'BAD DATA'])
```

[41]:
```
pd.to_numeric(s, errors='coerce')
```

[41]:
```
0    1.0
1    2.0
2    NaN
dtype: float64
```

Read in the diamonds dataset

Execute the next cell to read in the diamonds dataset.

[42]:
```
diamonds = pd.read_csv('../data/diamonds.csv')
diamonds.head(3)
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31

Exercise 15

Select the `cut` column as a Series and convert it to an ordered categorical. Use the data dictionary from above.

[43]:
```
categories = ['Fair', 'Good', 'Very Good', 'Premium', 'Ideal']
cut_dtype = pd.CategoricalDtype(categories, ordered=True)
cut_cat = diamonds['cut'].astype(cut_dtype)
cut_cat.head()
```

[43]:
```
0      Ideal
1    Premium
2       Good
3    Premium
4       Good
Name: cut, dtype: category
Categories (5, object): [Fair < Good < Very Good < Premium < Ideal]
```

Exercise 16

By only knowing that `cut_cat` is an ordered categorical, write an expression to get the percentage of diamonds that have the lowest category.

[44]:
```
cut_cat.value_counts(normalize=True).sort_index().iloc[-1]
```

[44]:
```
0.3995365220615499
```

5.3 3. Datetime, Timedelta, and Period Data Types

[45]:
```
import numpy as np, pandas as pd
```

Exercise 1

Create a numpy array of datetimes with year precision for the years 2000, 2010, and 2020. Assign the result to a variable.

[46]:
```
# epoch is 1970
a = np.array([30, 40, 50], dtype='datetime64[Y]')
a
```

[46]:
```
array(['2000', '2010', '2020'], dtype='datetime64[Y]')
```

Exercise 2

Staying in numpy, convert the array created in exercise 1 to a data type with second precision and assign the result to a new variable.

[47]:
```
b = a.astype('datetime64[s]')
b
```

[47]:
```
array(['2000-01-01T00:00:00', '2010-01-01T00:00:00',
       '2020-01-01T00:00:00'], dtype='datetime64[s]')
```

Exercise 3

Staying in numpy, use the `astype` method to return the number of seconds after the epoch for each value from the array created in exercise 2.

[48]:
```
b.astype('int64')
```

[48]:
```
array([ 946684800, 1262304000, 1577836800])
```

Exercise 4

Use the integers from exercise 3 to in the numpy array constructor to get the same result as exercise 2.

[49]:
```
np.array([ 946684800, 1262304000, 1577836800], dtype='datetime64[s]')
```

[49]:
```
array(['2000-01-01T00:00:00', '2010-01-01T00:00:00',
       '2020-01-01T00:00:00'], dtype='datetime64[s]')
```

Exercise 5

Construct a Series of integers for the years 2000, 2010, and 2020. Then convert it to datetime with the `astype` method.

[50]:
```
s = pd.Series([30, 40, 50])
s
```

[50]:
```
0    30
1    40
2    50
dtype: int64
```

[51]:
```
s.astype('datetime64[Y]')
```

[51]:
```
0   2000-01-01
1   2010-01-01
2   2020-01-01
dtype: datetime64[ns]
```

Exercise 6

What month is it 1 million minutes after the unix epoch?

[52]:
```
s = pd.Series([1000000]).astype('datetime64[m]')
s
```

[52]:
```
0   1971-11-26 10:40:00
dtype: datetime64[ns]
```

[53]:
```
# get month as a string
s.dt.month_name()
```

[53]:
```
0    November
dtype: object
```

In the time series part, you will learn how to do this in a more direct manner using the Timestamp constructor.

[54]:
```
pd.Timestamp(1000000, unit='m').month_name()
```

[54]:
```
'November'
```

Exercise 7

Construct a datetime Series using strings with precision down to nanoseconds (9 digits after the decimal)

[55]:
```
pd.Series(['2020-01-31 15:45:59.123456789',
           '2020-02-29 15:45:59.123456789'], dtype='datetime64[ns]')
```

[55]:
```
0   2020-01-31 15:45:59.123456789
1   2020-02-29 15:45:59.123456789
dtype: datetime64[ns]
```

Exercise 8

Using only arithmetic operations, find the amount of time 1 million seconds is. Report your answer as 'W days, X hours, Y minutes, Z seconds'.

[56]:
```
num = 1_000_000
seconds_in_day = 24 * 60 * 60
days, seconds_remaining = divmod(num, seconds_in_day)
days, seconds_remaining
```

[56]:
```
(11, 49600)
```

[57]:
```
seconds_in_hour = 60 * 60
hours, seconds_remaining = divmod(seconds_remaining, seconds_in_hour)
hours, seconds_remaining
```

[57]:
```
(13, 2800)
```

[58]:
```
seconds_in_minutes = 60
minutes, seconds = divmod(seconds_remaining, seconds_in_minutes)
minutes, seconds
```

[58]:
```
(46, 40)
```

[59]:
```
f'{days} days, {hours} hours, {minutes} minutes, {seconds} seconds'
```

[59]:
```
'11 days, 13 hours, 46 minutes, 40 seconds'
```

Exercise 9

Verify the results of exercise 8 by creating a pandas timedelta Series.

[60]:
```
pd.Series([1_000_000]).astype('timedelta64[s]')
```

[60]:
```
0   11 days 13:46:40
dtype: timedelta64[ns]
```

The `to_timedelta` function will be covered in the time series part.

[61]:
```
pd.to_timedelta(1_000_000, 's')
```

[61]:
```
Timedelta('11 days 13:46:40')
```

Exercise 10

Construct a Series with the data type period that has the hour 10 a.m. through 12 a.m. as the time period on January 1st for the years 2019, 2020, and 2021.

[62]:
```
pd.Series(['2019-01-01 10', '2020-01-01 10', '2020-01-01 10'], dtype='Period[h]')
```

[62]:
```
0    2019-01-01 10:00
1    2020-01-01 10:00
2    2020-01-01 10:00
dtype: period[H]
```

5.4 4. DataFrame Data Type Conversion

[63]:
```
import pandas as pd, numpy as np
```

Exercise 1

Read in the bikes data and select the `tripduration` column. Find its data type and then use the `memory_usage` method to find how much memory (in bytes) it is using. Change its data type to the smallest possible type so that no information is lost. What percentage of memory has been saved?

[64]:
```
bikes = pd.read_csv('../data/bikes.csv')
td = bikes['tripduration']
td.head()
```

[64]:
```
0     993
1     623
2    1040
3     667
4     130
Name: tripduration, dtype: int64
```

[65]:
```
td.memory_usage()
```

[65]:
```
400840
```

Find the min and max values

[66]:
```
td.agg(['min', 'max'])
```

[66]:
```
min       60
max    86188
Name: tripduration, dtype: int64
```

Unfortunately an unsigned integer, 'uint16', doesn't quite have enough memory to fit the max.

[67]:
```
np.iinfo('uint16')
```

[67]:
```
iinfo(min=0, max=65535, dtype=uint16)
```

We need to use 32 bits. Although you can use uint32 its probably best to stick with int32 as this is much more common.

[68]:
```
np.iinfo('int32')
```

[68]:
```
iinfo(min=-2147483648, max=2147483647, dtype=int32)
```

[69]:
```
td2 = td.astype('int32')
```

32-bit integers take up half as much space as 64-bit integers. Let's verify this.

[70]:
```
td2.memory_usage(index=False) / td.memory_usage(index=False)
```

[70]:
```
0.5
```

Exercise 2

Read in the diamonds dataset and convert the data types of each column so they use the least amount of memory without losing any information.

[71]:
```
diamonds = pd.read_csv('../data/diamonds.csv')
diamonds.head(3)
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31

[72]:
```
np.finfo('float16')
```

[72]:
```
finfo(resolution=0.001, min=-6.55040e+04, max=6.55040e+04, dtype=float16)
```

[73]:
```
np.iinfo('uint16')
```

[73]:
```
iinfo(min=0, max=65535, dtype=uint16)
```

[74]:
```
diamonds.agg(['min', 'max'])
```

	carat	cut	color	clarity	depth	table	price	x	y	z
min	0.20	Fair	D	I1	43.0	43.0	326	0.00	0.0	0.0
max	5.01	Very Good	J	VVS2	79.0	95.0	18823	10.74	58.9	31.8

[75]:
```
clarity_cats = ['I1', 'SI2', 'SI1', 'VS2', 'VS1', 'VVS2', 'VVS1', 'IF']
clarity_dtype = pd.CategoricalDtype(clarity_cats, ordered=True)

color_cats = ['J', 'I', 'H', 'G', 'F', 'E', 'D']
color_dtype = pd.CategoricalDtype(color_cats, ordered=True)

cut_cats = ['Fair', 'Good', 'Very Good', 'Premium', 'Ideal']
cut_dtype = pd.CategoricalDtype(cut_cats, ordered=True)

dtype_dict = {'carat': 'float32',
              'cut': cut_dtype,
              'color': color_dtype,
              'clarity': clarity_dtype,
              'carat': 'float32',
              'depth': 'float32',
              'table': 'float32',
              'price': 'uint16',
              'x': 'float32',
              'y': 'float32',
              'z': 'float32'}

diamonds2 = diamonds.astype(dtype_dict).round(3)
diamonds2.head(3)
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.500000	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.799999	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.900002	65.0	327	4.05	4.07	2.31

[76]:
```
np.float16(59.1281232)
```

[76]:
```
59.12
```

Part VI

Grouping Data

Chapter 6

Solutions

6.1 1. Groupby Aggregation Basics

[1]:
```
import pandas as pd
emp = pd.read_csv('../data/employee.csv')
emp.head(3)
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black

Exercise 1

Find the maximum salary for each sex.

[2]:
```
emp.groupby('sex').agg(max_salary=('salary', 'max'))
```

	max_salary
sex	
Female	342784.0
Male	342784.0

Exercise 2

Find the median salary for each department.

[3]:
```
emp.groupby('dept').agg(median_salary=('salary', 'median')).head()
```

dept	median_salary
Fire	61921.08
Health & Human Services	50773.00
Houston Airport System	44200.00
Houston Public Works	46841.50
Library	34611.00

Exercise 3

Find the average salary for each race. Return a DataFrame with the race as a column.

[4]:
```
emp.groupby('race').agg(avg_salary=('salary', 'mean')).round(-3).reset_index()
```

	race	avg_salary
0	Asian	65000.0
1	Black	52000.0
2	Hispanic	55000.0
3	Native American	58000.0
4	White	67000.0

Exercise 4

Find the number of employees in each department.

It's not necessary to use a groupby.

[5]:
```
emp['dept'].value_counts()
```

[5]:
```
Police                      7573
Fire                        4376
Houston Public Works        4190
Other                       3373
Health & Human Services     1353
Houston Airport System      1216
Parks & Recreation          1152
Library                      563
Solid Waste Management       512
Name: dept, dtype: int64
```

If you do use a groupby, it doesn't matter what column you use, but you must use `size` and not `count` because `count` will not count missing values. It is possible to use the grouping column as the aggregating column.

[6]:
```
emp.groupby('dept').agg(num_employees=('dept', 'size'))
```

dept	num_employees
Fire	4376
Health & Human Services	1353
Houston Airport System	1216
Houston Public Works	4190
Library	563
Other	3373
Parks & Recreation	1152
Police	7573
Solid Waste Management	512

Exercise 5

Find the number of unique titles there are for each department.

[7]:
```
emp.groupby('dept').agg(unique_titles=('title', 'nunique'))
```

dept	unique_titles
Fire	77
Health & Human Services	161
Houston Airport System	137
Houston Public Works	215
Library	66
Other	358
Parks & Recreation	109
Police	145
Solid Waste Management	44

Exercise 6

Find the index of the employee with the maximum salary for each department and then use those index values to select their entire rows from the original DataFrame.

[8]:
```
df = emp.groupby('dept').agg(idx_sal=('salary', 'idxmax'))
df
```

dept	idx_sal
Fire	1732
Health & Human Services	8405
Houston Airport System	3897
Houston Public Works	10704
Library	7564
Other	13338
Parks & Recreation	11679
Police	4413
Solid Waste Management	20244

[9]:
```
idx = df['idx_sal']
emp.loc[idx]
```

	dept	title	hire_date	salary	sex	race
1732	Fire	PHYSICIAN,MD	2014-09-27	342784.0	Male	White
8405	Health & Human Services	CHIEF PHYSICIAN,MD	2017-07-31	186685.0	Female	White
3897	Houston Airport System	AVIATION DIRECTOR	2010-06-01	275000.0	Male	Hispanic
10704	Houston Public Works	PUBLIC WORKS DIRECTOR	2005-08-10	275000.0	Female	White
7564	Library	LIBRARY DIRECTOR	2005-11-07	170000.0	Female	Black
13338	Other	CITY ATTORNEY	2016-05-02	275000.0	Male	Black
11679	Parks & Recreation	PARKS & RECREATION DIRECTOR	2017-07-05	150000.0	Male	White
4413	Police	POLICE CHIEF	2016-11-30	280000.0	Male	Hispanic
20244	Solid Waste Management	SOLID WASTE DIRECTOR	2001-05-14	195000.0	Male	Black

Use the NYC deaths dataset for the remaining exercises

Execute the cell below to read in the NYC deaths dataset and use it to answer the following exercises.

[10]:
```
deaths = pd.read_csv('../data/nyc_deaths.csv')
deaths.head(3)
```

	year	cause	sex	race	deaths
0	2007	Accidents	F	Asian	32
1	2007	Accidents	F	Black	87
2	2007	Accidents	F	Hispanic	71

Exercise 7

What year had the most deaths?

[11]:
```
year_deaths = deaths.groupby('year').agg(total=('deaths', 'sum'))
year_deaths
```

	total
year	
2007	53996
2008	54138
2009	52820
2010	52505
2011	52726
2012	52420
2013	53387
2014	53006

[12]:
```
year_deaths.agg(['max', 'idxmax'])
```

	total
max	54138
idxmax	2008

Exercise 8

Find the total number of deaths by race and sort by most to least.

[13]:
```
deaths.groupby('race').agg(total=('deaths', 'sum')).sort_values('total',␣
↪ascending=False)
```

race	total
White	206487
Black	111116
Hispanic	74802
Asian	26355
Unknown	6238

Exercise 9

Find the total number of deaths by cause and then select the five highest causes.

[14]:
```
deaths.groupby('cause').agg(total=('deaths', 'sum')).nlargest(5, 'total')
```

cause	total
Heart Disease	147551
Cancer	106367
Other	77999
Flu and Pneumonia	18678
Diabetes	13794

6.2 2. Grouping and Aggregating with Multiple Columns

Execute the following cell to read in the City of Houston employee data and use it for the first few exercises.

[15]:
```
import pandas as pd
emp = pd.read_csv('../data/employee.csv', parse_dates=['hire_date'])
emp.head(3)
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black

Exercise 1

For each department and sex, find the number of unique position titles, the total number of employees, and the average salary. Make sure there is no multi-level index.

[16]:
```
data = emp.groupby(['dept', 'sex']).agg(num_unique_titles=('title', 'nunique'),
                                        num_employees=('title', 'size'),
                                        avg_salaray=('salary', 'mean')).reset_index()
data.head(10)
```

	dept	sex	num_unique_titles	num_employees	avg_salaray
0	Fire	Female	51	240	62212.637250
1	Fire	Male	54	4136	60479.306862
2	Health & Human Services	Female	136	987	53838.310780
3	Health & Human Services	Male	110	366	59230.425956
4	Houston Airport System	Female	85	443	51099.300226
5	Houston Airport System	Male	113	773	57278.306598
6	Houston Public Works	Female	151	1195	51294.453004
7	Houston Public Works	Male	180	2995	51490.113309
8	Library	Female	55	404	41126.962921
9	Library	Male	44	159	44399.943396

Exercise 2

For each department, race, and sex find the min and max and salaries.

[17]:
```
emp.groupby(['dept','race', 'sex']).agg(min_salary=('salary', 'min'),
                                        max_salary=('salary', 'max')).head(10)
```

			min_salary	max_salary
dept	**race**	**sex**		
Fire	**Asian**	**Female**	39104.0	342784.00
		Male	28024.0	342784.00
	Black	**Female**	16411.0	342784.00
		Male	28024.0	342784.00
	Hispanic	**Female**	28024.0	89590.02
		Male	26000.0	342784.00
	Native American	**Female**	48189.7	70181.28
		Male	28024.0	115835.98
	White	**Female**	16910.0	342784.00
		Male	16515.0	342784.00

Execute the following cell to read in the college dataset and use it for the remaining exercises.

[18]:
```
pd.set_option('display.max_columns', 100)
college = pd.read_csv('../data/college.csv')
college.head(3)
```

	instnm	city	stabbr	hbcu	menonly	...	pctpell	pctfloan	ug25abv	md_earn_wne_p10	grad_debt_mdn_supp
0	Alabama A & M University	Normal	AL	1.0	0.0	...	0.7356	0.8284	0.1049	30300	33888
1	University of Alabama at Birmingham	Birmingham	AL	0.0	0.0	...	0.3460	0.5214	0.2422	39700	21941.5
2	Amridge University	Montgomery	AL	0.0	0.0	...	0.6801	0.7795	0.8540	40100	23370

Exercise 3

Which city name appears the most frequently. Do this in two different ways. Do it once with and once without the `groupby` method?

[19]:
```
size = college.groupby('city').agg(size=('stabbr', 'size'))
size.head()
```

	size
city	
Aberdeen	3
Abilene	5
Abingdon	2
Abington	1
Ada	3

[20]:
```
size.sort_values('size', ascending=False).head()
```

	size
city	
New York	87
Chicago	78
Houston	72
Los Angeles	56
Miami	51

Can call `idxmax` directly.

[21]:
```
college.groupby('city').agg(size=('stabbr', 'size')).idxmax()
```

[21]:
```
size    New York
dtype: object
```

Without groupby

Use value_counts

[22]:
```
college['city'].value_counts().head()
```

[22]:
```
New York       87
Chicago        78
Houston        72
Los Angeles    56
Miami          51
Name: city, dtype: int64
```

Exercise 4

Does the city 'Houston' only appear in the state of Texas (abbreviated 'TX')?

NO! It also appears in Missouri.

[23]:
```
filt = college['city'] == 'Houston'
college.loc[filt, 'stabbr'].unique()
```

[23]:
```
array(['TX', 'MO'], dtype=object)
```

Can see exact counts

[24]:
```
college.loc[filt, 'stabbr'].value_counts()
```

[24]:
```
TX    71
MO     1
Name: stabbr, dtype: int64
```

You can use a groupby and find the number of unique states for each city. This is not very efficient.

[25]:
```
city_unique_state = college.groupby('city').agg(num_unique_states=('stabbr',␣
↪'nunique'))
city_unique_state.head()
```

city	num_unique_states
Aberdeen	2
Abilene	1
Abingdon	1
Abington	1
Ada	2

[26]:
```
city_unique_state.loc['Houston']
```

[26]:
```
num_unique_states    2
Name: Houston, dtype: int64
```

Also with `drop_duplicates`

[27]:
```
college[['city', 'stabbr']].query('city == "Houston"') \
                           .drop_duplicates(subset='stabbr')
```

	city	stabbr
3617	Houston	TX
5366	Houston	MO

Exercise 5

Find the maximum undergraduate population for each state?

[28]:
```
college.groupby('stabbr').agg(max_ugds=('ugds', 'max')).head(10)
```

	max_ugds
stabbr	
AK	12865.0
AL	29851.0
AR	21405.0
AS	1276.0
AZ	151558.0
CA	44744.0
CO	25873.0
CT	18016.0
DC	10433.0
DE	18222.0

Exercise 6

Find the largest college from each state. From those colleges, find the difference between the largest and smallest.

[29]:
```
largest_per_state = college.groupby('stabbr').agg(max_ugds=('ugds', 'max'))
largest_per_state.max() - largest_per_state.min()
```

[29]:
```
max_ugds    150956.0
dtype: float64
```

Exercise 7

Find the name and population of the largest college per state.

Find the index of the maximum college per state first.

[30]:
```
ugds_idx = college.groupby('stabbr').agg(idx=('ugds', 'idxmax'))
ugds_idx.head()
```

	idx
stabbr	
AK	60
AL	5
AR	137
AS	4138
AZ	7116

[31]:
```
idx = ugds_idx['idx']
idx.head()
```

[31]:
```
stabbr
AK      60
AL       5
AR     137
AS    4138
AZ    7116
Name: idx, dtype: int64
```

Use the index to select the desired rows.

[32]:
```
college.loc[idx, ['stabbr', 'instnm', 'ugds']].head(10)
```

	stabbr	instnm	ugds
60	AK	University of Alaska Anchorage	12865.0
5	AL	The University of Alabama	29851.0
137	AR	University of Arkansas	21405.0
4138	AS	American Samoa Community College	1276.0
7116	AZ	University of Phoenix-Arizona	151558.0
1299	CA	Ashford University	44744.0
574	CO	University of Colorado Boulder	25873.0
641	CT	University of Connecticut	18016.0
701	DC	George Washington University	10433.0
691	DE	University of Delaware	18222.0

Second method - set the index first to be instnm so that you can take advantage of idxmax

[33]:
```
c2 = college.set_index('instnm')
max_indexes = c2.groupby('stabbr').agg(max_ugds_college=('ugds', 'idxmax'),
                                       max_ugds=('ugds', 'max'))
max_indexes.head()
```

stabbr	max_ugds_college	max_ugds
AK	University of Alaska Anchorage	12865.0
AL	The University of Alabama	29851.0
AR	University of Arkansas	21405.0
AS	American Samoa Community College	1276.0
AZ	University of Phoenix-Arizona	151558.0

Third method - Sort the data first, then sse the `first` groupby method to return the first row of each group after sorting.

[34]:
```
college.sort_values('ugds', ascending=False).groupby('stabbr') \
       .agg(max_ugds_college=('instnm', 'first'),
            max_ugds=('ugds', 'first')).head()
```

stabbr	max_ugds_college	max_ugds
AK	University of Alaska Anchorage	12865.0
AL	The University of Alabama	29851.0
AR	University of Arkansas	21405.0
AS	American Samoa Community College	1276.0
AZ	University of Phoenix-Arizona	151558.0

Fourth method - Done previously without grouping

[35]:
```
college.sort_values(['stabbr', 'ugds'], ascending=[True, False]) \
       .drop_duplicates(subset='stabbr')[['stabbr', 'instnm', 'ugds']] \
       .head()
```

	stabbr	instnm	ugds
60	AK	University of Alaska Anchorage	12865.0
5	AL	The University of Alabama	29851.0
137	AR	University of Arkansas	21405.0
4138	AS	American Samoa Community College	1276.0
7116	AZ	University of Phoenix-Arizona	151558.0

Exercise 8

Do distance only schools tend to have more or less student population than non-distance-only schools?

[36]:
```
# They have more
college.groupby('distanceonly').agg(mean_ugds=('ugds', 'mean'))
```

	mean_ugds
distanceonly	
0.0	2334.648135
1.0	6245.743590

Exercise 9

Do distance only schools tend to be more or less religiously affiliated than non-distance-only schools?

