2.1 Filtering Data

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1 Chapter 2. Subgroup Analysis

2 2.1 Filtering Data

In [1]:
```
%matplotlib inline

import pandas as pd
pd.options.display.max_rows = 5
titanic_df = pd.read_csv(
    "https://raw.githubusercontent.com/dlsun/data-science-book/master/data/titanic.csv"
)
titanic_df
```

Out[1]:
```
      pclass  survived                           name     sex      age  \
0          1         1   Allen, Miss. Elisabeth Walton  female  29.0000
1          1         1  Allison, Master. Hudson Trevor    male   0.9167
...      ...       ...                             ...     ...      ...
1307       3         0             Zakarian, Mr. Ortin    male  27.0000
1308       3         0              Zimmerman, Mr. Leo    male  29.0000

      sibsp  parch  ticket      fare    cabin embarked boat  body  \
0         0      0   24160  211.3375       B5        S    2   NaN
1         1      2  113781  151.5500  C22 C26        S   11   NaN
...     ...    ...     ...       ...      ...      ...  ...   ...
1307      0      0    2670    7.2250      NaN        C  NaN   NaN
1308      0      0  315082    7.8750      NaN        S  NaN   NaN

                            home.dest
0                        St Louis, MO
1     Montreal, PQ / Chesterville, ON
...                               ...
1307                              NaN
1308                              NaN

[1309 rows x 14 columns]
```

In the previous chapter, we only analyzed one variable at a time, but we always analyzed *all* of the observations in a data set. But what if we want to analyze, say, only the passengers on the

Titanic who were *male*? To do this, we have to **filter** the data. That is, we have to remove the rows of the `titanic_df` `DataFrame` where `sex` is not equal to `"male"`. In this section, we will learn several ways to obtain such a subsetted `DataFrame`.

2.1 Two Ways to Filter a DataFrame

One way to filter a `pandas` `DataFrame`, that uses a technique we learned in Chapter 1, is to set the filtering variable as the index and select the value you want using `.loc`.

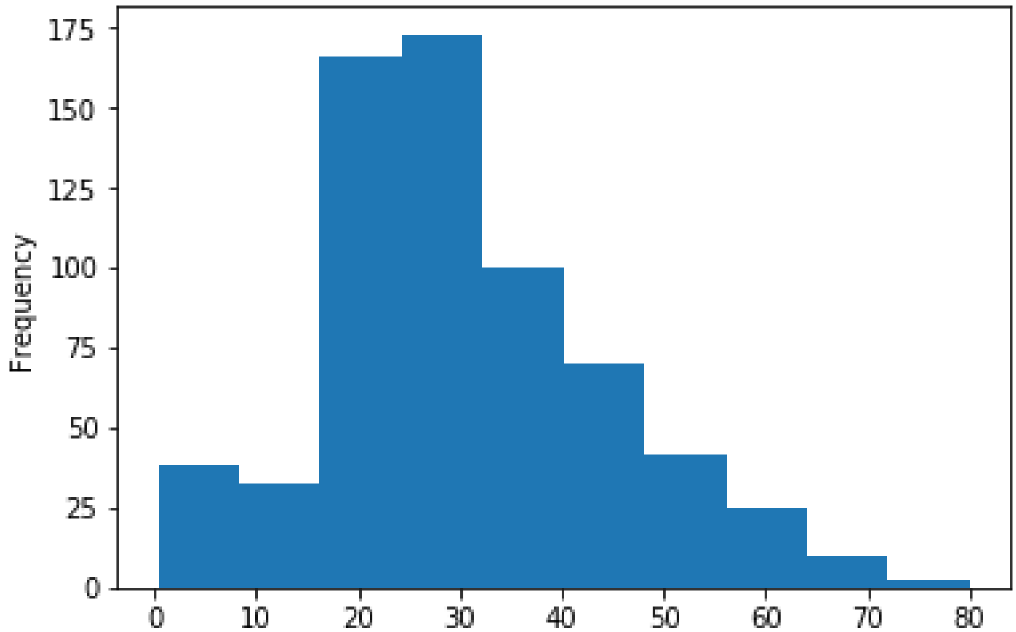
So for example, if we wanted a `DataFrame` with just the male passengers, we could do:

```
In [2]: males = titanic_df.set_index("sex").loc["male"]
        males
```

```
Out[2]:       pclass  survived                              name      age  sibsp  \
        sex
        male       1         1       Allison, Master. Hudson Trevor   0.9167      1
        male       1         0  Allison, Mr. Hudson Joshua Creighton  30.0000      1
        ...      ...       ...                                  ...      ...    ...
        male       3         0                 Zakarian, Mr. Ortin  27.0000      0
        male       3         0                  Zimmerman, Mr. Leo  29.0000      0

              parch  ticket     fare    cabin embarked boat   body  \
        sex
        male      2  113781  151.550  C22 C26        S   11    NaN
        male      2  113781  151.550  C22 C26        S  NaN  135.0
        ...     ...     ...      ...      ...      ...  ...    ...
        male      0    2670    7.225      NaN        C  NaN    NaN
        male      0  315082    7.875      NaN        S  NaN    NaN

                                   home.dest
        sex
        male  Montreal, PQ / Chesterville, ON
        male  Montreal, PQ / Chesterville, ON
        ...                               ...
        male                             NaN
        male                             NaN

        [843 rows x 13 columns]
```

```
In [3]: males.age.plot.hist()
```

```
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0e4ec5ac8>
```



The more common way to filter a DataFrame is to use a **boolean mask**. A boolean mask is simply a Series of booleans whose index matches the index of the DataFrame.

The easiest way to create a boolean mask is to use one of the standard comparison operators ==, <, >, and != on an existing column in the DataFrame. For example, the following code produces a boolean mask that is equal to True for the male passengers and False otherwise.

```
In [4]: titanic_df.sex == "male"
```

```
Out[4]: 0        False
        1         True
                 ...
        1307      True
        1308      True
        Name