[37]:
```
# Less
college.groupby('distanceonly').agg(mean_relaffil=('relaffil', 'mean'))
```

	mean_relaffil
distanceonly	
0.0	0.149635
1.0	0.050000

Exercise 10

What state has the lowest percentage of currently operating schools of those that have religious affiliation?

[38]:
```
rel_oper_mean = college.query('relaffil == 1') \
                       .groupby('stabbr').agg(mean_curroper=('curroper', 'mean')) \
                       .round(2)
rel_oper_mean.head()
```

stabbr	mean_curroper
AK	1.00
AL	0.92
AR	0.94
AZ	0.44
CA	0.59

[39]:
```
rel_oper_mean.sort_values('mean_curroper').head()
```

stabbr	mean_curroper
UT	0.40
AZ	0.44
NV	0.50
CA	0.59
CT	0.65

Exercise 11

Find the top 5 historically black colleges that have the highest undergraduate white percentage (ugds_white)?

[40]:
```
filt = college['hbcu'] == 1
cols = ['instnm', 'ugds_white']
college.loc[filt, cols].sort_values('ugds_white', ascending=False).head()
```

	instnm	ugds_white
4021	Bluefield State College	0.8437
17	Gadsden State Community College	0.6921
4050	West Virginia State University	0.5816
48	Shelton State Community College	0.5613
55	H Councill Trenholm State Community College	0.3951

6.3 3. Grouping with Pivot Tables

[41]:
```
import pandas as pd
flights = pd.read_csv('../data/flights.csv', parse_dates=['date'])
flights.insert(1, 'day_of_week', flights['date'].dt.day_name())
flights.insert(2, 'month', flights['date'].dt.month_name())
flights.head(3)
```

	date	day_of_week	month	airline	origin	...	carrier_delay	weather_delay	nas_delay	security_delay	late_aircraft_delay
0	2018-01-01	Monday	January	UA	LAS	...	0	0	0	0	0
1	2018-01-01	Monday	January	WN	DEN	...	0	0	0	0	0
2	2018-01-01	Monday	January	B6	JFK	...	0	83	8	0	0

[42]:
```
flights.shape
```

[42]:
```
(65923, 16)
```

Exercise 1

What is the average carrier delay for each day of the week for each airline? Highlight the worst day of the week for each airline.

[43]:
```
avg_delay = flights.pivot_table(index='airline', columns='day_of_week',
                                values='carrier_delay').round(1)
avg_delay.style.highlight_max(axis='columns')
```

day_of_week	Friday	Monday	Saturday	Sunday	Thursday	Tuesday	Wednesday
airline							
9E	3.400000	4.700000	1.800000	3.300000	7.700000	3.000000	4.200000
AA	3.900000	3.700000	3.800000	3.800000	4.900000	4.100000	2.800000
AS	3.000000	1.500000	3.600000	3.700000	2.900000	2.600000	2.100000
B6	7.000000	4.000000	5.500000	5.100000	5.100000	6.200000	4.000000
DL	3.500000	2.600000	3.000000	3.600000	3.900000	3.300000	3.300000
EV	5.200000	8.500000	2.400000	7.200000	0.000000	6.000000	1.700000
F9	7.900000	3.600000	9.500000	4.100000	7.800000	6.600000	1.800000
MQ	2.100000	4.200000	0.000000	5.400000	4.200000	1.500000	2.300000
NK	2.200000	1.500000	5.800000	1.700000	2.200000	2.500000	1.200000
OH	6.300000	4.900000	2.500000	9.200000	19.900000	0.500000	1.500000
OO	6.500000	9.500000	2.000000	4.800000	3.500000	1.900000	10.200000
UA	3.200000	2.400000	3.200000	4.000000	3.700000	3.700000	2.600000
VX	2.600000	1.700000	10.100000	0.300000	2.800000	3.200000	5.200000
WN	5.000000	3.400000	2.200000	2.000000	4.800000	3.500000	3.200000
YV	5.500000	5.600000	5.600000	7.800000	8.600000	1.800000	4.000000
YX	2.200000	4.100000	2.500000	2.100000	2.900000	1.500000	1.400000

You can highlight min and max by chaining style methods.

[44]:
```
avg_delay.style.highlight_max(axis='columns') \
         .highlight_min(axis='columns', color='lightblue')
```

day_of_week	Friday	Monday	Saturday	Sunday	Thursday	Tuesday	Wednesday
airline							
9E	3.400000	4.700000	1.800000	3.300000	7.700000	3.000000	4.200000
AA	3.900000	3.700000	3.800000	3.800000	4.900000	4.100000	2.800000
AS	3.000000	1.500000	3.600000	3.700000	2.900000	2.600000	2.100000
B6	7.000000	4.000000	5.500000	5.100000	5.100000	6.200000	4.000000
DL	3.500000	2.600000	3.000000	3.600000	3.900000	3.300000	3.300000
EV	5.200000	8.500000	2.400000	7.200000	0.000000	6.000000	1.700000
F9	7.900000	3.600000	9.500000	4.100000	7.800000	6.600000	1.800000
MQ	2.100000	4.200000	0.000000	5.400000	4.200000	1.500000	2.300000
NK	2.200000	1.500000	5.800000	1.700000	2.200000	2.500000	1.200000
OH	6.300000	4.900000	2.500000	9.200000	19.900000	0.500000	1.500000
OO	6.500000	9.500000	2.000000	4.800000	3.500000	1.900000	10.200000
UA	3.200000	2.400000	3.200000	4.000000	3.700000	3.700000	2.600000
VX	2.600000	1.700000	10.100000	0.300000	2.800000	3.200000	5.200000
WN	5.000000	3.400000	2.200000	2.000000	4.800000	3.500000	3.200000
YV	5.500000	5.600000	5.600000	7.800000	8.600000	1.800000	4.000000
YX	2.200000	4.100000	2.500000	2.100000	2.900000	1.500000	1.400000

Exercise 2

Use a pivot table to find the total number of canceled flights for each origin airport and airline. Place the airlines in the columns. Use the result to find the origin airport with the most cancelled flights for each airline. Also return this maximum number of cancelled flights.

[45]:
```
airline_cancel = flights.pivot_table(index='origin', columns='airline',
                                     values='cancelled', aggfunc='sum', fill_value=0)
airline_cancel.head(10)
```

airline	9E	AA	AS	B6	DL	...	UA	VX	WN	YV	YX
origin											
ATL	0	5	0	2	19	...	2	0	8	4	9
BOS	5	41	1	31	9	...	18	0	2	0	12
CLT	6	33	0	2	1	...	0	0	0	0	11
DCA	1	27	0	3	3	...	2	0	6	0	31
DEN	0	3	1	0	0	...	10	0	9	0	0
DFW	1	33	0	0	1	...	1	0	0	1	7
DTW	1	4	0	3	8	...	0	0	1	1	8
EWR	2	10	6	8	0	...	27	1	1	0	15
IAH	0	7	0	0	1	...	7	0	0	4	4
JFK	10	6	3	17	3	...	0	1	0	0	4

[46]:
```
airline_cancel.agg(['max', 'idxmax'])
```

	9E	AA	AS	B6	DL	...	UA	VX	WN	YV	YX
max	10	41	9	31	19	...	27	6	18	4	31
idxmax	JFK	BOS	SEA	BOS	ATL	...	EWR	LAX	LAX	ATL	DCA

Exercise 3

Find the total distance flown for each airline for each month. Highlight the month with the most number of miles flown and use the style `format` method to put commas in the numbers so that they are easier to read.

[47]:
```
total_dist = flights.pivot_table(index='airline', columns='month',
                                 values='distance', aggfunc='sum')
total_dist.style.format('{:,.0f}').highlight_max(axis='columns')
```

month airline	April	August	December	February	January	July	June	March	May	November	October	September
9E	54,592	62,216	46,032	51,784	47,230	53,868	50,421	61,460	42,423	42,275	48,106	45,745
AA	1,586,655	1,649,436	1,444,276	1,371,620	1,473,883	1,669,007	1,619,325	1,528,361	1,545,453	1,409,540	1,588,285	1,482,841
AS	454,146	451,512	399,787	201,275	195,553	455,061	496,358	199,288	495,090	391,304	409,479	429,045
B6	352,234	404,458	427,097	348,189	385,517	478,230	443,151	382,666	410,877	384,038	425,712	384,008
DL	1,265,266	1,315,865	1,160,997	997,216	1,017,440	1,396,697	1,292,928	1,215,516	1,253,361	1,100,681	1,214,950	1,173,359
EV	6,847	1,194	3,933	11,854	10,186	927	5,926	4,511	3,569	1,592	2,587	995
F9	117,439	97,777	97,846	97,879	118,067	84,417	116,116	80,444	78,807	110,423	105,833	89,938
MQ	13,060	15,787	14,057	17,539	15,170	20,057	15,310	13,349	13,656	15,559	16,884	14,767
NK	250,683	270,894	232,613	219,678	249,461	273,963	318,648	228,829	261,421	266,838	253,692	235,754
OH	8,280	7,986	8,596	9,911	14,802	6,461	5,808	14,664	5,296	4,948	6,028	7,674
OO	124,729	90,098	123,870	112,342	114,927	87,394	87,014	116,430	130,298	133,669	122,277	113,162
UA	1,211,211	1,350,333	1,184,206	1,023,812	1,055,351	1,353,485	1,332,403	1,101,258	1,303,095	1,125,754	1,251,047	1,272,765
VX	nan	nan	nan	180,621	168,486	nan	nan	244,380	nan	nan	nan	nan
WN	367,918	339,114	327,634	288,393	347,737	350,299	383,858	332,745	347,911	329,873	333,324	288,325
YV	57,510	45,114	73,982	45,261	36,986	59,699	60,166	44,678	51,225	59,978	52,643	36,430
YX	164,271	177,050	141,817	174,891	163,374	179,511	162,816	178,524	164,673	116,173	148,398	160,317

Exercise 4

Create a pivot table that shows the number of flights flown for every day of the week for every month.

[48]:
```
flights.pivot_table(index='month', columns='day_of_week', aggfunc='size')
```

day_of_week month	Friday	Monday	Saturday	Sunday	Thursday	Tuesday	Wednesday
April	786	943	644	898	818	755	754
August	1006	785	592	776	982	757	963
December	707	840	750	897	759	634	695
February	748	725	544	639	753	716	719
January	673	862	536	696	739	821	838
July	808	936	677	932	765	1012	780
June	1005	792	817	809	842	779	822
March	974	734	705	687	884	676	751
May	766	798	597	726	1058	913	894
November	887	710	624	737	871	707	709
October	773	961	554	711	790	939	894
September	739	742	742	902	761	719	762

Exercise 5

In exercise 4, the months and days of week are ordered alphabetically. It would be better if these values were ordered chronologically. Can you return a result that has both groups in the correct order. Use Monday as the first day of the week.

Convert to ordered categorical first overwriting the original columns.

[49]:
```
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
          'August', 'September', 'October', 'November', 'December']
days =  ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',
         'Sunday']
month_dtype = pd.CategoricalDtype(months, ordered=True)
day_dtype = pd.CategoricalDtype(days, ordered=True)
flights = flights.astype({'month': month_dtype, 'day_of_week': day_dtype})
```

Call the same pivot table and the index and columns will be automatically sorted by their category order.

[50]:
```
flights.pivot_table(index='month', columns='day_of_week', aggfunc='size')
```

day_of_week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
month							
January	862	821	838	739	673	536	696
February	725	716	719	753	748	544	639
March	734	676	751	884	974	705	687
April	943	755	754	818	786	644	898
May	798	913	894	1058	766	597	726
June	792	779	822	842	1005	817	809
July	936	1012	780	765	808	677	932
August	785	757	963	982	1006	592	776
September	742	719	762	761	739	742	902
October	961	939	894	790	773	554	711
November	710	707	709	871	887	624	737
December	840	634	695	759	707	750	897

Exercise 6

Create a new column in the flights dataset called `'dep_time_hour'` and set it equal to the hour (this will be an integer 0 through 23) of the flight. Find the average carrier delay for every month and dep_time_hour. Place the month in the columns.

[51]:
```
flights['dep_time_hour'] = flights['dep_time'] // 100
```

[52]:
```
flights.pivot_table(index='dep_time_hour', columns='day_of_week',
                    values='carrier_delay', aggfunc='mean').round(1)
```

day_of_week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
dep_time_hour							
0	0.2	3.6	1.2	2.4	6.5	1.7	2.4
1	0.0	0.0	1.1	0.7	0.0	1.7	2.3
2	NaN	NaN	0.0	NaN	NaN	0.0	0.0
4	NaN	NaN	NaN	NaN	0.0	NaN	NaN
5	5.9	1.5	1.8	2.4	4.4	3.0	1.8
6	2.5	2.8	2.6	2.8	5.2	4.0	3.5
7	2.0	3.5	1.8	3.7	3.8	4.1	1.8
8	3.6	3.1	7.2	4.3	2.3	4.0	3.7
9	3.1	2.8	2.5	3.8	3.3	3.4	3.0
10	2.8	2.9	2.1	3.4	3.3	3.2	2.1
11	3.8	3.4	2.0	2.0	2.5	1.6	3.3
12	3.1	4.0	3.1	4.1	3.0	4.2	4.3
13	2.3	3.6	3.1	2.8	4.7	2.6	2.9
14	3.0	4.1	2.3	5.0	1.9	3.6	3.1
15	3.1	3.5	3.0	4.9	3.8	3.7	4.7
16	3.0	3.3	2.5	4.6	3.8	3.8	3.2
17	4.3	3.7	4.9	4.4	3.4	3.2	5.0
18	4.1	4.3	2.9	9.4	2.8	5.3	4.1
19	2.9	2.6	2.9	4.7	6.8	3.3	6.3
20	5.3	4.3	4.2	4.8	4.8	4.1	4.3
21	2.6	6.1	3.4	7.6	6.7	3.4	4.5
22	4.2	7.6	4.5	4.4	6.1	2.5	5.6
23	5.1	2.4	0.9	4.2	10.9	10.3	2.6

Exercise 7

Use both `groupby` and `pivot_table` to compute the average and median distance flown by day of the week.

[53]:
```
flights.groupby('day_of_week').agg(median_dist=('distance', 'median'),
                                   mean_dist=('distance', 'mean')) \
       .style.format('{:,.0f}')
```

day_of_week	median_dist	mean_dist
Monday	912	1,071
Tuesday	888	1,052
Wednesday	868	1,053
Thursday	907	1,066
Friday	868	1,051
Saturday	937	1,107
Sunday	925	1,093

[54]:
```
flights.pivot_table(index='day_of_week', values='distance',
                    aggfunc=['median', 'mean']).style.format('{:,.0f}')
```

day_of_week	median distance	mean distance
Monday	912	1,071
Tuesday	888	1,052
Wednesday	868	1,053
Thursday	907	1,066
Friday	868	1,051
Saturday	937	1,107
Sunday	925	1,093

6.4 4. Counting with Crosstabs

[55]:
```
import pandas as pd
pd.options.display.max_columns = 100
pd.options.display.max_colwidth = 200
mh = pd.read_csv('../data/mental_health.csv')
mh.head(3)
```

	year	age	gender	country	family_history	...	leave	mental_health_consequence	phys_health_consequence	coworkers	supervisor
0	2014	37	Female	United States	No	...	Somewhat easy	No	No	Some of them	Yes
1	2014	44	Male	United States	No	...	Don't know	Maybe	No	No	No
2	2014	32	Male	Canada	No	...	Somewhat difficult	No	No	Yes	Yes

Exercise 1

Do people with a family history of mental illness seek treatment more often than those who do not?

[56]:
```
pd.crosstab(index=mh['family_history'], columns=mh['treatment'])
```

family_history	treatment No	Yes
No	414	241
Yes	111	325

[57]:
```
pd.crosstab(index=mh['family_history'], columns=mh['treatment'], normalize='index').
↪round(2)
```

family_history	treatment No	Yes
No	0.63	0.37
Yes	0.25	0.75

Yes, there is a large difference. 75% of people with a family history seek treatment vs 37% for those who have not.

Exercise 2

Find the total number and ratio of employees that seek treatment for companies that provide health benefits vs those that do not.

[58]:
```
pd.crosstab(index=mh['benefits'], columns=mh['treatment'])
```

benefits	treatment No	Yes
Don't know	225	134
No	142	150
Yes	158	282

[59]:
```
pd.crosstab(index=mh['benefits'], columns=mh['treatment'], normalize='index').round(2)
```

benefits	treatment No	Yes
Don't know	0.63	0.37
No	0.49	0.51
Yes	0.36	0.64

Exercise 3

You can provide a list of multiple columns to both the `index` and `columns` parameters of the `crosstab` function. Put country and number of employees in the index and benefits and treatment in the columns. It's probably easier to make separate list variables first.

[60]:
```
index = [mh['country'], mh['no_employees']]
columns = [mh['benefits'], mh['treatment']]
pd.crosstab(index=index, columns=columns)
```

	benefits	Don't know		No		Yes	
	treatment	No	Yes	No	Yes	No	Yes
country	no_employees						
Australia	1-5	1	0	1	1	0	0
	100-500	1	0	1	2	0	2
	26-100	0	0	1	3	0	0
	500-1000	1	0	0	0	0	0
	6-25	0	1	0	3	0	0
	More than 1000	1	0	0	0	1	1
Canada	1-5	1	0	5	5	0	0
	100-500	2	3	0	0	1	3
	26-100	4	4	2	1	3	3
	500-1000	0	0	0	0	0	1
	6-25	4	2	6	1	3	5
	More than 1000	0	2	0	0	2	5
France	100-500	1	0	1	0	0	0
	26-100	0	0	3	0	0	0
	500-1000	1	0	0	0	1	0
...	...	...	...	...	...	...	...
Netherlands	500-1000	1	0	0	0	0	0
	6-25	1	1	7	1	0	0
	More than 1000	0	0	0	0	1	0
United Kingdom	1-5	6	3	7	13	0	1
	100-500	5	6	2	3	2	1
	26-100	11	5	7	10	3	2
	500-1000	2	3	1	0	1	0
	6-25	11	7	23	13	1	1
	More than 1000	5	4	3	7	0	8
United States	1-5	11	4	16	30	3	8
	100-500	21	14	3	8	23	41
	26-100	41	26	7	6	18	61
	500-1000	8	1	1	1	9	20
	6-25	30	22	14	19	17	25
	More than 1000	35	15	5	2	65	87

6.5 5. Alternate Groupby Syntax

6.6 6. Custom Aggregation

Execute the cell below to read in the flights dataset and then use it for the following exercises.

[61]:
```
import pandas as pd
flights = pd.read_csv('../data/flights.csv', parse_dates=['date'])
flights.head(3)
```

	date	airline	origin	dest	dep_time	...	carrier_delay	weather_delay	nas_delay	security_delay	late_aircraft_delay
0	2018-01-01	UA	LAS	IAH	100	...	0	0	0	0	0
1	2018-01-01	WN	DEN	PHX	515	...	0	0	0	0	0
2	2018-01-01	B6	JFK	BOS	550	...	0	83	8	0	0

Exercise 1

What are the three airlines with the least number of flights?

[62]:
```
flights['airline'].value_counts().tail(3)
```

[62]:
```
MQ    373
OH    257
EV    171
Name: airline, dtype: int64
```

Exercise 2

For each airline, find the 75th percentile of flight distance. Use a custom aggregation function.

[63]:
```
def per_75(s):
    return s.quantile(.75)
```

[64]:
```
flights.groupby('airline').agg(dist_75=('distance', per_75))
```

airline	dist_75
9E	852.0
AA	1558.0
AS	2402.0
B6	2381.0
DL	1587.0
EV	514.5
F9	1476.0
MQ	612.0
NK	1379.0
OH	500.0
OO	912.0
UA	1635.0
VX	2475.0
WN	1024.0
YV	1075.0
YX	912.0

Exercise 3

For each airline, find out what percentage of its flights leave on a Tuesday. Use a custom aggregation function.

[65]:
```
def tuesday_pct(s):
    return (s.dt.day_name() == 'Tuesday').mean()

flights.groupby('airline').agg(percent_tuesday=('date', tuesday_pct)).round(3) * 100
```

airline	percent_tuesday
9E	14.5
AA	14.6
AS	13.8
B6	13.5
DL	14.4
EV	15.8
F9	12.9
MQ	16.1
NK	12.8
OH	16.7
OO	14.3
UA	14.0
VX	13.3
WN	15.3
YV	13.9
YX	15.0

Exercise 4

Optimize exercise 2 without using a custom aggregation. What is the performance difference?

[66]:
```
flights['airline_cat'] = flights['airline'].astype('category')
flights['is_tuesday'] = flights['date'].dt.day_name() == 'Tuesday'
flights.groupby('airline_cat')['is_tuesday'].mean().round(3) * 100
```

[66]:
```
airline_cat
9E    14.5
AA    14.6
AS    13.8
B6    13.5
DL    14.4
EV    15.8
F9    12.9
MQ    16.1
NK    12.8
OH    16.7
OO    14.3
UA    14.0
VX    13.3
WN    15.3
```

```
YV    13.9
YX    15.0
Name: is_tuesday, dtype: float64
```

About 50% improvement

[67]:
```
%timeit -r 1 -n 5 flights.groupby('airline').agg(percent_tuesday=('date', tuesday_pct))
```

```
43.5 ms ± 0 ns per loop (mean ± std. dev. of 1 run, 5 loops each)
```

[68]:
```
%%timeit -r 1 -n 5
flights['is_tuesday'] = flights['date'].dt.day_name() == 'Tuesday'
flights.groupby('airline_cat')['is_tuesday'].mean().round(3) * 100
```

```
22 ms ± 0 ns per loop (mean ± std. dev. of 1 run, 5 loops each)
```

Exercise 5

The range of salaries per department was calculated using the `min_max` custom function from the beginning of this chapter. Use this same function to calculate the range of distance for each airline. Then calculate this range again without a custom function.

[69]:
```
def min_max(s):
    return s.max() - s.min()
```

[70]:
```
flights.groupby('airline').agg(dist_range=('distance', min_max))
```

airline	dist_range
9E	1297.0
AA	2515.0
AS	2468.0
B6	2520.0
DL	2610.0
EV	876.0
F9	2042.0
MQ	831.0
NK	2166.0
OH	835.0
OO	1405.0
UA	2505.0
VX	2468.0
WN	1940.0
YV	1192.0
YX	1320.0

[71]:
```
d_max = flights.groupby('airline')['distance'].max()
d_min = flights.groupby('airline')['distance'].min()
d_max - d_min
```

[71]:
```
airline
9E    1297.0
AA    2515.0
AS    2468.0
B6    2520.0
DL    2610.0
EV     876.0
F9    2042.0
MQ     831.0
NK    2166.0
OH     835.0
OO    1405.0
UA    2505.0
VX    2468.0
WN    1940.0
YV    1192.0
YX    1320.0
Name: distance, dtype: float64
```

Alternatively, create an entire DataFrame.

[72]:
```
dist_min_max = flights.groupby('airline').agg(max_dist=('distance', 'max'),
                                              min_dist=('distance', 'min'))
dist_min_max['dist range'] = dist_min_max['max_dist'] - dist_min_max['min_dist']
dist_min_max
```

airline	max_dist	min_dist	dist range
9E	1391.0	94.0	1297.0
AA	2611.0	96.0	2515.0
AS	2704.0	236.0	2468.0
B6	2704.0	184.0	2520.0
DL	2704.0	94.0	2610.0
EV	1075.0	199.0	876.0
F9	2446.0	404.0	2042.0
MQ	925.0	94.0	831.0
NK	2402.0	236.0	2166.0
OH	931.0	96.0	835.0
OO	1589.0	184.0	1405.0
UA	2704.0	199.0	2505.0
VX	2704.0	236.0	2468.0
WN	2176.0	236.0	1940.0
YV	1416.0	224.0	1192.0
YX	1416.0	96.0	1320.0

Exercise 6

Which origin airport has the highest percentage of its flights cancelled?

[73]:
```
# no custom aggregation function needed
flights.groupby('origin').agg(pct_cancelled=('cancelled', 'mean')) \
       .nlargest(1, 'pct_cancelled').round(3) * 100
```

origin	pct_cancelled
BOS	3.4

Use the college dataset

Execute the following cell which reads in a few columns from the college dataset, sets the institution name as the index and converts 'stabbr' and 'relaffil' to categorical.

[74]:
```
cols = ['instnm', 'stabbr', 'relaffil', 'satvrmid', 'satmtmid', 'ugds']
college = pd.read_csv('../data/college.csv', usecols=cols,
                      index_col='instnm', dtype={'stabbr': 'category',
                                                 'relaffil': 'category'})
college.head(3)
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds
Alabama A & M University	AL	0	424.0	420.0	4206.0
University of Alabama at Birmingham	AL	0	570.0	565.0	11383.0
Amridge University	AL	1	NaN	NaN	291.0

Exercise 7

How many states have more schools with a higher 'satvrmid' than 'satmtmid'? Make sure to not count schools that have missing values for either one.

Make a new DataFrame that drops rows when one of the sat columns is missing.

[75]:
```
col_has_sat = college.dropna(subset=['satvrmid', 'satmtmid']).copy()
col_has_sat.head(3)
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds
Alabama A & M University	AL	0	424.0	420.0	4206.0
University of Alabama at Birmingham	AL	0	570.0	565.0	11383.0
University of Alabama in Huntsville	AL	0	595.0	590.0	5451.0

Only a fraction of the schools have both scores.

[76]:
```
len(col_has_sat)
```

[76]: 1184

[77]:
```
len(college)
```

[77]: 7535

Create a new boolean column that determines which score is higher.

[78]:
```
col_has_sat['higher_verbal'] = col_has_sat['satvrmid'] > col_has_sat['satmtmid']
col_has_sat.head(3)
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds	higher_verbal
Alabama A & M University	AL	0	424.0	420.0	4206.0	True
University of Alabama at Birmingham	AL	0	570.0	565.0	11383.0	True
University of Alabama in Huntsville	AL	0	595.0	590.0	5451.0	True

Group by state to determine percentage with higher verbal. Only those greater than .5 have more verbal than math.

[79]:
```
avg_verbal_higher = col_has_sat.groupby('stabbr')['higher_verbal'].mean()
avg_verbal_higher.sort_values(ascending=False).head(10)
```

[79]:
```
stabbr
AK    1.000000
VI    1.000000
GA    0.690476
FL    0.684211
OR    0.588235
AL    0.571429
VA    0.564103
MN    0.560000
AZ    0.500000
DC    0.500000
Name: higher_verbal, dtype: float64
```

Technically, have to check for ties. No custom function needed.

[80]:
```
(avg_verbal_higher > .5).sum()
```

[80]:
```
8
```

Exercise 8

Create a pivot table that shows the percentage of schools with less than 1,000 students in each state by religious affiliation. Also return the count of schools.

[81]:
```
def less_1k(s):
    return (s < 1_000).mean().round(3) * 100
```

[82]:
```
result = college.pivot_table(index='stabbr', columns='relaffil', values='ugds',
                             aggfunc=[less_1k, 'count'])
result.head(10)
```

	less_1k		count	
relaffil	0	1	0	1
stabbr				
AK	42.9	100.0	7.0	3.0
AL	44.4	37.5	71.0	18.0
AR	58.8	61.1	68.0	14.0
AS	0.0	NaN	1.0	NaN
AZ	63.7	77.8	118.0	8.0
CA	61.4	27.4	579.0	76.0
CO	64.4	28.6	113.0	4.0
CT	58.8	23.5	82.0	7.0
DC	52.9	0.0	14.0	4.0
DE	75.0	0.0	16.0	3.0

6.7 7. Transform and Filter with Groupby

Execute the cell below to reread the college dataset and use it for the exercises below.

[83]:
```
import pandas as pd
cols = ['instnm', 'stabbr', 'relaffil', 'satvrmid', 'satmtmid', 'ugds']
college = pd.read_csv('../data/college.csv', usecols=cols, index_col='instnm')
college.head(3)
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds
Alabama A & M University	AL	0	424.0	420.0	4206.0
University of Alabama at Birmingham	AL	0	570.0	565.0	11383.0
Amridge University	AL	1	NaN	NaN	291.0

Exercise 1

Filter the college DataFrame for states that have more than 500,000 total undergraduate students. Can you verify your results?

[84]:
```
def filt_500k(sub_df):
    return sub_df['ugds'].sum() > 500_000

college_large = college.groupby('stabbr').filter(filt_500k)
college_large.head()
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds
Prince Institute-Southeast	IL	0	NaN	NaN	84.0
Everest College-Phoenix	AZ	1	NaN	NaN	4102.0
Collins College	AZ	0	NaN	NaN	83.0
Empire Beauty School-Paradise Valley	AZ	1	NaN	NaN	25.0
Empire Beauty School-Tucson	AZ	0	NaN	NaN	126.0

[85]:
```
college_large.groupby('stabbr').agg(ugds_total=('ugds', 'sum')) \
             .sort_values('ugds_total', ascending=False).round(-3)
```

stabbr	ugds_total
CA	2304000.0
TX	1277000.0
NY	994000.0
FL	960000.0
PA	605000.0
IL	600000.0
OH	538000.0
AZ	520000.0

Exercise 2

Filter the college DataFrame for states that have a an average undergraduate student population greater than 2,500 and have more than 30 religiously affiliated schools. Can you verify your results?

[86]:
```
def func2(sub_df):
    return sub_df['ugds'].mean() > 2_500 and sub_df['relaffil'].sum() > 30
```

[87]:
```
c2 = college.groupby('stabbr').filter(func2)
c2.head(3)
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds
Academy of Art University	CA	0	NaN	NaN	9885.0
ITT Technical Institute-Rancho Cordova	CA	0	NaN	NaN	500.0
Academy of Chinese Culture and Health Sciences	CA	0	NaN	NaN	NaN

[88]:
```
c2.groupby('stabbr').agg(mean_ugds=('ugds', 'mean'),
                         num_relaffil=('relaffil', 'sum'))
```

stabbr	mean_ugds	num_relaffil
CA	3518.308397	164
GA	2642.571429	37
IN	2653.559055	62
MI	2643.016043	48
TX	2998.530516	96
VA	2694.900000	44

Exercise 3

The maximum SAT score for each test is 800. Create a new column in the college dataset that shows each school's percentage of maximum for each SAT score.

No need to use transform here.

[89]:
```
college['pct_max_sat_verbal'] = (college['satvrmid'] / 800).round(3) * 100
college['pct_max_sat_math'] = (college['satmtmid'] / 800).round(3) * 100
college.head(3)
```

instnm	stabbr	relaffil	satvrmid	satmtmid	ugds	pct_max_sat_verbal	pct_max_sat_math
Alabama A & M University	AL	0	424.0	420.0	4206.0	53.0	52.5
University of Alabama at Birmingham	AL	0	570.0	565.0	11383.0	71.2	70.6
Amridge University	AL	1	NaN	NaN	291.0	NaN	NaN

Use the City of Houston dataset

Execute the following cell to read in the City of Houston employee dataset and then use it for the following exercises.

[90]:
```
emp = pd.read_csv('../data/employee.csv')
emp.head(3)
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black

Exercise 4

Filter it so that only position titles with an average salary of 100,000 remain. Can you verify your results?

[91]:
```
high_sal = emp.groupby('title').filter(lambda sub_df: sub_df['salary'].mean() >␣
↪100_000)
high_sal.head()
```

	dept	title	hire_date	salary	sex	race
16	Other	ASSOCIATE JUDGE OF MUNICIPAL COURTS	2005-11-09	107744.00	Male	Hispanic
17	Police	POLICE COMMANDER	1983-02-07	115821.42	Male	White
19	Other	ASSISTANT DIRECTOR (EXECUTIVE LEVEL)	2002-05-28	95783.00	Female	Hispanic
39	Houston Airport System	DEPUTY ASSISTANT DIRECTOR (EXECUTIVE LEV	2017-08-15	112270.00	Male	Black
48	Fire	ASSISTANT FIRE CHIEF	1994-11-07	115835.98	Male	Hispanic

[92]:
```
high_sal.groupby('title').agg(avg_salary=('salary', 'mean')).min()
```

[92]:
```
avg_salary    100038.0
dtype: float64
```

Exercise 5

Filter the employee dataset so that only position titles with at least 5 employees and an average salary of 80,000 remain. Can you verify the results?

[93]:
```
def sal_count(sub_df):
    return sub_df['salary'].mean() > 80000 and len(sub_df) >= 5
```

[94]:
```
high_sal_count = emp.groupby('title').filter(sal_count)
high_sal_count.head()
```

	dept	title	hire_date	salary	sex	race
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic
16	Other	ASSOCIATE JUDGE OF MUNICIPAL COURTS	2005-11-09	107744.00	Male	Hispanic
17	Police	POLICE COMMANDER	1983-02-07	115821.42	Male	White
19	Other	ASSISTANT DIRECTOR (EXECUTIVE LEVEL)	2002-05-28	95783.00	Female	Hispanic

[95]:
```
high_sal_count.groupby('title').agg(avg_salary=('salary', 'mean'),
                                    size=('salary', 'size')).min()
```

[95]:
```
avg_salary    80153.202222
size              5.000000
dtype: float64
```

Exercise 6

Add a column to the DataFrame that contains the median salary based on department, sex, and race.

[96]:
```
emp['median_drs'] = emp.groupby(['dept', 'sex', 'race'])['salary'].transform('median')
emp.head()
```

	dept	title	hire_date	salary	sex	race	median_drs
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White	73479.00
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic	47445.00
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black	38813.00
3	Police	SENIOR POLICE OFFICER	1997-05-27	75942.10	Male	Hispanic	68116.62
4	Police	SENIOR POLICE OFFICER	2006-01-23	69355.26	Male	White	73479.00

Exercise 7

Add a new column, `pct_max_dept_sex`, to the employee DataFrame that holds the employees percentage of the maximum salary for each department and sex. For instance, if a male HPD employee makes 80,000 and the maximum male HPD salary is 120,000 then the value for this employee would be 80,000/120,000 or .666. Verify this value for the first employee.

[97]:
```
def pct_max(sub_series):
    return sub_series / sub_series.max()
```

[98]:
```
emp['pct_max_dept_sex'] = emp.groupby(['dept', 'sex'])['salary'].transform(pct_max)
emp.head()
```

	dept	title	hire_date	salary	sex	race	median_drs	pct_max_dept_sex
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White	73479.00	0.312662
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic	47445.00	0.298844
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black	38813.00	0.227809
3	Police	SENIOR POLICE OFFICER	1997-05-27	75942.10	Male	Hispanic	68116.62	0.271222
4	Police	SENIOR POLICE OFFICER	2006-01-23	69355.26	Male	White	73479.00	0.247697

[99]:
```
filt = (emp['dept'] == 'Police') & (emp['sex'] == 'Male')
max_sal = emp.loc[filt, 'salary'].max()
max_sal
```

[99]:
```
280000.0
```

[100]:
```
emp.loc[0, 'salary'] / max_sal
```

[100]:
```
0.31266207142857144
```

6.8 8. Other Groupby Methods

Execute the next cell to read in some of the columns from the flights dataset and use it to answer the following exercises.

[101]:
```
import pandas as pd
cols = ['date', 'airline', 'origin', 'dest', 'dep_time', 'arr_time',
       'cancelled', 'air_time', 'distance', 'carrier_delay']
flights = pd.read_csv('../data/flights.csv', parse_dates=['date'], usecols=cols)
flights.head(3)
```

	date	airline	origin	dest	dep_time	arr_time	cancelled	air_time	distance	carrier_delay
0	2018-01-01	UA	LAS	IAH	100	547	0	134.0	1222.0	0
1	2018-01-01	WN	DEN	PHX	515	720	0	91.0	602.0	0
2	2018-01-01	B6	JFK	BOS	550	657	0	39.0	187.0	0

Exercise 1

For each airline, return the first and last row of each group. Use the `nth` group by method.

[102]:
```
flights.groupby('airline').nth([0, -1]).head(8)
```

airline	date	origin	dest	dep_time	arr_time	cancelled	air_time	distance	carrier_delay
9E	2018-12-31	CLT	JFK	1400	1603	0	80.0	541.0	0
9E	2018-01-01	IAH	ATL	1346	1651	0	86.0	689.0	0
AA	2018-01-01	DFW	DCA	610	959	0	131.0	1192.0	0
AA	2018-12-31	DFW	SFO	2047	2245	0	194.0	1464.0	0
AS	2018-12-31	SEA	DFW	2315	502	0	210.0	1660.0	3
AS	2018-01-01	SEA	SFO	605	816	0	97.0	679.0	0
B6	2018-12-31	PHX	JFK	2234	509	0	233.0	2153.0	0
B6	2018-01-01	JFK	BOS	550	657	0	39.0	187.0	0

Exercise 2

For every origin and destination combination, select the 5000th flight.

Only the combinations that have at least 500 flights will have a returned value.

[103]:
```
flights.groupby(['origin', 'dest']).nth(499)
```

origin	dest	date	airline	dep_time	arr_time	cancelled	air_time	distance	carrier_delay
JFK	**LAX**	2018-11-27	DL	1925	2300	0	325.0	2475.0	0
LAS	**LAX**	2018-12-21	WN	545	655	0	48.0	236.0	0
LAX	**JFK**	2018-11-29	DL	1145	2007	0	269.0	2475.0	0
	LAS	2018-12-25	AA	1955	2107	0	54.0	236.0	0
	SFO	2018-10-15	WN	955	1115	0	56.0	337.0	0
LGA	**ORD**	2018-10-17	UA	1700	1836	0	129.0	733.0	0
ORD	**LGA**	2018-10-14	UA	1300	1615	0	95.0	733.0	0
SFO	**LAX**	2018-10-19	UA	1300	1435	0	58.0	337.0	0

Exercise 3

Find the date of the 10th cancelled flight for each airline.

[104]:
```
flights['cancelled_running_total'] = flights.groupby('airline')['cancelled'].cumsum()
flights.head(3)
```

	date	airline	origin	dest	dep_time	...	cancelled	air_time	distance	carrier_delay	cancelled_running_total
0	2018-01-01	UA	LAS	IAH	100	...	0	134.0	1222.0	0	0
1	2018-01-01	WN	DEN	PHX	515	...	0	91.0	602.0	0	0
2	2018-01-01	B6	JFK	BOS	550	...	0	39.0	187.0	0	0

[105]:
```
flights.query("cancelled == 1 and cancelled_running_total == 10")
```

	date	airline	origin	dest	dep_time	...	cancelled	air_time	distance	carrier_delay	cancelled_running_total
535	2018-01-04	UA	BOS	EWR	800	...	1	NaN	200.0	0	10
627	2018-01-04	AA	EWR	PHX	1620	...	1	NaN	2133.0	0	10
641	2018-01-04	DL	DTW	PHL	1745	...	1	NaN	453.0	0	10
702	2018-01-05	B6	BOS	DFW	731	...	1	NaN	1562.0	0	10
794	2018-01-05	YX	JFK	BOS	1700	...	1	NaN	187.0	0	10
6988	2018-02-12	NK	IAH	EWR	630	...	1	NaN	1400.0	0	10
9812	2018-02-27	WN	PHX	LAS	2115	...	1	NaN	255.0	0	10
10128	2018-03-01	OO	SFO	LAX	1650	...	1	NaN	337.0	0	10
12161	2018-03-13	9E	JFK	BOS	905	...	1	NaN	187.0	0	10
13472	2018-03-20	VX	SFO	LAX	2140	...	1	NaN	337.0	0	10
18329	2018-04-16	MQ	LGA	PHL	1815	...	1	NaN	96.0	0	10
30049	2018-06-17	AS	EWR	SFO	1725	...	1	NaN	2565.0	0	10
43852	2018-08-29	YV	ATL	IAH	940	...	1	NaN	689.0	0	10
46921	2018-09-15	F9	MSP	DEN	840	...	1	NaN	680.0	0	10
46964	2018-09-15	OH	DCA	CLT	1355	...	1	NaN	331.0	0	10
54726	2018-10-28	EV	DCA	EWR	600	...	1	NaN	199.0	0	10

Exercise 4

Find the average carrier delay for each origin and destination combination with more than 300 flights.

[106]:
```
delay = flights.groupby(['origin', 'dest'])['carrier_delay'].agg(['size', 'mean']).
↪round(1)
```

```
delay.head()
```

		size	mean
origin	**dest**		
ATL	**BOS**	304	2.5
	CLT	262	5.0
	DCA	287	2.2
	DEN	215	3.0
	DFW	289	2.3

[107]:
```
delay.query('size > 300').head(10)
```

		size	mean
origin	**dest**		
ATL	**BOS**	304	2.5
	LGA	411	1.5
	MCO	373	4.6
	ORD	319	2.5
BOS	**DCA**	383	3.4
	LGA	416	3.3
	ORD	314	1.8
DCA	**BOS**	348	1.7
	ORD	339	1.2
DEN	**LAX**	345	6.7

Part VII

Time Series

Chapter 7

Solutions

7.1 1. Datetime and Timedelta

[1]:
```
import pandas as pd
```

Exercise 1

What day of the week was Jan 15, 1997?

[2]:
```
dt = pd.to_datetime('Jan 15, 1997')
dt.day_name()
```

[2]:
```
'Wednesday'
```

Exercise 2

Was 1925 a leap year?

[3]:
```
dt = pd.to_datetime('Jan 1, 1924')
dt.is_leap_year
```

[3]:
```
True
```

Exercise 3

What year will it be 1 million hours after the UNIX epoch?

[4]:
```
dt = pd.to_datetime(10 ** 6, unit='h')
dt
```

[4]:
```
Timestamp('2084-01-29 16:00:00')
```

[5]:
```
dt.year
```

[5]:
```
2084
```

Exercise 4

Create the datetime July 20, 1969 at 2:56 a.m. and 15 seconds.

[6]:
```
dt = pd.to_datetime('1969-07-20 2:56:15')
dt
```

[6]:
```
Timestamp('1969-07-20 02:56:15')
```

Exercise 5

Neil Armstrong stepped on the moon at the time in the last Exercise. How many days have passed since that happened? Use the string 'today' when creating your datetime.

[7]:
```
dt1 = pd.to_datetime('1969-07-20 2:56:15')
dt2 = pd.to_datetime('today')
dt2
```

[7]:
```
Timestamp('2020-04-06 21:24:16.520141')
```

[8]:
```
td = dt2 - dt1
td
```

[8]:
```
Timedelta('18523 days 18:28:01.520141')
```

[9]:
```
td.days
```

[9]:
```
18523
```

Exercise 6

Which is larger - 35 days or 700 hours?

[10]:
```
td1 = pd.to_timedelta(35, unit='d')
td2 = pd.to_timedelta(700, unit='h')
```

[11]:
```
td1
```

[11]:
```
Timedelta('35 days 00:00:00')
```

[12]:
```
td2
```

[12]:
```
Timedelta('29 days 04:00:00')
```

[13]:
```
td1 > td2
```

[13]:
```
True
```

Can also use a string for hours

[14]:
```
pd.to_timedelta('700 hours')
```

[14]:
```
Timedelta('29 days 04:00:00')
```

[15]:
```
pd.to_timedelta('700h')
```

[15]:
```
Timedelta('29 days 04:00:00')
```

Exercise 7

The City of Houston employee data was retrieved on June 1, 2019. Can you calculate the exact amount of years of experience and assign as a new column named `experience`?

[16]:
```
emp = pd.read_csv('../data/employee.csv', parse_dates=['hire_date'])
```

One year is approximately 365.25 days.

[17]:
```
pull_date = pd.to_datetime('2019-6-1')
one_year = pd.to_timedelta(365.25, unit='D')
```

[18]:
```
pull_date
```

[18]:
```
Timestamp('2019-06-01 00:00:00')
```

[19]:
```
one_year
```

[19]:
```
Timedelta('365 days 06:00:00')
```

[20]:
```
emp['experience'] = (pull_date - emp['hire_date']) / one_year
emp.head()
```

	dept	title	hire_date	salary	sex	race	experience
0	Police	POLICE SERGEANT	2001-12-03	87545.38	Male	White	17.492129
1	Other	ASSISTANT CITY ATTORNEY II	2010-11-15	82182.00	Male	Hispanic	8.542094
2	Houston Public Works	SENIOR SLUDGE PROCESSOR	2006-01-09	49275.00	Male	Black	13.390828
3	Police	SENIOR POLICE OFFICER	1997-05-27	75942.10	Male	Hispanic	22.012320
4	Police	SENIOR POLICE OFFICER	2006-01-23	69355.26	Male	White	13.352498

7.2 2. Introduction to Time Series

Exercise 1

Read in the weather time series dataset and place the date column in the index.

[21]:
```
weather = pd.read_csv('../data/weather.csv', parse_dates=['date'], index_col='date')
weather.head()
```

date	rain	snow	temperature
2007-01-01	Yes	No	68.0
2007-01-02	No	No	55.9
2007-01-03	No	No	62.1
2007-01-04	No	No	69.1
2007-01-05	Yes	No	72.0

Exercise 2

What was the temperature on June 11, 2011?

[22]:
```
weather.loc['2011-6-11', 'temperature']
```

[22]:
```
93.9
```

Exercise 3

How many days did it rain during the last three months of 2011?

[23]:
```
weather.loc['2011-10':'2011-12', 'rain'].value_counts()
```

[23]:
```
No     69
Yes    23
Name: rain, dtype: int64
```

Exercise 4

Which year had more snow days, 2007 or 2012?

[24]:
```
weather.loc['2007', 'snow'].value_counts()
```

[24]:
```
No     360
Yes      5
Name: snow, dtype: int64
```

[25]:
```
weather.loc['2012', 'snow'].value_counts()
```

[25]:
```
No     364
Yes      2
Name: snow, dtype: int64
```

Exercise 5

Select every other thursday

[26]:
```
weather.asfreq('2W-THU').head()
```

date	rain	snow	temperature
2007-01-04	No	No	69.1
2007-01-18	Yes	Yes	35.1
2007-02-01	Yes	Yes	34.0
2007-02-15	No	No	39.9
2007-03-01	Yes	No	66.9

Exercise 6

Select the first day of each month.

[27]:
```
weather.asfreq('MS').head()
```

date	rain	snow	temperature
2007-01-01	Yes	No	68.0
2007-02-01	Yes	Yes	34.0
2007-03-01	Yes	No	66.9
2007-04-01	Yes	No	77.0
2007-05-01	No	No	91.9

[28]:
```
weather.asfreq('4M')
```

date	rain	snow	temperature
2007-01-31	No	No	39.9
2007-05-31	No	No	91.0
2007-09-30	No	No	80.1
2008-01-31	No	No	51.1
2008-05-31	No	No	89.1
2008-09-30	Yes	No	81.0
2009-01-31	No	No	46.9
2009-05-31	Yes	No	88.0
2009-09-30	No	No	75.0
2010-01-31	Yes	Yes	37.9
2010-05-31	Yes	No	88.0
2010-09-30	Yes	No	77.0
2011-01-31	No	No	46.9
2011-05-31	No	No	95.0
2011-09-30	Yes	No	84.0
...	...	...	...
2014-01-31	No	No	53.1
2014-05-31	No	No	82.0
2014-09-30	No	No	75.0
2015-01-31	No	No	48.0
2015-05-31	No	No	89.1
2015-09-30	No	No	82.9
2016-01-31	No	No	70.0
2016-05-31	No	No	84.9
2016-09-30	No	No	82.9
2017-01-31	No	No	68.0
2017-05-31	No	No	86.0
2017-09-30	No	No	77.0
2018-01-31	No	No	46.9
2018-05-31	No	No	88.0
2018-09-30	No	No	81.0

7.3 3. Grouping by Time

[29]:
```
import pandas as pd
msft = pd.read_csv('../data/stocks/msft20.csv', parse_dates=['date'], index_col='date')
msft.head(3)
```

date	open	high	low	close	adjusted_close	volume	dividend_amount
1999-10-19	88.250	89.250	85.25	86.313	27.8594	69945600	0.0
1999-10-20	91.563	92.375	90.25	92.250	29.7758	88090600	0.0
1999-10-21	90.563	93.125	90.50	93.063	30.0381	60801200	0.0

Exercise 1

In which week did MSFT have the greatest number of its shares (volume) traded?

[30]:
```
volume = msft.resample('W').agg({'volume':'sum'})
volume.head()
```

date	volume
1999-10-24	262488000
1999-10-31	287399400
1999-11-07	268534000
1999-11-14	541663200
1999-11-21	295783800

[31]:
```
volume.agg(['max', 'idxmax'])
```

	volume
max	879723200
idxmax	2006-05-07 00:00:00

Pandas Trick

Turn into a period to get Monday-Sunday date range

[32]:
```
msft.resample('W', kind='period').agg({'volume':'sum'}).agg(['max', 'idxmax'])
```

	volume
max	879723200
idxmax	2006-05-01/2006-05-07

Exercise 2

With help from the `diff` method, find the quarter containing the most number of up days.

Use diff to find the difference between the current row and the one directly above it.

[33]:
```
msft['adjusted_close'].diff().head()
```

[33]:
```
date
1999-10-19       NaN
1999-10-20    1.9164
1999-10-21    0.2623
1999-10-22   -0.1210
1999-10-25   -0.0807
Name: adjusted_close, dtype: float64
```

[34]:
```
up_days = msft['adjusted_close'].diff() > 0
up_days.head()
```

[34]:
```
date
1999-10-19    False
1999-10-20     True
1999-10-21     True
1999-10-22    False
1999-10-25    False
Name: adjusted_close, dtype: bool
```

[35]:
```
up_days.resample('Q').sum().head()
```

[35]:
```
date
1999-12-31    24.0
2000-03-31    32.0
2000-06-30    30.0
2000-09-30    23.0
2000-12-31    29.0
Freq: Q-DEC, Name: adjusted_close, dtype: float64
```

[36]:
```
up_days.resample('Q').sum().agg(['max', 'idxmax'])
```

[36]:
```
max                        43
idxmax    2001-12-31 00:00:00
Name: adjusted_close, dtype: object
```

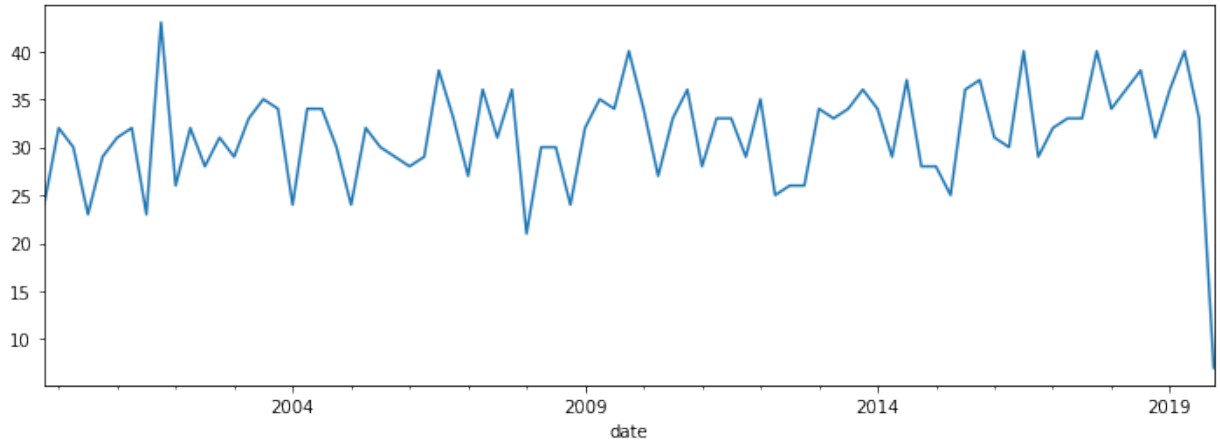
Pandas trick

[37]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

Can visually verify with plot:

[38]:
```
up_days.resample('Q', kind='period').sum().plot(figsize=(12,4))
```

[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1186458d0>
```



Exercise 3

Find the mean price per year along with the minimum and maximum volume.

[39]:
```
msft.resample('Y', kind='period').agg({'adjusted_close': 'mean',
                                       'volume':['min', 'max']}).head()
```

	adjusted_close	volume	
	mean	min	max
date			
1999	31.267802	12517600	243819200
2000	24.601943	15734800	313645800
2001	20.186950	11701600	209348800
2002	17.606981	18386000	202307800
2003	16.917920	12076900	210558300

Execute the cell below to read in the employee dataset and use it for the rest of the exercises.

[40]:
```
emp = pd.read_csv('../data/employee.csv')
```

Exercise 4

Use the `to_datetime` function to convert the hire date column into datetimes. Reassign this column in the `emp` DataFrame.

[41]:
```
emp['hire_date'] = pd.to_datetime(emp['hire_date'])
```

Exercise 5

Without putting `hire_date` into the index, find the mean salary based on `hire_date` over 5 year periods. Also return the number of salaries used in the mean calculation for each period.

[42]:
```
emp.resample('5Y', on='hire_date').agg({'salary':['mean', 'count']})
```

	salary	
	mean	count
hire_date		
1968-12-31	NaN	0
1973-12-31	64574.640000	4
1978-12-31	78074.008667	30
1983-12-31	73504.712738	336
1988-12-31	70655.520653	613
1993-12-31	69255.759681	1946
1998-12-31	67875.931733	2424
2003-12-31	63357.963896	2618
2008-12-31	60447.709702	4329
2013-12-31	56581.778488	3453
2018-12-31	48230.686634	7609

7.4 4. Rolling Windows

Exercise 1

Attempt to take a rolling average on salary using a 30 day time span on hire date. Does the error message make sense?

[43]:
```
emp = pd.read_csv('../data/employee.csv', parse_dates=['hire_date'])
```

[44]:
```
emp.rolling('30D', on='hire_date')
```

```
ValueError: hire_date must be monotonic
```

Yes, the error message makes sense. If you are going to do a rolling average by an amount of time, then the dates need to be sorted. Monotonic means all increasing or all decreasing.

Exercise 2

Set hire date as the index and then select the salary column as a Series. Sort the Series by date and drop the missing values. Now select a subset that only has hire dates from 1990 onwards. Then find a 1,000 day

rolling average. Finally make a call to the `plot` method. Make sure you inline matplotlib if you did not do it earlier.

[45]:
```
%matplotlib inline
```

[46]:
```
sal = emp.set_index('hire_date')['salary'].sort_index().dropna()
```

[47]:
```
sal['1990':].rolling('1000D').mean().plot()
```

[47]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x118a611d0>
```

Exercise 3

Read in the energy consumption dataset. Select just the residential source and plot a 12 month trailing rolling mean of the energy.

[48]:
```
energy = pd.read_csv('../data/energy_consumption.csv', parse_dates=['date'],␣
↪index_col='date')
energy.head()
```

date	source	energy (btu)
1973-01-01	residential	1932.187
1973-02-01	residential	1687.255
1973-03-01	residential	1497.067
1973-04-01	residential	1177.661
1973-05-01	residential	1015.008

[49]:
```
filt = energy['source'] == 'residential'
res_energy = energy.loc[filt, 'energy (btu)']
res_energy.head()
```

[49]:
```
date
1973-01-01    1932.187
1973-02-01    1687.255
1973-03-01    1497.067
1973-04-01    1177.661
1973-05-01    1015.008
Name: energy (btu), dtype: float64
```

If you try to use an offset alias here, you will get an error because Pandas does not consider a year to be a fixed frequency.

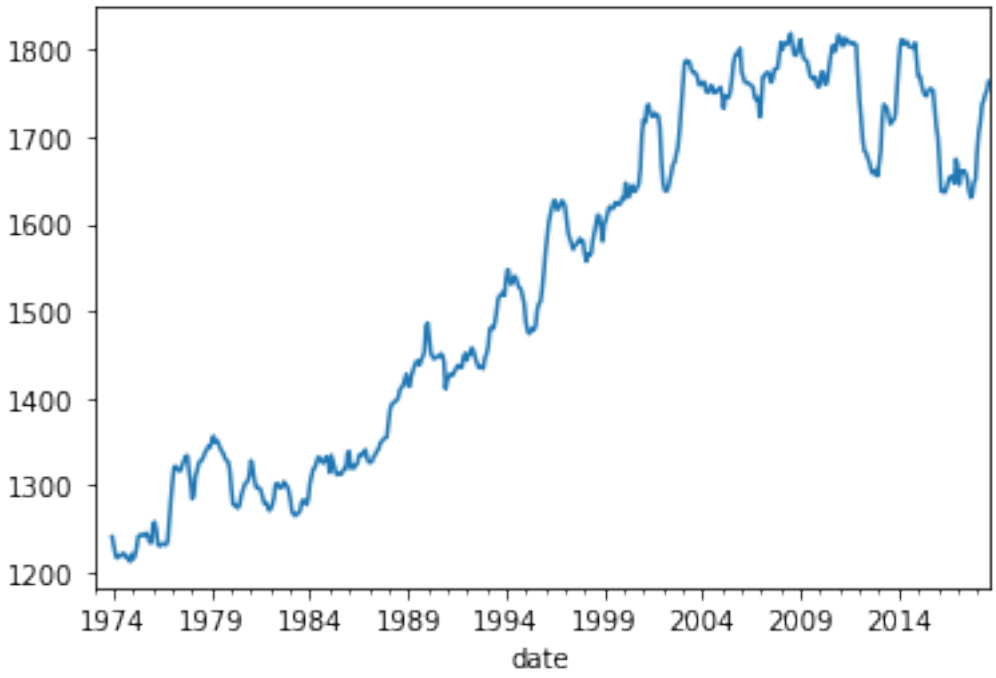
[50]:
```
res_energy.rolling('Y').mean()
```

```
ValueError: <YearEnd: month=12> is a non-fixed frequency
```

Instead, you can use the integer 12 (assuming you check that there is data for each month).

[51]:
```
res_energy.rolling(12).mean().plot()
```

[51]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11990cd90>
```



7.5 5. Grouping by Time and another Column

[52]:
```
import numpy as np
import pandas as pd
```

Exercise 1

Read in the energy consumption dataset. Find the average energy consumption per sector per 10 year time span beginning from the first year of data. Return the results as both a groupby and a pivot table. Experiment with adding 'S' to the end of your offset alias. How does this change the results?

[53]:
```
energy = pd.read_csv('../data/energy_consumption.csv', parse_dates=['date'],
                     index_col='date')
energy.head()
```

date	source	energy (btu)
1973-01-01	residential	1932.187
1973-02-01	residential	1687.255
1973-03-01	residential	1497.067
1973-04-01	residential	1177.661
1973-05-01	residential	1015.008

By default, the offset alias 'Y' represents the year end. So the first date for each source is the time span of Jan 1, 1964 - Dec 31, 1973. It is instructive to also find the size of each group to determine how many rows were aggregated.

[54]:
```
tg = pd.Grouper(freq='10Y')
energy.groupby(['source', tg]).agg({'energy (btu)':['sum', np.size]}).astype('int')
```

		energy (btu)	
		sum	size
source	date		
commercial	1973-12-31	9544	12
	1983-12-31	103325	120
	1993-12-31	126317	120
	2003-12-31	161011	120
	2013-12-31	179146	120
	2023-12-31	84850	56
industrial	1973-12-31	32622	12
	1983-12-31	309268	120
	1993-12-31	306423	120
	2003-12-31	339772	120
	2013-12-31	314844	120
	2023-12-31	148435	56
residential	1973-12-31	14895	12
	1983-12-31	154427	120
	1993-12-31	169077	120
	2003-12-31	195951	120
	2013-12-31	211653	120
	2023-12-31	96460	56
transportation	1973-12-31	18612	12
	1983-12-31	193850	120
	1993-12-31	216420	120
	2003-12-31	253859	120
	2013-12-31	274295	120
	2023-12-31	129451	56

Appending an 'S' to the offset alias string makes pandas treat the first observation as the beginning of the time period. The first group is from Jan 1, 1973 to Dec 31, 1982 and this is likely what you would want.

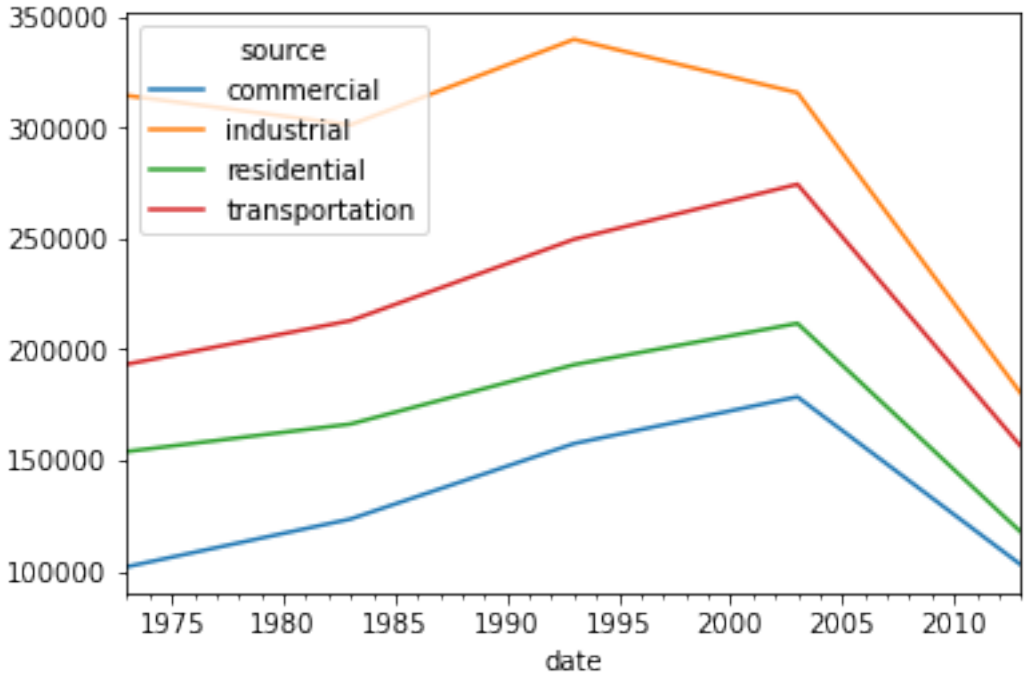
[55]:
```
tg = pd.Grouper(freq='10YS')
energy.groupby(['source', tg]).agg({'energy (btu)':['sum', np.size]}).astype('int')
```

		energy (btu)	
		sum	size
source	date		
commercial	1973-01-01	101931	120
	1983-01-01	123438	120
	1993-01-01	157480	120
	2003-01-01	178566	120
	2013-01-01	102779	68
industrial	1973-01-01	314461	120
	1983-01-01	301236	120
	1993-01-01	339833	120
	2003-01-01	315776	120
	2013-01-01	180058	68
residential	1973-01-01	153900	120
	1983-01-01	166286	120
	1993-01-01	193051	120
	2003-01-01	211705	120
	2013-01-01	117522	68
transportation	1973-01-01	193286	120
	1983-01-01	212926	120
	1993-01-01	249648	120
	2003-01-01	274455	120
	2013-01-01	156173	68

[56]:
```
df = energy.pivot_table(index=tg, columns='source',
                        values='energy (btu)', aggfunc='sum').astype('int')
df
```

source	commercial	industrial	residential	transportation
date				
1973-01-01	101931	314461	153900	193286
1983-01-01	123438	301236	166286	212926
1993-01-01	157480	339833	193051	249648
2003-01-01	178566	315776	211705	274455
2013-01-01	102779	180058	117522	156173

[57]:
```
df.plot();
```


source
commercial
industrial
residential
transportation
350000
300000
250000
200000
150000
100000
1975
1980
1985
1990
1995
2000
2005
2010
date

Part VIII

Regular Expressions

Chapter 8

Solutions

[1]:
```
import pandas as pd
import numpy as np
```

8.1 1. Introduction to Regular Expressions

[2]:
```
movie = pd.read_csv('../data/movie.csv')
title = movie['title']
```

Exercise 1

Find all movies that have 2 consecutive z's in them.

[3]:
```
filt = title.str.contains('zz')
title[filt]
```

[3]:
```
416                All That Jazz
907         The Dukes of Hazzard
1041                    Bedazzled
2234                    Paparazzi
2524                     Hot Fuzz
2593    The Lizzie McGuire Movie
3215       Into the Grizzly Maze
3535                Mystic Pizza
4399              Blue Like Jazz
Name: title, dtype: object
```

Exercise 2

Find all movies that begin with 9.

[4]:
```
filt = title.str.contains('^9')
title[filt]
```

[4]:
```
1651                        9
2416                  9½ Weeks
3705    90 Minutes in Heaven
```

```
Name: title, dtype: object
```

Exercise 3

Find all movies that have a `b` as their third character.

[5]:
```
filt = title.str.contains('^..b')
title[filt].head()
```

[5]:
```
22                Robin Hood
228                  RoboCop
286           Public Enemies
448                   Robots
494    Babe: Pig in the City
Name: title, dtype: object
```

Exercise 4

Find all movies with a fourth-to-last character of `M` and a last character of `e`.

[6]:
```
filt = title.str.contains('M..e$')
title[filt].head()
```

[6]:
```
704     The Green Mile
1167            8 Mile
1616         Like Mike
2122    Moonlight Mile
2486      How She Move
Name: title, dtype: object
```

Exercise 5

Could you use a regular expression to find a movie that was exactly 6 characters in length?

[7]:
```
filt = title.str.contains('^......$')
title[filt].head(10)
```

[7]:
```
0      Avatar
41     Cars 2
58     WALL·E
125    Frozen
168    Sahara
292    Eraser
298    Eragon
368    Pixels
426    Jumper
428    Zodiac
Name: title, dtype: object
```

Exercise 6

What is a more natural way to complete Exercise 5 without a regex?

[8]:
```
filt = title.str.len() == 6
title[filt].head(10)
```

[8]:
```
0      Avatar
41     Cars 2
58     WALL·E
125    Frozen
168    Sahara
292    Eraser
298    Eragon
368    Pixels
426    Jumper
428    Zodiac
Name: title, dtype: object
```

8.2 2. Quantifiers

Read in the movie dataset first.

[9]:
```
movie = pd.read_csv('../data/movie.csv')
title = movie['title']
```

Exercise 1

Find all movies that have a 'z' as their 15th character.

[10]:
```
pattern = '^.{14}z'
filt = title.str.contains(pattern)
title[filt]
```

[10]:
```
2484      American Dreamz
2625    Ramona and Beezus
Name: title, dtype: object
```

Exercise 2

Find all movies that have the word 'Friend' or 'Friends' in them.

[11]:
```
pattern = 'Friends?'
filt = title.str.contains(pattern)
title[filt]
```

[11]:
```
1055                    My Best Friend's Wedding
1413                       Friends with Benefits
1775       How to Lose Friends & Alienate People
2216                       My Best Friend's Girl
3116    Seeking a Friend for the End of the World
3495                          Friends with Money
4184                        We Are Your Friends
4279                       Dysfunctional Friends
4670                              Mutual Friends
Name: title, dtype: object
```

Exercise 3

Find all movies that have between 40 and 43 characters in them. Can you verify the results with another `str` accessor method?

[12]:
```
pattern = '^.{40,43}$'
filt = title.str.contains(pattern)
m40_43 = title[filt]
m40_43.head()
```

[12]:
```
1        Pirates of the Caribbean: At World's End
4      Star Wars: Episode VII - The Force Awakens
13     Pirates of the Caribbean: Dead Man's Chest
16       The Chronicles of Narnia: Prince Caspian
18    Pirates of the Caribbean: On Stranger Tides
Name: title, dtype: object
```

[13]:
```
m40_43.str.len().head()
```

[13]:
```
1     40
4     42
13    42
16    40
18    43
Name: title, dtype: int64
```

[14]:
```
m40_43.str.len().value_counts()
```

[14]:
```
40    15
41    12
43     9
42     9
Name: title, dtype: int64
```

Exercise 4

Find all movies that begin with 'The' and end in 'Movie'

[15]:
```
pattern = '^The.*Movie$'
filt = title.str.contains(pattern)
title[filt]
```

[15]:
```
319                                    The Peanuts Movie
561                                 The Angry Birds Movie
569                                    The Simpsons Movie
759                                       The Lego Movie
1586                    The SpongeBob SquarePants Movie
1734                                   The Rugrats Movie
1895                         The Wild Thornberrys Movie
2162                                    The Tigger Movie
2593                              The Lizzie McGuire Movie
2645    The Pirates Who Don't Do Anything: A VeggieTal…
3296                                   The Muppet Movie
```

```
4597                              The Kentucky Fried Movie
Name: title, dtype: object
```

Exercise 5

Create your own Series and make a regular expression that uses the + metacharacter. Is this character necessary?

[ ]:

8.3 3. Or Conditions

[16]:
```
import pandas as pd
title = pd.read_csv('../data/movie.csv')['title']
title.head()
```

[16]:
```
0                                       Avatar
1     Pirates of the Caribbean: At World's End
2                                      Spectre
3                       The Dark Knight Rises
4    Star Wars: Episode VII - The Force Awakens
Name: title, dtype: object
```

Exercise 1

Find all movies that begin with 'The' followed by the next word that begins with digits.

[17]:
```
pattern = '^The [0-9]'
filt = title.str.contains(pattern)
title[filt]
```

[17]:
```
212                                    The 13th Warrior
429                                         The 6th Day
1354                                       The 5th Wave
1817                              The 40-Year-Old Virgin
1958                                            The 33
3567                                     The 5th Quarter
4373    The 41-Year-Old Virgin Who Knocked Up Sarah Ma…
Name: title, dtype: object
```

Exercise 2

Find all movies that have three consecutive capital letters in them.

[18]:
```
pattern = '[A-Z]{3}'
filt = title.str.contains(pattern)
title[filt].head()
```

[18]:
```
4      Star Wars: Episode VII - The Force Awakens
40                                    TRON: Legacy
58                                          WALL·E
```

```
140                      Mission: Impossible III
177                                      The BFG
Name: title, dtype: object
```

Exercise 3

Find all movies that have begin and end with a capital letter.

[19]:
```
pattern = '^[A-Z].*[A-Z]$'
filt = title.str.contains(pattern)
title[filt].head()
```

[19]:
```
46                 World War Z
58                      WALL·E
140    Mission: Impossible III
151            Men in Black II
177                    The BFG
Name: title, dtype: object
```

Exercise 4

Find all the movies that have a digit followed by a comma followed by a digit.

[20]:
```
pattern = r'[0-9],[0-9]'
filt = title.str.contains(pattern)
title[filt].head()
```

[20]:
```
276                                10,000 B.C.
3266    Ultramarines: A Warhammer 40,000 Movie
3641              20,000 Leagues Under the Sea
4775             The Beast from 20,000 Fathoms
Name: title, dtype: object
```

Exercise 5

Find all the movies that have either an ampersand or a question mark in them.

[21]:
```
pattern = '[&?]'
filt = title.str.contains(pattern)
title[filt].head()
```

[21]:
```
129          Angels & Demons
145    Mr. Peabody & Sherman
214           Batman & Robin
252         Mr. & Mrs. Smith
278           Town & Country
Name: title, dtype: object
```

Exercise 6

Which movie has the most ampersands, question marks, and periods in it?

[22]:
```
pattern = '[&.?]'
count = title.str.count(pattern)
count.head()
```

[22]:
```
0    0
1    0
2    0
3    0
4    0
Name: title, dtype: int64
```

[23]:
```
filt = count == count.max()
title[filt]
```

[23]:
```
542    The Man from U.N.C.L.E.
Name: title, dtype: object
```

[24]:
```
count.max()
```

[24]:
```
5
```

8.4 4. Character Sets and Grouping

Exercise 1

For all movies that begin with 'The' and are followed by the next word that begins with a digit, extract just the digits part of this word.

[25]:
```
pattern = r'^The (\d+)'
title.str.extract(pattern).dropna()
```

	0
212	13
429	6
1354	5
1817	40
1958	33
3567	5
4373	41

Exercise 2

Find all movies that have two separate numbers in them. An example would be, '7 days and 7 nights'.

[26]:
```
pattern = r'\d+\D+\d+'
filt = title.str.contains(pattern)
title[filt]
```

[26]:
```
276                                10,000 B.C.
289                 The Taking of Pelham 1 2 3
509                            2 Fast 2 Furious
1043                               3:10 to Yuma
1610                             13 Going on 30
1617        Naked Gun 33 1/3: The Final Insult
2466                      40 Days and 40 Nights
2646                                      U2 3D
3266    Ultramarines: A Warhammer 40,000 Movie
3308                                      50/50
3516                             Fahrenheit 9/11
3576                                      11:14
3641              20,000 Leagues Under the Sea
3934                                      2:13
4210                   24 7: Twenty Four Seven
4376                    Friday the 13th Part 2
4532              4 Months, 3 Weeks and 2 Days
4775             The Beast from 20,000 Fathoms
Name: title, dtype: object
```

Exercise 3

Find all the movies that have 6 or more non-vowel and non-space characters in a row.

[27]:
```
pattern = r'[^aeiouAEIOU ]{6,}'
filt = title.str.contains(pattern)
title[filt]
```

[27]:
```
276                                10,000 B.C.
542                   The Man from U.N.C.L.E.
1935                         Punch-Drunk Love
2392                                 Catch-22
2480                        Brooklyn's Finest
2507                   When Harry Met Sally…
2912        Tales from the Crypt: Demon Knight
3266    Ultramarines: A Warhammer 40,000 Movie
3641              20,000 Leagues Under the Sea
4775             The Beast from 20,000 Fathoms
Name: title, dtype: object
```

Exercise 4

Extract the very next character after ‘t’ or ‘T’ for each movie.

[28]:
```
pattern = r'[Tt](.)'
title.str.extract(pattern).head()
```

	0
0	a
1	e
2	r
3	h
4	a

Exercise 5

What is the most common character after 't' or 'T'?

[29]:
```
pattern = r'[Tt](.)'
letters = title.str.extract(pattern)
letters.head()
```

	0
0	a
1	e
2	r
3	h
4	a

This is a DataFrame. The column name is the integer 0. Let's select it as a Series.

[30]:
```
letter_series = letters[0]
letter_series.head()
```

[30]:
```
0    a
1    e
2    r
3    h
4    a
Name: 0, dtype: object
```

[31]:
```
letter_series.value_counts().head()
```

[31]:
```
h    1431
      311
e     266
o     183
i     169
Name: 0, dtype: int64
```

Minor detail here - there is an `expand` parameter than you can set to `False` to return a Series.

[32]:
```
pattern = r'[Tt](.)'
letters = title.str.extract(pattern, expand=False)
letters.head()
```

[32]:
```
0    a
1    e
2    r
3    h
4    a
Name: title, dtype: object
```

[33]:
```
letters.value_counts().head()
```

[33]:
```
h    1431
      311
e     266
o     183
i     169
Name: title, dtype: int64
```

The above only extracts the character after first appearance of the letter 't'. Use the `extractall` string method to get the first characters after each 't'.

[34]:
```
pattern = r'[Tt](.)'
letters = title.str.extractall(pattern)
letters.head()
```

		0
	match	
0	0	a
1	0	e
	1	h
	2	
2	0	r

[35]:
```
letters[0].value_counts().head()
```

[35]:
```
h    1942
      620
e     480
o     354
i     343
Name: 0, dtype: int64
```

Exercise 6

Extract all the words that begin with 'T' or 't' and end in 'e' then find their frequency. Research the word boundaray special character.

[36]:
```
pattern = r'\b([tT]\w*e)\b'
letters = title.str.extractall(pattern)
letters[0].str.lower().value_counts()
```

[36]:
```
the              1555
time               26
tale               12
true               10
three               8
teenage             7
take                6
there               6
trouble             4
trade               4
terrace             2
twice               2
treasure            2
temple              1
throttle            1
trance              1
tide                1
transcendence       1
tootsie             1
tease               1
triple              1
tape                1
thr3e               1
tadpole             1
twelve              1
tae                 1
terrible            1
triangle            1
turtle              1
torture             1
thunderdome         1
timeline            1
tree                1
trapeze             1
tombstone           1
turbulence          1
torque              1
Name: 0, dtype: int64
```

8.5 Project - Explore Newsgroups with Regexes

[37]:
```
news = pd.read_csv('../data/newsgroups.csv')
news.head()
```

	category	text
0	sci.med	From: nyeda@cnsvax.uwec.edu (David Nye)\nSubje...
1	talk.politics.guns	From: ndallen@r-node.hub.org (Nigel Allen)\nSu...
2	misc.forsale	From: mark@ardsley.business.uwo.ca (Mark Bramw...
3	misc.forsale	From: zmed16@trc.amoco.com (Michael)\nSubject:...
4	talk.politics.guns	From: fcrary@ucsu.Colorado.EDU (Frank Crary)\n...

Extracting emails

It appears all emails follow the line in the header that begins with 'From:'. The following captures emails as the sequence of characters that do not have a space, parentheses or greater than or less than signs, or line breaks in them. There must also be an at symbol in the sequence.

[38]:
```
pattern = r'\bFrom:.*?([^ ()<]+@[^ (>\n]+)'
emails = news['text'].str.extract(pattern)
emails.head()
```

	0
0	nyeda@cnsvax.uwec.edu
1	ndallen@r-node.hub.org
2	mark@ardsley.business.uwo.ca
3	zmed16@trc.amoco.com
4	fcrary@ucsu.Colorado.EDU

Extracting the header

It appears that the header begins at the start of the email and continues until it hits an empty line. The following matches all characters (including line breaks) up until two line breaks in a row. This should represent the header. The pattern `[\s\S]` represents all characters. The dot special character does not match line breaks.

The `*?` represents a non-greedy match, meaning the pattern will stop after the first match. If the question mark was absent, then it would match until the last two line breaks in a row. That's called **greedy**.

[39]:
```
headers = news['text'].str.extract(r'([\s\S]*?)\n\n')
headers.head()
```

	0
0	From: nyeda@cnsvax.uwec.edu (David Nye)\nSubje...
1	From: ndallen@r-node.hub.org (Nigel Allen)\nSu...
2	From: mark@ardsley.business.uwo.ca (Mark Bramw...
3	From: zmed16@trc.amoco.com (Michael)\nSubject:...
4	From: fcrary@ucsu.Colorado.EDU (Frank Crary)\n...

Example header

[40]:
```
print(headers.loc[100, 0])
```

```
From: c23reg@kocrsv01.delcoelect.com (Ron Gaskins)
Subject: Re: Dumbest automotive concepts of all tim
Originator: c23reg@koptsw21
Keywords: Dimmer switch location (repost)
Organization: Delco Electronics Corp.
Lines: 22
```

Finding posts with quotes

The assumption here is that the line begins with a greater than symbol.

[41]:
```
filt = news['text'].str.contains(r'\n>')
posts_with_quotes = news.loc[filt, 'text']
print(posts_with_quotes.values[0])
```

```
From: nyeda@cnsvax.uwec.edu (David Nye)
Subject: Re: Post Polio Syndrome Information Needed Please !!!
Organization: University of Wisconsin Eau Claire
Lines: 21

[reply to keith@actrix.gen.nz (Keith Stewart)]

>My wife has become interested through an acquaintance in Post-Polio
>Syndrome This apparently is not recognised in New Zealand and different
>symptons ( eg chest complaints) are treated separately. Does anone have
>any information on it

It would help if you (and anyone else asking for medical information on
some subject) could ask specific questions, as no one is likely to type
in a textbook chapter covering all aspects of the subject.  If you are
looking for a comprehensive review, ask your local hospital librarian.
Most are happy to help with a request of this sort.

Briefly, this is a condition in which patients who have significant
residual weakness from childhood polio notice progression of the
weakness as they get older.  One theory is that the remaining motor
neurons have to work harder and so die sooner.
```

```
David Nye (nyeda@cnsvax.uwec.edu).  Midelfort Clinic, Eau Claire WI
This is patently absurd; but whoever wishes to become a philosopher
must learn not to be frightened by absurdities. -- Bertrand Russell
```

Counting words per category

We first put the category into the index and extract just the body of the posts (this excludes the header). This returns a DataFrame with a single column with name 0. We select this column in the second line.

[42]:
```
body = news.set_index('category')['text'].str.extract(r'[\s\S]*?\n\n([\s\S]+)')
body_series = body[0]
body_series.head()
```

[42]:
```
category
sci.med                [reply to keith@actrix.gen.nz (Keith Stewart)]…
talk.politics.guns    Here is a press release from the White House.\…
misc.forsale           >\n>I hope you realize that for a cellular pho…
misc.forsale           \nI have an Alesis HR-16 drum machine for sale…
talk.politics.guns     In article <C4tsHu.Ew6@magpie.linknet.com> man…
Name: 0, dtype: object
```

Extract each individual non-quote line

We then use `extractall` to capture a pattern for each individual line. The assumption we make is that the line must begin with a word character.

[43]:
```
body_lines = body_series.str.extractall(r'[\n]+(\w.*)')
body_lines.head(20)
```

		0
category	**match**	
sci.med	**0**	It would help if you (and anyone else asking f...
	1	some subject) could ask specific questions, as...
	2	in a textbook chapter covering all aspects of ...
	3	looking for a comprehensive review, ask your l...
	4	Most are happy to help with a request of this ...
	5	Briefly, this is a condition in which patients...
	6	residual weakness from childhood polio notice ...
	7	weakness as they get older. One theory is tha...
	8	neurons have to work harder and so die sooner.
	9	David Nye (nyeda@cnsvax.uwec.edu). Midelfort ...
	10	This is patently absurd; but whoever wishes to...
	11	must learn not to be frightened by absurdities...
talk.politics.guns	**0**	Clinton in a question and answer session with ...
	1	1:36 P.M. EDT
	2	agents were killed in the line of duty trying ...
	3	against the Branch Davidian compound, which ha...
	4	weaponry and ammunition, and placed innocent c...
	5	Because the BATF operation had failed to meet ...
	6	standoff ensued.
	7	reasonable effort to bring this perilous situa...

Split into individual words

We then split on any non-word character and use `expand=True` to put each word in its own column.

[44]:
```
split_words = body_lines[0].str.split(r'\W+', expand=True)
split_words.head()
```

		0	1	2	3	4	...	32	33	34	35	36
category	**match**											
sci.med	**0**	It	would	help	if	you	...	None	None	None	None	None
	1	some	subject	could	ask	specific	...	None	None	None	None	None
	2	in	a	textbook	chapter	covering	...	None	None	None	None	None
	3	looking	for	a	comprehensive	review	...	None	None	None	None	None
	4	Most	are	happy	to	help	...	None	None	None	None	None

Stack words into a single column

Use the stack method to put all the words in a single column. This will put the column names into the index. We also,

[45]:
```
stacked_words = split_words.stack().str.lower()
stacked_words.head(30)
```

[45]:
```
category  match
sci.med   0      0             it
                 1          would
                 2           help
                 3             if
                 4            you
                 5            and
                 6         anyone
                 7           else
                 8         asking
                 9            for
                 10       medical
                 11   information
                 12            on
          1      0           some
                 1        subject
                 2          could
                 3            ask
                 4       specific
                 5      questions
                 6             as
                 7             no
                 8            one
                 9             is
                 10       likely
                 11           to
                 12         type
          2      0             in
                 1              a
                 2       textbook
                 3        chapter
dtype: object
```

Remove words less than 7 characters in length

These shorter words won't give us as much information about the topic as the longer ones.

[46]:
```
long_word = stacked_words[stacked_words.str.len() >= 7]
long_word.head(20)
```

[46]:
```
category  match
sci.med   0      10          medical
                 11      information
          1      1           subject
```

```
                4          specific
                5         questions
          2     2          textbook
                3           chapter
                4          covering
                6           aspects
                9           subject
          3     0           looking
                3     comprehensive
                8          hospital
                9         librarian
          4     7           request
          5     0           briefly
                4         condition
                7          patients
                10     significant
          6     0          residual
dtype: object
```

Groupby category and count the unique values

You can groupby an index level and the count the values for each group.

[47]:
```
category_counts = long_word.groupby('category').value_counts().reset_index()
category_counts.columns = ['category', 'word', 'count']
category_counts.head(10)
```

	category	word	count
0	misc.forsale	condition	17
1	misc.forsale	excellent	11
2	misc.forsale	interested	9
3	misc.forsale	shipping	9
4	misc.forsale	windows	9
5	misc.forsale	printer	8
6	misc.forsale	publish	8
7	misc.forsale	contact	7
8	misc.forsale	software	7
9	misc.forsale	compatible	6

Select top 10 words per category

[48]:
```
top10_words = category_counts.groupby('category').head(10)
top10_words.head(20)
```

	category	word	count
0	misc.forsale	condition	17
1	misc.forsale	excellent	11
2	misc.forsale	interested	9
3	misc.forsale	shipping	9
4	misc.forsale	windows	9
5	misc.forsale	printer	8
6	misc.forsale	publish	8
7	misc.forsale	contact	7
8	misc.forsale	software	7
9	misc.forsale	compatible	6
475	rec.autos	someone	13
476	rec.autos	problem	11
477	rec.autos	anything	9
478	rec.autos	without	9
479	rec.autos	driving	8
480	rec.autos	traffic	8
481	rec.autos	because	7
482	rec.autos	between	7
483	rec.autos	information	7
484	rec.autos	business	6

Fix the index

The index values are the old location of the rows. They don't make sense. Let's drop it.

[49]:
```
top10_words = top10_words.reset_index(drop=True)
top10_words.head(20)
```

	category	word	count
0	misc.forsale	condition	17
1	misc.forsale	excellent	11
2	misc.forsale	interested	9
3	misc.forsale	shipping	9
4	misc.forsale	windows	9
5	misc.forsale	printer	8
6	misc.forsale	publish	8
7	misc.forsale	contact	7
8	misc.forsale	software	7
9	misc.forsale	compatible	6
10	rec.autos	someone	13
11	rec.autos	problem	11
12	rec.autos	anything	9
13	rec.autos	without	9
14	rec.autos	driving	8
15	rec.autos	traffic	8
16	rec.autos	because	7
17	rec.autos	between	7
18	rec.autos	information	7
19	rec.autos	business	6

Get unique categories for querying

[50]:
```
top10_words['category'].unique()
```

[50]:
```
array(['misc.forsale', 'rec.autos', 'rec.sport.baseball', 'sci.med',
       'sci.space', 'talk.politics.guns'], dtype=object)
```

Choose a couple categories

[51]:
```
filt = top10_words['category'] == 'sci.space'
top10_words[filt]
```

	category	word	count
40	sci.space	telescope	27
41	sci.space	satellite	25
42	sci.space	national	24
43	sci.space	shuttle	22
44	sci.space	vehicle	18
45	sci.space	observatory	16
46	sci.space	because	15
47	sci.space	international	15
48	sci.space	spacecraft	14
49	sci.space	astronomical	13

[52]:
```
filt = top10_words['category'] == 'talk.politics.guns'
top10_words[filt]
```

	category	word	count
50	talk.politics.guns	because	27
51	talk.politics.guns	federal	26
52	talk.politics.guns	believe	24
53	talk.politics.guns	against	23
54	talk.politics.guns	weapons	23
55	talk.politics.guns	without	23
56	talk.politics.guns	defense	22
57	talk.politics.guns	firearms	22
58	talk.politics.guns	control	21
59	talk.politics.guns	government	19

8.6 Project - Feature Engineering on the Titanic

Exercise 1

Extract the first character of the `Ticket` column and save it as a new column `ticket_first`. Find the total number of survivors, the total number of passengers, and the percentage of those who survived **by this column**. Next find the total survival rate for the entire dataset. Does this new column help predict who survived?

[53]:
```
titanic = pd.read_csv('../data/titanic.csv')
titanic.head()
```

	PassengerId	Survived	Pclass	Name	Sex	...	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	...	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	...	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	...	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	...	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	...	0	373450	8.0500	NaN	S

[54]:
```
titanic['ticket_first'] = titanic.Ticket.str[0]
titanic.head()
```

	PassengerId	Survived	Pclass	Name	Sex	...	Ticket	Fare	Cabin	Embarked	ticket_first
0	1	0	3	Braund, Mr. Owen Harris	male	...	A/5 21171	7.2500	NaN	S	A
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	...	PC 17599	71.2833	C85	C	P
2	3	1	3	Heikkinen, Miss. Laina	female	...	STON/O2. 3101282	7.9250	NaN	S	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	...	113803	53.1000	C123	S	1
4	5	0	3	Allen, Mr. William Henry	male	...	373450	8.0500	NaN	S	3

[55]:
```
ticket_first_survival = titanic.groupby('ticket_first').agg({'Survived': ['mean',␣
↪'sum', 'size']})
ticket_first_survival
```

	Survived		
	mean	sum	size
ticket_first			
1	0.630137	92	146
2	0.464481	85	183
3	0.239203	72	301
4	0.200000	2	10
5	0.000000	0	3
6	0.166667	1	6
7	0.111111	1	9
8	0.000000	0	2
9	1.000000	1	1
A	0.068966	2	29
C	0.340426	16	47
F	0.571429	4	7
L	0.250000	1	4
P	0.646154	42	65
S	0.323077	21	65
W	0.153846	2	13

[56]:
```
# overall survival rate
titanic['Survived'].mean()
```

[56]:
```
0.3838383838383838
```

It does look like **`ticket_first`** has predictive power. 63% of those tickets beginning with '1' survived while versus 24% for '3'. Only 2 out of 29 people survived with tickets beginning with 'A'.

Exercise 2

If you did Exercise 2 correctly, you should see that only 7% of the people with tickets that began with 'A' survived. Find the survival rate for all those 'A' tickets by `Sex`.

[57]:
```
filt = titanic['ticket_first'] == 'A'
ticket_A = titanic[filt]
ticket_A.groupby('Sex').agg({'Survived': ['mean', 'size']})
```

	Survived	
	mean	size
Sex		
female	0.000000	2
male	0.074074	27

Exercise 3

Find the survival rate by the last letter of the ticket. Is there any predictive power here?

[58]:
```
titanic['ticket_last'] = titanic['Ticket'].str[-1]
ticket_last_survival = titanic.groupby('ticket_last').agg({'Survived': ['mean', 'sum',␣
↪'size']})
ticket_last_survival
```

	Survived		
	mean	sum	size
ticket_last			
0	0.395062	32	81
1	0.430000	43	100
2	0.364706	31	85
3	0.339286	38	112
4	0.297297	22	74
5	0.392405	31	79
6	0.419355	39	93
7	0.355556	32	90
8	0.453488	39	86
9	0.390805	34	87
E	0.250000	1	4

No predictive power. They are all about equal.

Exercise 4

Find the length of each passengers name and assign to the `name_len` column. What is the minimum and maximum name length?

[59]:
```
titanic['name_len'] = titanic['Name'].str.len()
titanic['name_len'].min()
```

[59]: 12

[60]:
```
titanic['name_len'].max()
```

[60]:
```
82
```

Exercise 5

Pass the `name_len` column to the `pd.cut` function. Also, pass a list of equal-sized cut points to the `bins` parameter. Assign the resulting Series to the `name_len_cat` column. Find the frequency count of each bin in this column.

[61]:
```
titanic['name_len_cat'] = pd.cut(titanic['name_len'], bins=[0, 20, 40, 60, 80, 100])
titanic['name_len_cat'].head()
```

[61]:
```
0    (20, 40]
1    (40, 60]
2    (20, 40]
3    (40, 60]
4    (20, 40]
Name: name_len_cat, dtype: category
Categories (5, interval[int64]): [(0, 20] < (20, 40] < (40, 60] < (60, 80] < (80, 100]]
```

[62]:
```
titanic['name_len_cat'].value_counts()
```

[62]:
```
(20, 40]     558
(0, 20]      243
(40, 60]      86
(60, 80]       3
(80, 100]      1
Name: name_len_cat, dtype: int64
```

Exercise 6

Is name length a good predictor of survival?

[63]:
```
titanic.groupby('name_len_cat').agg({'Survived': ['mean', 'size']})
```

	Survived	
	mean	size
name_len_cat		
(0, 20]	0.230453	243
(20, 40]	0.383513	558
(40, 60]	0.790698	86
(60, 80]	1.000000	3
(80, 100]	1.000000	1

Yes, the longer the name, the higher the survival rate.

Exercise 7

Why do you think people with longer names had a better chance at survival?

Let's output the shortest and longest 10 names

[64]:
```
names = titanic.sort_values(by='name_len')['Name']
```

[65]:
```
names.head(10)
```

[65]:
```
826       Lam, Mr. Len
692       Lam, Mr. Ali
74       Bing, Mr. Lee
169      Ling, Mr. Lee
509     Lang, Mr. Fang
832     Saad, Mr. Amin
210     Ali, Mr. Ahmed
694    Weir, Col. John
108    Rekic, Mr. Tido
838    Chip, Mr. Chang
Name: Name, dtype: object
```

[66]:
```
# Names exceed pandas display settings.
# change them with pd.options.display.max_colwidth
# or just print out values
names.tail(10).values
```

[66]:
```
array(['Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)',
       'Rothes, the Countess. of (Lucy Noel Martha Dyer-Edwards)',
       'Spedden, Mrs. Frederic Oakley (Margaretta Corning Stone)',
       'Turpin, Mrs. William John Robert (Dorothy Ann Wonnacott)',
       'Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)',
       'Andersson, Mrs. Anders Johan (Alfrida Konstantia Brogren)',
       'Brown, Mrs. Thomas William Solomon (Elizabeth Catherine Ford)',
       'Duff Gordon, Lady. (Lucille Christiana Sutherland) ("Mrs Morgan")',
       'Phillips, Miss. Kate Florence ("Mrs Kate Louise Phillips Marshall")',
       'Penasco y Castellana, Mrs. Victor de Satode (Maria Josefa Perez de Soto y
Vallejo)'],
      dtype=object)
```

[67]:
```
# temporarily set options in a context manager
with pd.option_context('display.max_colwidth', 100):
    print(names.tail(10))
```

```
18                                  Vander Planke, Mrs. Julius (Emelia Maria Vandemoortele)
759                                Rothes, the Countess. of (Lucy Noel Martha Dyer-Edwards)
319                                Spedden, Mrs. Frederic Oakley (Margaretta Corning Stone)
41                                 Turpin, Mrs. William John Robert (Dorothy Ann Wonnacott)
25                                Asplund, Mrs. Carl Oscar (Selma Augusta Emilia Johansson)
610                               Andersson, Mrs. Anders Johan (Alfrida Konstantia Brogren)
670                         Brown, Mrs. Thomas William Solomon (Elizabeth Catherine Ford)
556                   Duff Gordon, Lady. (Lucille Christiana Sutherland) ("Mrs Morgan")
427                 Phillips, Miss. Kate Florence ("Mrs Kate Louise Phillips Marshall")
```

```
307    Penasco y Castellana, Mrs. Victor de Satode (Maria Josefa Perez de Soto y Vallejo)
Name: Name, dtype: object
```

Looks like all the people with short names are men. All people with long names are females.

Exercise 8

Using the titanic dataset, do your best to extract the title from a person's name. Examples of title are 'Mr.', 'Dr.', 'Miss', etc… Save this to a column called `title`. Find the frequency count of the titles.

[68]:
```
titanic['title'] = titanic['Name'].str.extract(r'(\w+[.])')
titanic['title'].value_counts()
```

[68]:
```
Mr.          517
Miss.        182
Mrs.         125
Master.       40
Dr.            7
Rev.           6
Mlle.          2
Col.           2
Major.         2
Ms.            1
Lady.          1
Sir.           1
Capt.          1
Don.           1
Mme.           1
Countess.      1
Jonkheer.      1
Name: title, dtype: int64
```

Exercise 9

Does the title have good predictive value of survival?

[69]:
```
titanic.groupby('title').agg({'Survived':['mean', 'size']})
```

	Survived	
	mean	size
title		
Capt.	0.000000	1
Col.	0.500000	2
Countess.	1.000000	1
Don.	0.000000	1
Dr.	0.428571	7
Jonkheer.	0.000000	1
Lady.	1.000000	1
Major.	0.500000	2
Master.	0.575000	40
Miss.	0.697802	182
Mlle.	1.000000	2
Mme.	1.000000	1
Mr.	0.156673	517
Mrs.	0.792000	125
Ms.	1.000000	1
Rev.	0.000000	6
Sir.	1.000000	1

Exercise 10

Create a pivot table of survival by title and sex. Use two aggregation functions, mean and size

[70]:
```
titanic.pivot_table(index='title', columns='Sex',
                    values='Survived', aggfunc=['mean', 'size'])
```

	mean		size	
Sex	female	male	female	male
title				
Capt.	NaN	0.000000	NaN	1.0
Col.	NaN	0.500000	NaN	2.0
Countess.	1.000000	NaN	1.0	NaN
Don.	NaN	0.000000	NaN	1.0
Dr.	1.000000	0.333333	1.0	6.0
Jonkheer.	NaN	0.000000	NaN	1.0
Lady.	1.000000	NaN	1.0	NaN
Major.	NaN	0.500000	NaN	2.0
Master.	NaN	0.575000	NaN	40.0
Miss.	0.697802	NaN	182.0	NaN
Mlle.	1.000000	NaN	2.0	NaN
Mme.	1.000000	NaN	1.0	NaN
Mr.	NaN	0.156673	NaN	517.0
Mrs.	0.792000	NaN	125.0	NaN
Ms.	1.000000	NaN	1.0	NaN
Rev.	NaN	0.000000	NaN	6.0
Sir.	NaN	1.000000	NaN	1.0

Exercise 11

Attempt to extract the first name of each passenger into the column `first_name`. Are there are males and females with the same first name?

Most can be found like this following the title

[71]:
```
pattern = r'\w+[.] (\w+)'
titanic['first_name'] = titanic['Name'].str.extract(pattern)
```

To be more precise, we can do this:

[72]:
```
pattern = r'\w+[.][a-z (]+([A-Z]\w+)'
titanic['first_name'] = titanic['Name'].str.extract(pattern)
```

[73]:
```
first_name_ct = titanic.groupby('first_name').agg({'Sex': 'nunique'})
first_name_ct.head()
```

first_name	Sex
Abraham	1
Achille	1
Ada	1
Adele	1
Adola	1

[74]:
```
filt = first_name_ct['Sex'] == 2
first_name_ct[filt].head(10)
```

first_name	Sex
Albert	2
Alexander	2
Amin	2
Anders	2
Antoni	2
Benjamin	2
Carl	2
Charles	2
Dickinson	2
Edgar	2

Looks like some female first names are actually in parentheses after their husband/father name.

[75]:
```
filt = titanic['first_name'] == 'Albert'
titanic.loc[filt, 'Name']
```

[75]:
```
64                                  Stewart, Mr. Albert A
107                                Moss, Mr. Albert Johan
323    Caldwell, Mrs. Albert Francis (Sylvia Mae Harb…
690                               Dick, Mr. Albert Adrian
781           Dick, Mrs. Albert Adrian (Vera Gillespie)
817                                    Mallet, Mr. Albert
833                               Augustsson, Mr. Albert
Name: Name, dtype: object
```

Exercise 12

The past several exercises have been an exercise in **feature engineering**. Several new features (columns) have been created from existing columns. Come up with your own feature and test it out on survival.

Get first letter of cabin. Use 'Missing' if not present.

[76]:
```
titanic['cabin_first'] = titanic.Cabin.str[0].fillna('Missing')
```

Just having a cabin is highly predictive.

[77]:
```
titanic.groupby('cabin_first').agg({'Survived': ['size', 'mean']})#.
↪sort_values('size', ascending=False)
```

	Survived	
	size	mean
cabin_first		
A	15	0.466667
B	47	0.744681
C	59	0.593220
D	33	0.757576
E	32	0.750000
F	13	0.615385
G	4	0.500000
Missing	687	0.299854
T	1	0.000000

Part IX

Tidy Data

Chapter 9

Solutions

9.1 1. Tidy Data with `melt`

[1]:
```
import pandas as pd
import numpy as np
pd.options.display.max_columns = 40
```

[2]:
```
movie = pd.read_csv('../data/movie.csv')
movie.head(2)
```

	title	year	color	content_rating	duration	...	plot_keywords	language	country	budget	imdb_score
0	Avatar	2009.0	Color	PG-13	178.0	...	avatar|future|marine|native|paraplegic	English	USA	237000000.0	7.9
1	Pirates of the Caribbean: At World's End	2007.0	Color	PG-13	169.0	...	goddess|marriage ceremony|marriage proposal|pi...	English	USA	300000000.0	7.1

Exercise 1

Read in the movie dataset. Select the title column and all of the actor name columns. Restructure the dataset so that there are only three variables - the title of the movie, the actor number (1, 2, or 3), and the actor name. Sort the result by title and output the result.

[3]:
```
actor_tidy = movie.melt(id_vars='title',
                        value_vars=['actor1', 'actor2', 'actor3'],
                        var_name='Actor Number',
                        value_name='Actor Name').sort_values('title')
actor_tidy.head(6)
```

	title	Actor Number	Actor Name
14181	#Horror	actor3	Lydia Hearst
9265	#Horror	actor2	Balthazar Getty
4349	#Horror	actor1	Timothy Hutton
13461	10 Cloverfield Lane	actor3	Sumalee Montano
8545	10 Cloverfield Lane	actor2	John Gallagher Jr.
3629	10 Cloverfield Lane	actor1	Bradley Cooper

Exercise 2

Using the original movie dataset (and keeping its structure), attempt to count the total appearances of each actor in the dataset regardless whether they are 1, 2, or 3. Then repeat this task with your tidy dataset.

We have not covered how to do the first part of the question. It becomes very easy with tidy data.

[4]:
```
actor_ct = actor_tidy['Actor Name'].value_counts()
actor_ct.head()
```

[4]:
```
Robert De Niro    53
Morgan Freeman    43
Bruce Willis      38
Matt Damon        37
Steve Buscemi     36
Name: Actor Name, dtype: int64
```

Advanced Pandas for first part. This is a pandas trick that uses the **add** method to add Series together:

[5]:
```
vc1 = movie['actor1'].value_counts()
vc2 = movie['actor2'].value_counts()
vc3 = movie['actor3'].value_counts()
```

[6]:
```
actor_ct2 = vc1.add(vc2, fill_value=0) \
               .add(vc3, fill_value=0) \
               .astype(int) \
               .sort_values(ascending=False)
actor_ct2.head()
```

[6]:
```
Robert De Niro    53
Morgan Freeman    43
Bruce Willis      38
Matt Damon        37
Steve Buscemi     36
dtype: int64
```

Exercise 3

Tidy the dataset in the `tidy/employee_messy1.csv` file. It contains the count of all employees by race and gender.

[7]:
```
em = pd.read_csv('../data/tidy/employee_messy1.csv')
em
```

	race	Female	Male
0	Native American	6	5
1	Asian	30	77
2	Black	305	395
3	Hispanic	139	341
4	White	108	557

[8]:
```
em.melt(id_vars='race', value_vars=['Female', 'Male'],
        var_name='gender', value_name='count')
```

	race	gender	count
0	Native American	Female	6
1	Asian	Female	30
2	Black	Female	305
3	Hispanic	Female	139
4	White	Female	108
5	Native American	Male	5
6	Asian	Male	77
7	Black	Male	395
8	Hispanic	Male	341
9	White	Male	557

Exercise 4

Tidy the dataset in the `tidy/employee_messy2.csv` file. It contains the count of all employees by department, race and gender.

[9]:
```
em2 = pd.read_csv('../data/tidy/employee_messy2.csv')
em2.head()
```

	dept	gender	Asian	Black	Hispanic	White
0	Health & Human Services	Female	6	43	22	6
1	Health & Human Services	Male	5	10	5	6
2	Houston Fire Department (HFD)	Female	0	7	8	6
3	Houston Fire Department (HFD)	Male	1	62	91	203
4	Houston Police Department-HPD	Female	6	76	35	35

[10]:
```
em2.melt(id_vars=['dept', 'gender'],
         var_name='race',
         value_name='count').head()
```

	dept	gender	race	count
0	Health & Human Services	Female	Asian	6
1	Health & Human Services	Male	Asian	5
2	Houston Fire Department (HFD)	Female	Asian	0
3	Houston Fire Department (HFD)	Male	Asian	1
4	Houston Police Department-HPD	Female	Asian	6

Exercise 5

Tidy the dataset in the `tidy/employee_salary_stats.csv` file. Save the tidy dataset to a variable and then select all the median salaries. The select all the median salaries with the original 'messy' dataset. Which one is easier to read summary statistics from?

[11]:
```
em_stats = pd.read_csv('../data/tidy/employee_salary_stats.csv')
em_stats.head()
```

	race	gender	min	mean	median	max
0	Native American	Female	26125	60238	58855	98536
1	Native American	Male	26125	60305	60347	81239
2	Asian	Female	26125	63226	57227	130416
3	Asian	Male	27914	61033	55461	163228
4	Black	Female	24960	48915	44491	150416

[12]:
```
df_tidy = em_stats.melt(id_vars=['race', 'gender'],
                        var_name='Statistic',
                        value_name='Salary Value')
df_tidy.head()
```

	race	gender	Statistic	Salary Value
0	Native American	Female	min	26125
1	Native American	Male	min	26125
2	Asian	Female	min	26125
3	Asian	Male	min	27914
4	Black	Female	min	24960

[13]:
```
filt = df_tidy['Statistic'] == 'median'
df_tidy[filt]
```

	race	gender	Statistic	Salary Value
20	Native American	Female	median	58855
21	Native American	Male	median	60347
22	Asian	Female	median	57227
23	Asian	Male	median	55461
24	Black	Female	median	44491
25	Black	Male	median	46486
26	Hispanic	Female	median	43087
27	Hispanic	Male	median	54090
28	White	Female	median	62264
29	White	Male	median	62540

[14]:
```
cols = ['race', 'gender', 'median']
em_stats[cols]
```

	race	gender	median
0	Native American	Female	58855
1	Native American	Male	60347
2	Asian	Female	57227
3	Asian	Male	55461
4	Black	Female	44491
5	Black	Male	46486
6	Hispanic	Female	43087
7	Hispanic	Male	54090
8	White	Female	62264
9	White	Male	62540

The messy dataset is probably easier, as it shows all the aggregated statistics for each race and gender in a single row. Aggregated values are generally easier to read as "messy" datasets.

9.2 2. Reshaping by Pivoting

Exercise 1

Read the file **`clean_movie1.csv`** and then use the **`pivot`** method to put the country names as the columns. Put the **`count`** as the new values for the DataFrame.

[15]:
```
cm = pd.read_csv('../data/tidy/clean_movie1.csv')
cm.head()
```

	content_rating	country	count
0	G	Australia	2
1	G	Canada	1
2	G	France	5
3	G	Germany	1
4	G	UK	11

[16]:
```
cm.pivot(index='content_rating', columns='country', values='count')
```

country	Australia	Canada	France	Germany	India	Spain	UK	USA
content_rating								
G	2.0	1.0	5.0	1.0	NaN	NaN	11.0	85.0
Not Rated	NaN	9.0	11.0	4.0	6.0	2.0	10.0	51.0
PG	11.0	10.0	12.0	11.0	2.0	2.0	70.0	544.0
PG-13	10.0	25.0	34.0	22.0	2.0	6.0	97.0	1168.0
R	25.0	64.0	63.0	49.0	3.0	21.0	198.0	1534.0

[17]:
```
# can fill in the missing value with 0 and change type to integer
cm.pivot(index='content_rating', columns='country', values='count').fillna(0).
↪astype(int)
```

country	Australia	Canada	France	Germany	India	Spain	UK	USA
content_rating								
G	2	1	5	1	0	0	11	85
Not Rated	0	9	11	4	6	2	10	51
PG	11	10	12	11	2	2	70	544
PG-13	10	25	34	22	2	6	97	1168
R	25	64	63	49	3	21	198	1534

Exercise 2

Read in the NYC deaths dataset and select only males from 2007. Pivot this information so we can more clearly see the breakdown of causes of death by race. Assign the result to a variable.

[18]:
```
nyc_deaths = pd.read_csv('../data/nyc_deaths.csv')
nyc_deaths.head()
```

	year	cause	sex	race	deaths
0	2007	Accidents	F	Asian	32
1	2007	Accidents	F	Black	87
2	2007	Accidents	F	Hispanic	71
3	2007	Accidents	F	White	162
4	2007	Accidents	M	Asian	53

[19]:
```
male_2007 = nyc_deaths[(nyc_deaths['year'] == 2007) & (nyc_deaths['sex'] == 'M')]
race_death = male_2007.pivot(index='cause', columns='race', values='deaths')
race_death
```

race	Asian	Black	Hispanic	Unknown	White
cause					
Accidents	53.0	158.0	154.0	13.0	297.0
Cancer	528.0	1523.0	1013.0	74.0	3356.0
Diabetes	47.0	246.0	177.0	20.0	237.0
Flu and Pneumonia	66.0	229.0	189.0	20.0	530.0
HIV	NaN	377.0	218.0	6.0	NaN
Heart Disease	496.0	2121.0	1327.0	122.0	5632.0
Homicide	NaN	267.0	114.0	NaN	NaN
Hypertension	25.0	137.0	NaN	NaN	123.0
Liver Disease	18.0	NaN	107.0	NaN	NaN
Other	221.0	1163.0	988.0	67.0	1749.0
Respiratory Diseases	43.0	137.0	NaN	NaN	345.0
Stroke	56.0	213.0	126.0	7.0	267.0
Substance Abuse	NaN	163.0	183.0	10.0	261.0
Suicide	36.0	NaN	NaN	5.0	187.0

Exercise 3

Use the result from Exercise 2 and highlight the leading cause of death for each race. Is it the same for each one?

Cancer is the most common among Asian and Pacific Islanders. Heart Disease for everyone else.

[20]:
```
race_death.style.highlight_max()
```

race cause	Asian	Black	Hispanic	Unknown	White
Accidents	53.000000	158.000000	154.000000	13.000000	297.000000
Cancer	528.000000	1523.000000	1013.000000	74.000000	3356.000000
Diabetes	47.000000	246.000000	177.000000	20.000000	237.000000
Flu and Pneumonia	66.000000	229.000000	189.000000	20.000000	530.000000
HIV	nan	377.000000	218.000000	6.000000	nan
Heart Disease	496.000000	2121.000000	1327.000000	122.000000	5632.000000
Homicide	nan	267.000000	114.000000	nan	nan
Hypertension	25.000000	137.000000	nan	nan	123.000000
Liver Disease	18.000000	nan	107.000000	nan	nan
Other	221.000000	1163.000000	988.000000	67.000000	1749.000000
Respiratory Diseases	43.000000	137.000000	nan	nan	345.000000
Stroke	56.000000	213.000000	126.000000	7.000000	267.000000
Substance Abuse	nan	163.000000	183.000000	10.000000	261.000000
Suicide	36.000000	nan	nan	5.000000	187.000000

Exercise 4

Read in the flights dataset. Find the total number of flights from each airline by their origin airport. Hint: When making a pivot table of just frequency, its not necessary to have a `values` column. Save the results to a variable.

[21]:
```
flights = pd.read_csv('../data/flights.csv')
flights.head()
```

	date	airline	origin	dest	dep_time	...	carrier_delay	weather_delay	nas_delay	security_delay	late_aircraft_delay
0	2018-01-01	UA	LAS	IAH	100	...	0	0	0	0	0
1	2018-01-01	WN	DEN	PHX	515	...	0	0	0	0	0
2	2018-01-01	B6	JFK	BOS	550	...	0	83	8	0	0
3	2018-01-01	B6	DTW	BOS	600	...	0	0	19	0	0
4	2018-01-01	UA	LAS	EWR	600	...	0	0	0	0	0

[22]:
```
airline_origin = flights.pivot_table(index='airline', columns='origin',
                                     aggfunc='size', fill_value=0)
airline_origin
```

origin	ATL	BOS	CLT	DCA	DEN	...	ORD	PHL	PHX	SEA	SFO
airline											
9E	7	102	88	55	0	...	47	14	0	0	0
AA	442	1084	1935	767	393	...	1716	1275	1264	340	492
AS	22	76	0	48	81	...	96	33	93	995	542
B6	113	1053	60	204	37	...	100	92	32	51	161
DL	2789	545	242	369	425	...	360	248	262	710	527
EV	0	0	11	66	0	...	0	0	0	0	0
F9	59	0	28	44	368	...	67	64	40	23	44
MQ	32	8	0	1	0	...	65	36	0	0	0
NK	190	85	0	0	104	...	247	97	21	66	0
OH	43	0	92	47	0	...	0	4	0	0	0
OO	47	17	73	35	60	...	449	22	82	51	143
UA	168	541	31	210	1338	...	1755	187	312	377	1415
VX	0	16	0	2	10	...	8	6	0	32	122
WN	531	70	0	70	866	...	0	134	710	156	382
YV	62	0	31	34	0	...	0	18	81	0	0
YX	176	130	154	607	30	...	258	64	0	0	0

Exercise 5

Highlight the origin airport with the most flights for each airline. Do a few online searches to determine if those airports are hubs for those airlines.

[23]:
```
airline_origin.style.highlight_max(axis=1)
```

origin	ATL	BOS	CLT	DCA	DEN	DFW	DTW	EWR	IAH	JFK	LAS	LAX	LGA	MCO	MSP	ORD	PHL	PHX	SEA	SFO
airline																				
9E	7	102	88	55	0	88	117	44	52	285	0	0	56	0	82	47	14	0	0	0
AA	442	1084	1935	767	393	2337	199	262	287	594	559	1152	780	631	270	1716	1275	1264	340	492
AS	22	76	0	48	81	51	21	134	24	155	259	535	0	44	35	96	33	93	995	542
B6	113	1053	60	204	37	32	46	172	0	701	107	220	127	474	34	100	92	32	51	161
DL	2789	545	242	369	425	243	1263	197	93	731	472	920	641	639	1428	360	248	262	710	527
EV	0	0	11	66	0	1	6	59	3	0	0	0	25	0	0	0	0	0	0	0
F9	59	0	28	44	368	19	22	0	21	0	92	42	34	140	34	67	64	40	23	44
MQ	32	8	0	1	0	6	49	12	57	34	0	0	65	0	8	65	36	0	0	0
NK	190	85	0	0	104	291	230	79	211	0	383	219	78	309	154	247	97	21	66	0
OH	43	0	92	47	0	0	51	2	0	5	0	0	8	0	5	0	4	0	0	0
OO	47	17	73	35	60	124	193	71	95	29	58	237	111	0	188	449	22	82	51	143
UA	168	541	31	210	1338	273	61	1420	1430	0	491	887	361	473	152	1755	187	312	377	1415
VX	0	16	0	2	10	0	0	13	0	36	50	127	0	7	0	8	6	0	32	122
WN	531	70	0	70	866	0	110	62	0	0	734	574	106	278	129	0	134	710	156	382
YV	62	0	31	34	0	70	38	0	346	0	0	0	6	0	43	0	18	81	0	0
YX	176	130	154	607	30	153	228	348	178	51	0	0	661	0	162	258	64	0	0	0

American Airlines (AA) has a hub at DFW

Exercise 6

Read in the bikes dataset. For each type of weather event (the `events` column) find the median temperature for males and females.

[24]:
```
bikes = pd.read_csv('../data/bikes.csv')
```

[25]:
```
bikes.pivot_table(index='events', columns='gender',
                  values='temperature', aggfunc='median').style.
↪highlight_max(axis='columns')
```

gender	Female	Male
events		
clear	64.000000	62.600000
cloudy	61.000000	57.000000
fog	54.000000	52.000000
hazy	60.100000	57.900000
mostlycloudy	72.000000	71.100000
partlycloudy	71.100000	69.100000
rain	59.000000	57.900000
sleet	30.900000	32.000000
snow	28.450000	28.000000
tstorms	74.450000	75.900000
unknown	-9999.000000	50.000000

Exercise 7

Reshape the movie dataset so that there are two columns, one for all of the actors and one for the content rating of each of their respective movies. Filter this DatFrame so that it contains the top 10 most common actors. Then create a table that displays the number of movies each actor made by content rating. The actor names should be in the index, with the content ratings in the columns, with the counts as the values.

[26]:
```
actor_rating = movie.melt(id_vars='content_rating', value_vars=['actor1', 'actor2',␣
↪'actor3'],
                          value_name='actor')
actor_rating = actor_rating.drop(columns='variable')
actor_rating.head()
```

	content_rating	actor
0	PG-13	CCH Pounder
1	PG-13	Johnny Depp
2	PG-13	Christoph Waltz
3	PG-13	Tom Hardy
4	NaN	Doug Walker

[27]:
```
top10_actors = actor_rating['actor'].value_counts().index[:10]
top10_actors
```

[27]:
```
Index(['Robert De Niro', 'Morgan Freeman', 'Bruce Willis', 'Matt Damon',
       'Steve Buscemi', 'Johnny Depp', 'Brad Pitt', 'Nicolas Cage',
       'Liam Neeson', 'Bill Murray'],
      dtype='object')
```

[28]:
```
actor_rating_top10 = actor_rating[actor_rating['actor'].isin(top10_actors)]
actor_rating_top10.head()
```

	content_rating	actor
1	PG-13	Johnny Depp
13	PG-13	Johnny Depp
14	PG-13	Johnny Depp
18	PG-13	Johnny Depp
28	PG-13	Liam Neeson

[29]:
```
actor_rating_top10.pivot_table(index='actor', columns='content_rating',␣
↪aggfunc='size', fill_value=0)
```

content_rating actor	G	Not Rated	PG	PG-13	R	X
Bill Murray	0	0	9	11	11	0
Brad Pitt	0	0	3	10	20	0
Bruce Willis	0	0	2	15	21	0
Johnny Depp	0	0	7	13	15	1
Liam Neeson	0	1	4	11	15	0
Matt Damon	1	0	2	18	16	0
Morgan Freeman	1	0	5	20	17	0
Nicolas Cage	0	0	5	9	19	0
Robert De Niro	0	0	4	12	37	0
Steve Buscemi	3	1	5	12	15	0

9.3 3. Common messy datasets

Exercise 1

Make the `country_hour_price.csv` dataset tidy by putting all the hour columns into a single column.

[30]:
```
df = pd.read_csv('../data/tidy/country_hour_price.csv')
df
```

	ASID	BORDER	HOUR1	HOUR2
0	21	GERMANY	2	3
1	32	FRANCE	2	3
2	99	ITALY	2	3
3	77	USA	4	5
4	66	CANADA	4	5
5	55	MEXICO	4	5
6	44	INDIA	6	7
7	88	CHINA	6	7
8	111	JAPAN	6	7

[31]:
```
df_tidy = df.melt(id_vars=['ASID', 'BORDER'],
                  value_vars=['HOUR1', 'HOUR2'],
                  var_name = 'Hour')
df_tidy.head()
```

	ASID	BORDER	Hour	value
0	21	GERMANY	HOUR1	2
1	32	FRANCE	HOUR1	2
2	99	ITALY	HOUR1	2
3	77	USA	HOUR1	4
4	66	CANADA	HOUR1	4

[32]:
```
df_tidy.dtypes
```

[32]:
```
ASID       int64
BORDER    object
Hour      object
value      int64
dtype: object
```

Exercise 2

If the resulting DataFrame from Exercise 1 has the strings 'HOUR1' and 'HOUR2' as values in the hour column, then extract just the numerical part of the strings and reassign the result to the hour column.

[33]:
```
df_tidy['Hour'] = df_tidy['Hour'].str.extract('(\d)').astype('int')
df_tidy.head()
```

	ASID	BORDER	Hour	value
0	21	GERMANY	1	2
1	32	FRANCE	1	2
2	99	ITALY	1	2
3	77	USA	1	4
4	66	CANADA	1	4

[34]:
```
df_tidy.dtypes
```

[34]:
```
ASID       int64
BORDER    object
Hour       int64
value      int64
dtype: object
```

Exercise 3

Tidy the `tidy/flights_status.csv` dataset.

[35]:
```
fs = pd.read_csv('../data/tidy/flight_status.csv')
fs.head()
```

	airline	status	ATL	DEN	DFW	...	LAX	MSP	ORD	PHX	SFO
0	AA	Delayed	42	57	893	...	202	25	378	170	68
1	AA	On Time	191	162	3113	...	783	122	1118	709	297
2	AS	Delayed	3	4	2	...	23	4	7	5	23
3	AS	On Time	10	46	45	...	239	11	45	59	114
4	B6	Delayed	0	10	5	...	32	0	30	5	33

[36]:
```
fs1 = fs.melt(id_vars=['airline', 'status'], var_name='airport', value_name='count')
fs1.head(15)
```

	airline	status	airport	count
0	AA	Delayed	ATL	42
1	AA	On Time	ATL	191
2	AS	Delayed	ATL	3
3	AS	On Time	ATL	10
4	B6	Delayed	ATL	0
5	B6	On Time	ATL	0
6	DL	Delayed	ATL	924
7	DL	On Time	ATL	5696
8	EV	Delayed	ATL	373
9	EV	On Time	ATL	1319
10	F9	Delayed	ATL	41
11	F9	On Time	ATL	107
12	HA	Delayed	ATL	0
13	HA	On Time	ATL	0
14	MQ	Delayed	ATL	23

[37]:
```
fs_tidy = fs1.pivot_table(index=['airline', 'airport'], columns='status',␣
↪values='count', aggfunc='max')
fs_tidy.head()
```

	status	Delayed	On Time
airline	**airport**		
AA	**ATL**	42	191
	DEN	57	162
	DFW	893	3113
	IAH	40	156
	LAS	79	295

[38]:
```
fs_tidy_final = fs_tidy.reset_index().rename_axis(None, axis='columns')
fs_tidy_final.head(10)
```

	airline	airport	Delayed	On Time
0	AA	ATL	42	191
1	AA	DEN	57	162
2	AA	DFW	893	3113
3	AA	IAH	40	156
4	AA	LAS	79	295
5	AA	LAX	202	783
6	AA	MSP	25	122
7	AA	ORD	378	1118
8	AA	PHX	170	709
9	AA	SFO	68	297

Exercise 4

Tidy the `tidy/metrics.csv` dataset.

[39]:
```
df = pd.read_csv('../data/tidy/metrics.csv')
df
```

	year	metric	Black Male	Black Female	White Male	White Female	Hispanic Male	Hispanic Female
0	2010	income	54885	51058	53941	58671	55344	52187
1	2010	life expectancy	77	72	73	70	79	73
2	2011	income	57073	58494	59718	58239	53891	59914
3	2011	life expectancy	70	76	79	79	77	74
4	2012	income	57028	50207	52610	58672	55844	55632
5	2012	life expectancy	78	72	73	73	75	74

[40]:
```
df1 = df.melt(id_vars=['year', 'metric'], var_name='race sex')
df1.head()
```

	year	metric	race sex	value
0	2010	income	Black Male	54885
1	2010	life expectancy	Black Male	77
2	2011	income	Black Male	57073
3	2011	life expectancy	Black Male	70
4	2012	income	Black Male	57028

[41]:
```
df2 = df1.pivot_table(index=['year', 'race sex'], columns='metric', values='value',␣
↪aggfunc='max')
df3 = df2.reset_index().rename_axis(None, axis='columns')
df3.head()
```

	year	race sex	income	life expectancy
0	2010	Black Female	51058	72
1	2010	Black Male	54885	77
2	2010	Hispanic Female	52187	73
3	2010	Hispanic Male	55344	79
4	2010	White Female	58671	70

[42]:
```
df3[['race', 'sex']] = df3['race sex'].str.split(expand=True)
df3.head()
```

	year	race sex	income	life expectancy	race	sex
0	2010	Black Female	51058	72	Black	Female
1	2010	Black Male	54885	77	Black	Male
2	2010	Hispanic Female	52187	73	Hispanic	Female
3	2010	Hispanic Male	55344	79	Hispanic	Male
4	2010	White Female	58671	70	White	Female

[43]:
```
df4 = df3.drop(columns='race sex')
df4.head()
```

	year	income	life expectancy	race	sex
0	2010	51058	72	Black	Female
1	2010	54885	77	Black	Male
2	2010	52187	73	Hispanic	Female
3	2010	55344	79	Hispanic	Male
4	2010	58671	70	White	Female

Part X

Joining Data

Chapter 10

Solutions

10.1 4. Data Normalization

[ ]:

Part XI

Visualization with Matplotlib

Chapter 11

Solutions

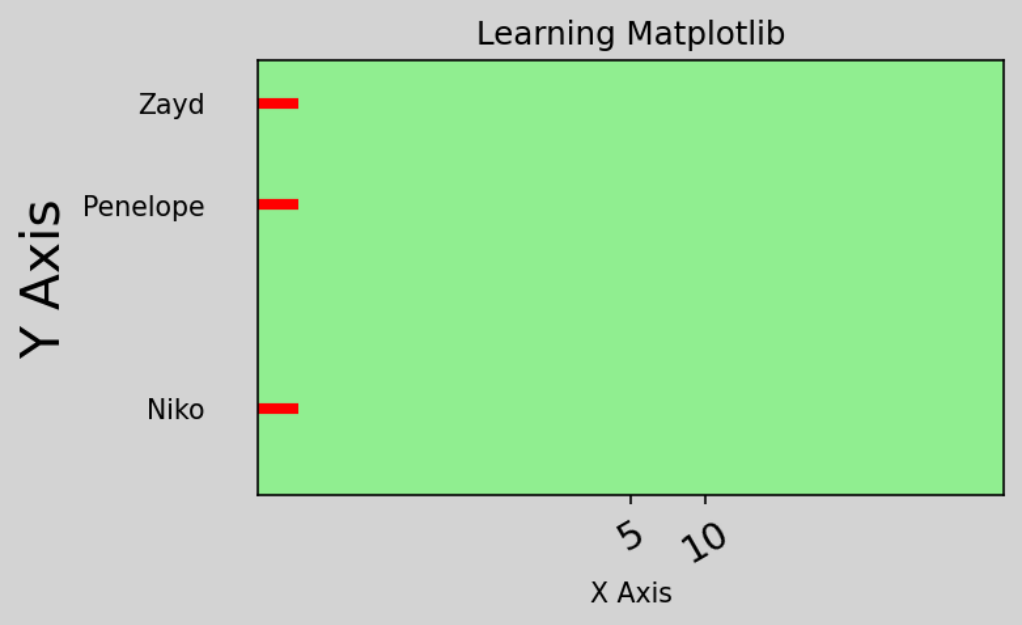
11.1 1. Introduction to matplotlib

[1]:
```
import matplotlib.pyplot as plt
```

Exercise 1

Create a figure with dimensions 5 inches by 3 inches with 147 DPI containing a single axes. Set the facecolor of the figure and the axes. Set a title and labels for the x and y axis. Set three ticks on the y-axis, and two on the x-axis. Give the three ticks on the y-axis a new string label. Change the limits of the x-axis and y-axis so they are larger than the minimum and maximum tick values. Change the size, shape, and color of the y-axis tick lines. Increase the size of the x tick labels and rotate them.

[2]:
```
fig, ax = plt.subplots(figsize=(5, 3), dpi=147)
fig.set_facecolor('lightgray')
ax.set_facecolor('lightgreen')
ax.set_title('Learning Matplotlib')
ax.set_ylabel('Y Axis', size=20)
ax.set_xlabel('X Axis')
ax.set_xticks([5, 10])
ax.set_yticks([-9, 5, 12])
ax.set_yticklabels(['Niko', 'Penelope', 'Zayd'])
ax.set_xlim(-20, 30)
ax.set_ylim(-15, 15)
ax.tick_params(axis='y', direction='in', length=15, width=4, pad=20, color='red')
ax.tick_params(axis='x', labelsize=14, labelrotation=30)
```



11.2 2. Matplotlib Text and Lines

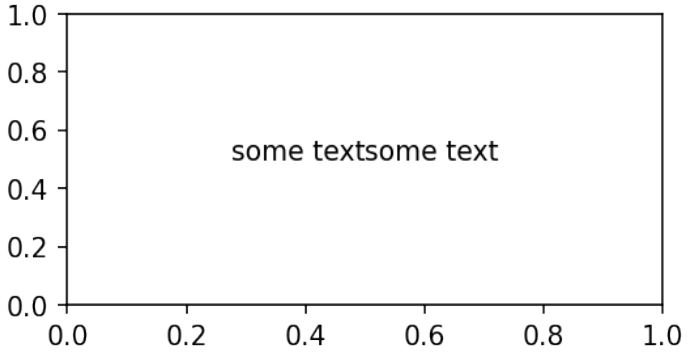
Create a new figure and axes for each exercise.

[3]:
```
import matplotlib.pyplot as plt
```

Exercise 1

Add the same text to the same location, but set the horizontal alignment of each so that they don't overlap.

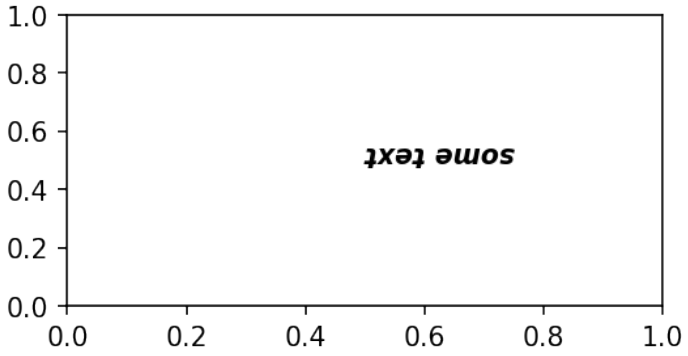
[4]:
```
fig, ax = plt.subplots(figsize=(4, 2), dpi=147)
ax.text(x=.5, y=.5, s='some text', ha='left')
ax.text(x=.5, y=.5, s='some text', ha='right');
```



Exercise 2

Add text so that it is upside down. Use `fontweight` and `fontstyle` to make the text bold and italic.

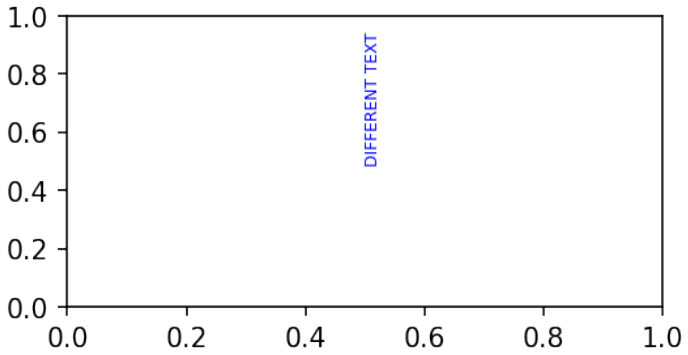
[5]:
```
fig, ax = plt.subplots(figsize=(4, 2), dpi=147)
ax.text(x=.5, y=.5, s='some text', rotation=180, fontweight='bold',␣
↪fontstyle='italic');
```



Exercise 3

Add a simple piece of text using no other parameters other than `x`, `y`, and `s`. Assign the result to a variable and then use the setter methods to set several properties.

[6]:
```
fig, ax = plt.subplots(figsize=(4, 2), dpi=147)
text = ax.text(x=.5, y=.5, s='some text')
text.set_text('DIFFERENT TEXT')
text.set_rotation(90)
text.set_fontsize(6)
text.set_color('blue');
```

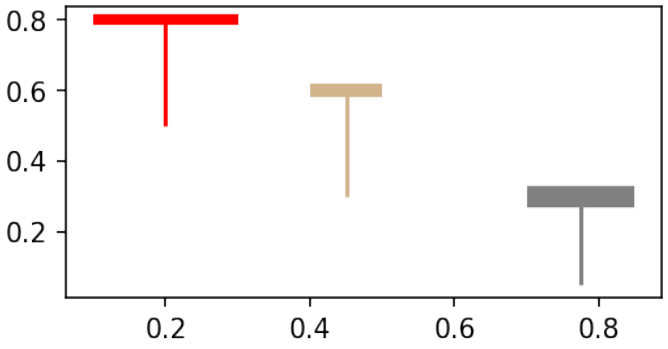


Exercise 4

Create three "T's" using `hlines` and `vlines` in different locations, each with a different color and line width.

[7]:
```
fig, ax = plt.subplots(figsize=(4, 2), dpi=147)
ax.hlines(y=[.8, .6, .3], xmin=[.1, .4, .7], xmax=[.3, .5, .85],
          colors=['red', 'tan', 'gray'], linewidth=[4, 5, 8])
ax.vlines(x=[.2, .45, .775], ymin=[.5, .3, .05], ymax=[.8, .6, .3],
          colors=['red', 'tan', 'gray'])
```

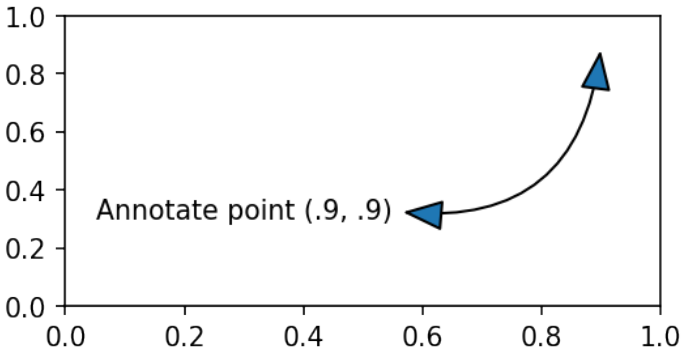
[7]:
```
<matplotlib.collections.LineCollection at 0x1185d7dd0>
```



Exercise 5

Annotate a point with a double-headed arrow.

[8]:
```
fig, ax = plt.subplots(figsize=(4, 2), dpi=147)
arrowprop_dict = {'arrowstyle': '<|-|>, head_length=1.3, head_width=.5',
                  'connectionstyle': 'arc3, rad=.5', 'relpos': (1, .5)}
ax.annotate(s='Annotate point (.9, .9)', xytext=(.3, .3), xy=(.9, .9),
            arrowprops=arrowprop_dict, ha='center');
```



11.3 3. Matplotlib Resolution

Create a new figure and axes for each exercise.

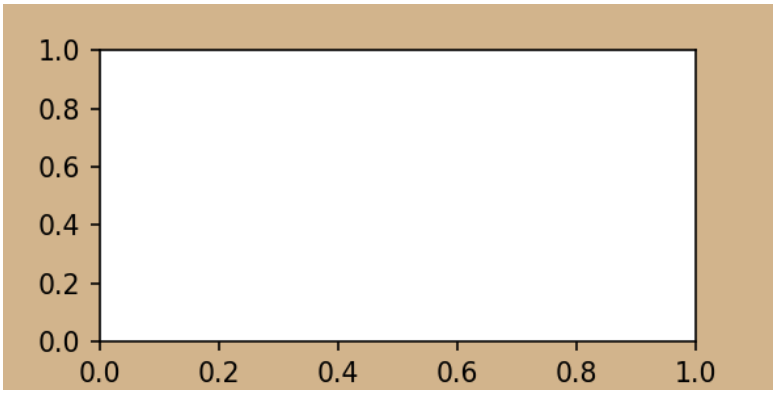
[9]:
```
import matplotlib.pyplot as plt
```

Exercise 1

Find your screen's DPI and verify it by creating a matplotlib figure with that DPI. Measure the figure with a ruler to verify that the figure-inches match the screen-inches. Set the `'bbox_inches'` notebook setting to `None` and then back to `'tight'` after the exercise.

[10]:
```
%config InlineBackend.print_figure_kwargs = {'bbox_inches': None}
```

[11]:
```
fig, ax = plt.subplots(figsize=(4, 2), dpi=147, facecolor='tan')
```



Exercise 2

If you create a figure that has a height of 3 inches and a DPI of 120 and add a line that has a width of 144 points, what fraction of the screen height will the line represent?

[12]:
```
# DPI has nothing to do with this
144 / (3 * 72)
```

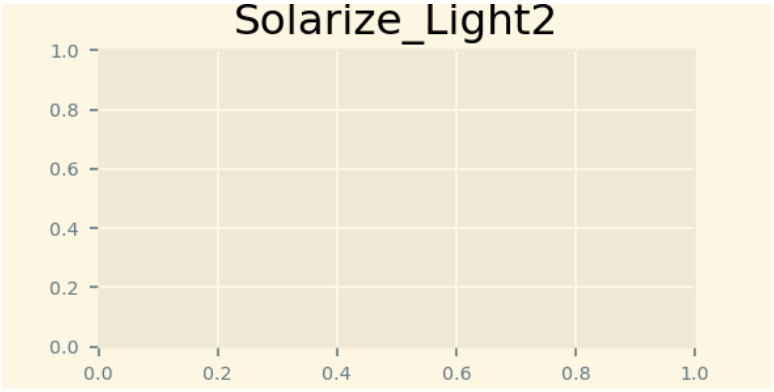
[12]:
```
0.6666666666666666
```

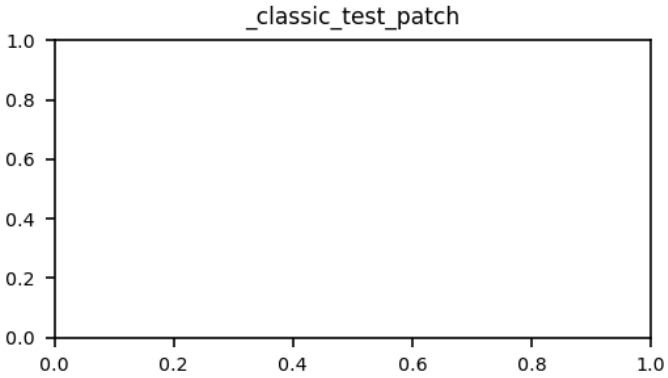
Exercise 3

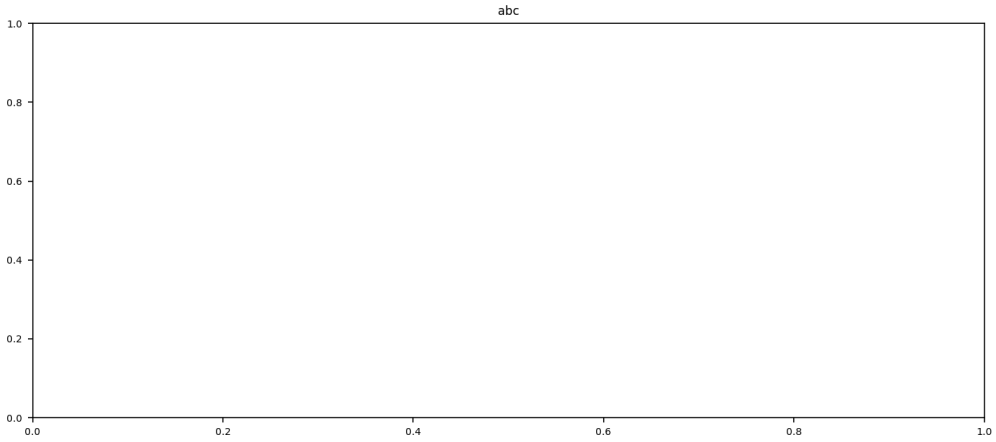
Iterate through all the available styles creating a figure and axes with each one. Put the name of the style in the axes title.

Only a few styles are show to avoid long output.

[13]:
```
for style in plt.style.available[:3]:
    plt.style.use(['default', '../../mdap.mplstyle', style])
    fig, ax = plt.subplots()
    ax.set_title(style)
```







Exercise 4

Create your own style sheet. You might want to begin by copying one of the pre-made stylesheets.

[ ]:

11.4 4. Matplotlib Patches and Colors

Create a new figure and axes for each exercise.

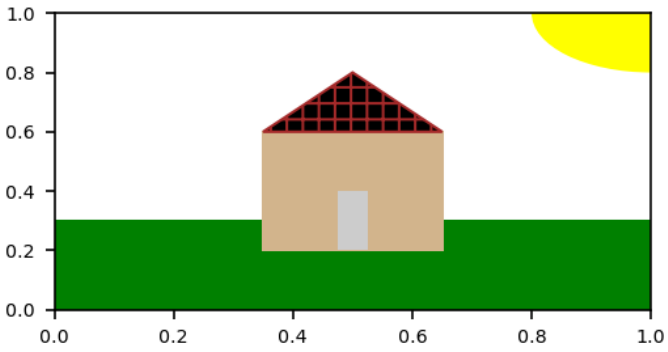
[14]:
```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import patches
plt.style.use(['default', '../../mdap.mplstyle'])
```

Exercise 1

Create a simple house with a roof, door, yard, and sun shinning overhead with matplotlib patches.

[15]:
```
fig, ax = plt.subplots()
ax.add_patch(patches.Rectangle((0, 0), width=1, height=.3, color='green'))
ax.add_patch(patches.Rectangle((.35, .2), width=.3, height=.4, color='tan'))
ax.add_patch(patches.Polygon([[.35, .6], [.5, .8], [.65, .6]],
                             fc='black', hatch='++', ec='brown'))
ax.add_patch(patches.Rectangle((.475, .2), width=.05, height=.2, fc='.8'))
```

```
ax.add_patch(patches.Circle((1, 1), radius=.2, fc='yellow'));
```



Exercise 2

Convert the RGB float triple `(.7, .03, .8)` to a hexadecimal string. Do so without using matplotlib, then verify with one of the functions from the `colors` module.

[16]:
```
hex(round(.7 * 255))
```

[16]:
```
'0xb2'
```

[17]:
```
hex(round(.03 * 255))
```

[17]:
```
'0x8'
```

[18]:
```
hex(round(.8 * 255))
```

[18]:
```
'0xcc'
```

The string should be `'#b208cc'`

[19]:
```
from matplotlib import colors
```

[20]:
```
colors.to_hex((.7, .03, .8))
```

[20]:
```
'#b208cc'
```

Exercise 3

Convert the RGB string `'#7cf2bb'` to an RGB float triple. Do so without using matplotlib, then verify with one of the functions from the `colors` module.

[21]:
```
r = int('7c', base=16) / 255
g = int('f2', base=16) / 255
b = int('bb', base=16) / 255
r, g, b
```

[21]:
```
(0.48627450980392156, 0.9490196078431372, 0.7333333333333333)
```

[22]:
```
colors.to_rgb('#7cf2bb')
```

[22]:
```
(0.48627450980392156, 0.9490196078431372, 0.7333333333333333)
```

Exercise 4

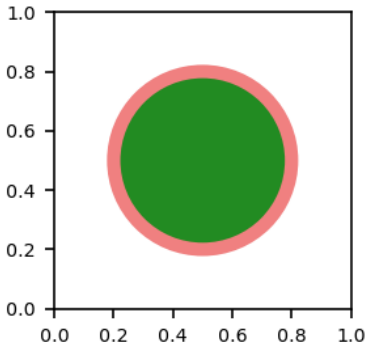
Create a circle that visually looks like a circle that has edge color of lightcoral and face color of forestgreen. Use the hexadecimal representation for these strings. Increase the edge width so that it is more visible.

[23]:
```
colors.to_hex('lightcoral'), colors.to_hex('forestgreen')
```

[23]:
```
('#f08080', '#228b22')
```

[24]:
```
fig, ax = plt.subplots()
ax.set_aspect('equal')
ax.add_patch(patches.Circle((.5, .5), radius=.3, ec='#f08080', fc='#228b22', lw=5))
```

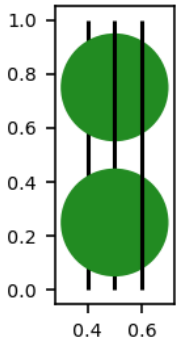
[24]:
```
<matplotlib.patches.Circle at 0x118ed5150>
```



Exercise 5

Create two circles of the same size vertically next to one another (same x-value, different y-value) without any overlap. Draw three vertical lines that pass through both circles. Place one of these lines underneath both circles, another on top of the top circle and below the bottom circle, and the last line on top of both circles.

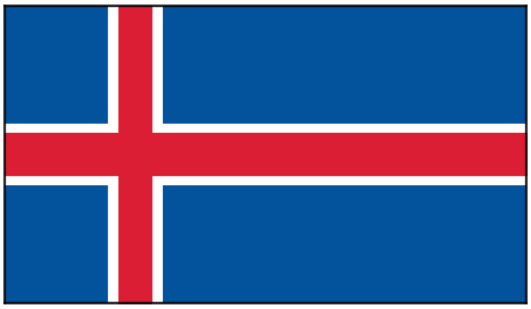
[25]:
```
fig, ax = plt.subplots()
ax.set_aspect('equal')
ax.add_patch(patches.Circle((.5, .75), radius=.2, fc='forestgreen', zorder=1))
ax.add_patch(patches.Circle((.5, .25), radius=.2, fc='forestgreen', zorder=3))
ax.vlines(x=.5, ymin=0, ymax=1, zorder=2)
ax.vlines(x=.4, ymin=0, ymax=1, zorder=0)
ax.vlines(x=.6, ymin=0, ymax=1, zorder=4);
```



Exercise 6

Create the flag of Iceland with matplotlib. Search online for its RGB color values.

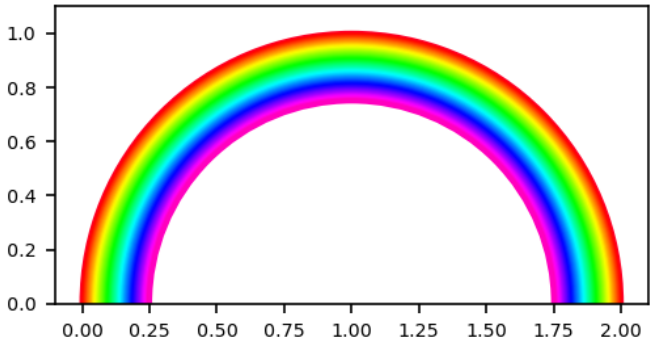
[26]:
```
fig, ax = plt.subplots(figsize=(3.5, 2))
ax.set_xticks([])
ax.set_yticks([])
ax.set_xlim(0, 1)
ax.set_ylim(0, 1)
ax.set_facecolor('#02529C')
ax.fill_between(x=[0, 1], y1=.4, y2=.6, color='#FFFFFF')
ax.fill_betweenx(y=[0, 1], x1=.2, x2=.3, color='#FFFFFF')
ax.fill_between(x=[0, 1], y1=.43, y2=.57, color='#DC1E35')
ax.fill_betweenx(y=[0, 1], x1=.22, x2=.28, color='#DC1E35');
```



Exercise 7

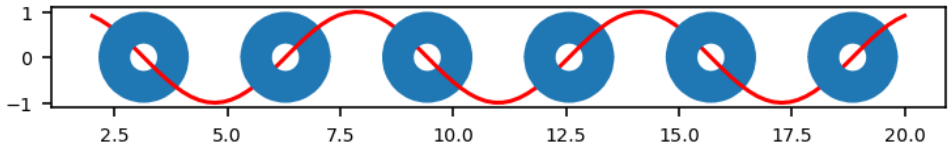
Create a rainbow. Use a colormap that has the colors of the rainbow.

[27]:
```
from matplotlib import cm
import numpy as np
fig, ax = plt.subplots(figsize=(4, 2))
ax.set_aspect('equal')
ax.set_xlim(-.1, 2.1)
ax.set_ylim(0, 1.1)
for val in np.linspace(0, 1, 50):
    ax.add_patch(patches.Arc((1, 0), width=2 - val / 2, height=2 - val / 2,
                             theta1=0, theta2=180, lw=2, color=cm.gist_rainbow(val)))
```

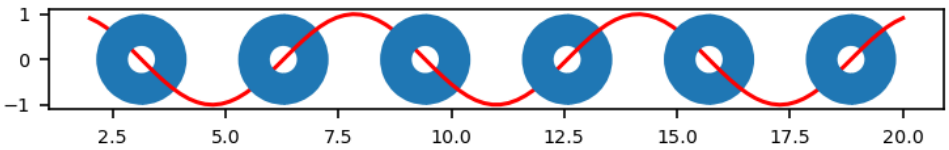


Exercise 8

Recreate the following image in matplotlib.



[28]:
```
fig, ax = plt.subplots(figsize=(6, 1))
ax.set_aspect('equal')
x = np.linspace(2, 20, 100)
y = np.sin(x)
ax.plot(x, y, color='red')
for i in range(1, 7):
    ax.add_patch(patches.Wedge((i * np.pi, 0), r=1, theta1=87, theta2=273,
                               width=.7, zorder=3))
    ax.add_patch(patches.Wedge((i * np.pi, 0), r=1, theta1=270, theta2=90,
                               width=.7, zorder=1))
```



11.5 5. Matplotlib Line Plots

Create a new figure and axes for each exercise.

[29]:
```
import matplotlib.pyplot as plt
plt.style.use('../../mdap.mplstyle')
from matplotlib import patches
import pandas as pd
```

[30]:
```
pd.set_option('display.max_columns', 100)

cols = ['GrLivArea', 'GarageArea', 'TotalBsmtSF',
        'OverallQual', 'Neighborhood', 'SalePrice']
```

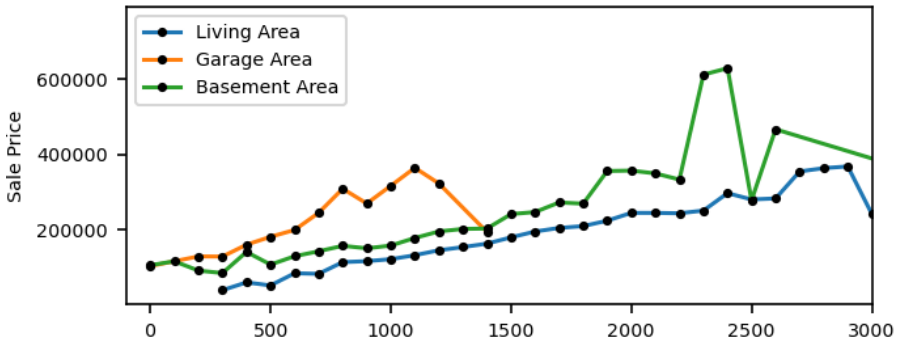
```
housing = pd.read_csv('../data/housing.csv', usecols=cols)

housing
```

	Neighborhood	OverallQual	TotalBsmtSF	GrLivArea	GarageArea	SalePrice
0	CollgCr	7	856	1710	548	208500
1	Veenker	6	1262	1262	460	181500
2	CollgCr	7	920	1786	608	223500
3	Crawfor	7	756	1717	642	140000
4	NoRidge	8	1145	2198	836	250000
5	Mitchel	5	796	1362	480	143000
6	Somerst	8	1686	1694	636	307000
7	NWAmes	7	1107	2090	484	200000
8	OldTown	7	952	1774	468	129900
9	BrkSide	5	991	1077	205	118000
10	Sawyer	5	1040	1040	384	129500
11	NridgHt	9	1175	2324	736	345000
12	Sawyer	5	912	912	352	144000
13	CollgCr	7	1494	1494	840	279500
14	NAmes	6	1253	1253	352	157000
...	...	...	...	...	...	...
1445	Sawyer	6	814	913	240	129000
1446	Mitchel	5	1188	1188	312	157900
1447	CollgCr	8	1220	2090	556	240000
1448	Edwards	4	560	1346	384	112000
1449	MeadowV	5	630	630	0	92000
1450	NAmes	5	896	1792	0	136000
1451	Somerst	8	1573	1578	840	287090
1452	Edwards	5	547	1072	525	145000
1453	Mitchel	5	1140	1140	0	84500
1454	Somerst	7	1221	1221	400	185000
1455	Gilbert	6	953	1647	460	175000
1456	NWAmes	6	1542	2073	500	210000
1457	Crawfor	7	1152	2340	252	266500
1458	NAmes	5	1078	1078	240	142125
1459	Edwards	5	1256	1256	276	147500

Exercise 1

Create line plots of the average sale price per every 100 square feet of living area, garage area, and basement area. Place markers at every point and add a legend.

[31]:
```
housing = housing.round({'GrLivArea': -2, 'GarageArea': -2, 'TotalBsmtSF': -2})
price_per_lasf = housing.groupby('GrLivArea').agg(avg_sale_price=('SalePrice', 'mean'))
price_per_gasf = housing.groupby('GarageArea').agg(avg_sale_price=('SalePrice',␣
↪'mean'))
price_per_bsf = housing.groupby('TotalBsmtSF').agg(avg_sale_price=('SalePrice',␣
↪'mean'))
fig, ax = plt.subplots(figsize=(5, 2))
ax.plot(price_per_lasf, marker='.', mec='black', mfc='black', ms=5, label='Living␣
↪Area')
ax.plot(price_per_gasf, marker='.', mec='black', mfc='black', ms=5, label='Garage␣
↪Area')
ax.plot(price_per_bsf, marker='.', mec='black', mfc='black', ms=5, label='Basement␣
↪Area')
ax.set_xlim(-100, 3000)
ax.set_xlabel('Square Feet')
ax.set_ylabel('Sale Price')
ax.legend();
```



Exercise 2

For every neighborhood that has at least 100 homes, find the average sale price by each overall quality between 3 and 8 (inclusive). Plot each neighborhood as a line with overall quality on the x-axis and sale price on the y-axis. Use one of the qualitative colormaps other than the default tab10. Add a legend inside the bounds of the axes that has a frame, a title, and all labels on one row.

[32]:
```
s = housing['Neighborhood'].value_counts()
neigh_ct = s[s >= 100]
neigh_ct
```

[32]:
```
NAmes      225
CollgCr    150
OldTown    113
Edwards    100
Name: Neighborhood, dtype: int64
```

[33]:
```
neigh = neigh_ct.index
h2 = housing.query('Neighborhood in @neigh and 3 <= OverallQual <= 8')
h2.head(3)
```

	Neighborhood	OverallQual	TotalBsmtSF	GrLivArea	GarageArea	SalePrice
0	CollgCr	7	900	1700	500	208500
2	CollgCr	7	900	1800	600	223500
8	OldTown	7	1000	1800	500	129900

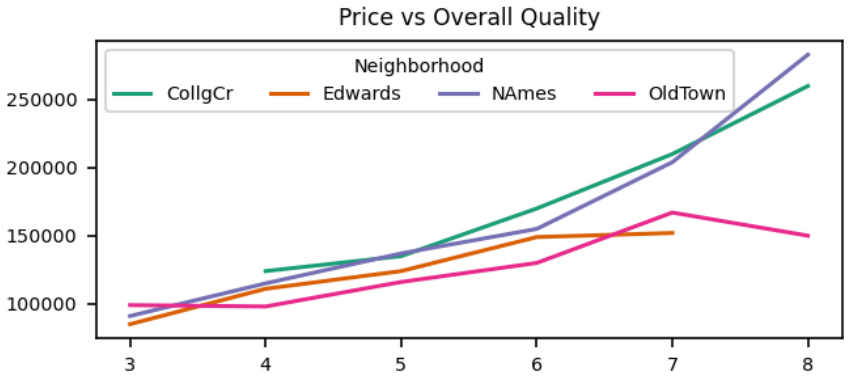
[34]:
```
housing
```

	Neighborhood	OverallQual	TotalBsmtSF	GrLivArea	GarageArea	SalePrice
0	CollgCr	7	900	1700	500	208500
1	Veenker	6	1300	1300	500	181500
2	CollgCr	7	900	1800	600	223500
3	Crawfor	7	800	1700	600	140000
4	NoRidge	8	1100	2200	800	250000
5	Mitchel	5	800	1400	500	143000
6	Somerst	8	1700	1700	600	307000
7	NWAmes	7	1100	2100	500	200000
8	OldTown	7	1000	1800	500	129900
9	BrkSide	5	1000	1100	200	118000
10	Sawyer	5	1000	1000	400	129500
11	NridgHt	9	1200	2300	700	345000
12	Sawyer	5	900	900	400	144000
13	CollgCr	7	1500	1500	800	279500
14	NAmes	6	1300	1300	400	157000
...	...	...	...	...	...	...
1445	Sawyer	6	800	900	200	129000
1446	Mitchel	5	1200	1200	300	157900
1447	CollgCr	8	1200	2100	600	240000
1448	Edwards	4	600	1300	400	112000
1449	MeadowV	5	600	600	0	92000
1450	NAmes	5	900	1800	0	136000
1451	Somerst	8	1600	1600	800	287090
1452	Edwards	5	500	1100	500	145000
1453	Mitchel	5	1100	1100	0	84500
1454	Somerst	7	1200	1200	400	185000
1455	Gilbert	6	1000	1600	500	175000
1456	NWAmes	6	1500	2100	500	210000
1457	Crawfor	7	1200	2300	300	266500
1458	NAmes	5	1100	1100	200	142125
1459	Edwards	5	1300	1300	300	147500

[35]:
```
pt = h2.pivot_table(index='OverallQual', columns='Neighborhood',
                    values='SalePrice', aggfunc='mean').round(-3)
pt
```

Neighborhood	CollgCr	Edwards	NAmes	OldTown
OverallQual				
3	NaN	85000.0	91000.0	99000.0
4	124000.0	111000.0	115000.0	98000.0
5	135000.0	124000.0	137000.0	116000.0
6	170000.0	149000.0	155000.0	130000.0
7	210000.0	152000.0	204000.0	167000.0
8	260000.0	NaN	283000.0	150000.0

[36]:
```
fig, ax = plt.subplots(figsize=(5, 2))
ax.set_prop_cycle(color=cm.Dark2(range(10)))
lines = ax.plot(pt)
ax.legend(handles=lines, labels=pt.columns.tolist(), frameon=True,␣
↪title='Neighborhood', ncol=4)
ax.set_title('Price vs Overall Quality');
```



11.6 6. Matplotlib Scatter and Bar Plots

Create a new figure and axes for each exercise.

[37]:
```
import matplotlib.pyplot as plt
import pandas as pd
plt.style.use('../../mdap.mplstyle')
```

Exercise 1

Read in the bikes dataset and select 500 rows of data at random. Filter for rides with a trip duration less than the 95th percentile. Remove any rows that have obviously bad data for temperature and wind speed. Make a scatter plot with temperature and trip duration as the x and y variables. Color by gender and size by wind speed using a qualitative color map. Use this tutorial to create two separate legends, one for gender, and the other for wind speed.

[38]:
```
bikes = pd.read_csv('../data/bikes.csv')
bikes.head(3)
```

	trip_id	gender	starttime	stoptime	tripduration	...	temperature	visibility	wind_speed	precipitation	events
0	7147	Male	2013-06-28 19:01:00	2013-06-28 19:17:00	993	...	73.9	10.0	12.7	-9999.0	mostlycloudy
1	7524	Male	2013-06-28 22:53:00	2013-06-28 23:03:00	623	...	69.1	10.0	6.9	-9999.0	partlycloudy
2	10927	Male	2013-06-30 14:43:00	2013-06-30 15:01:00	1040	...	73.0	10.0	16.1	-9999.0	mostlycloudy

[39]:
```
bikes2 = bikes.sample(500, random_state=40)
bikes2[['tripduration', 'temperature', 'wind_speed']].describe([.95])
```

	tripduration	temperature	wind_speed
count	500.000000	500.000000	500.000000
mean	696.688000	42.822800	-49.603800
std	442.267262	450.314855	773.790169
min	88.000000	-9999.000000	-9999.000000
50%	569.500000	66.900000	10.400000
95%	1498.400000	84.900000	19.600000
max	3838.000000	93.000000	31.100000

95th percentile of trip duration is about 1500. The minimum for both temperature and wind_speed is -9999.

[40]:
```
bikes3 = bikes2.query('tripduration < 1500 and temperature > -50 and wind_speed > 0').
↪copy()
bikes3.shape
```

[40]:
```
(455, 14)
```

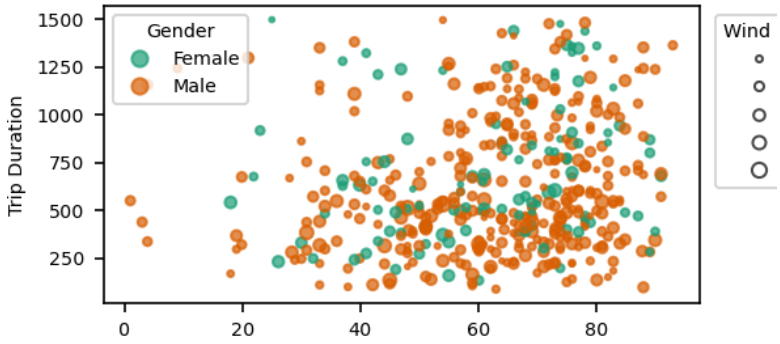
[41]:
```
bikes3['gender'] = bikes2['gender'].astype('category')
bikes3['gender_code'] = bikes3['gender'].cat.codes
gender_categories = bikes3['gender'].cat.categories.tolist()
gender_categories
```

[41]:
```
['Female', 'Male']
```

Wind speed happens to have values that make for good scatter point sizes, so we don't have to transform it.

[42]:
```
fig, ax = plt.subplots()
scatter_obj = ax.scatter('temperature', 'tripduration', s='wind_speed',␣
↪c='gender_code',
                         vmin=0, vmax=7, data=bikes3, cmap='Dark2', alpha=.7)
handles_colors, labels_colors = scatter_obj.legend_elements('colors')
handles_sizes, labels_sizes = scatter_obj.legend_elements('sizes', num=5, mfc='white')
ax.add_artist(ax.legend(handles=handles_colors, labels=gender_categories,
                        title='Gender', loc='upper left'))
```

```
ax.legend(handles_sizes, labels_sizes, title='Wind Speed', bbox_to_anchor=(1.01, 1))
ax.set_xlabel('Temperature')
ax.set_ylabel('Trip Duration');
```



[ ]: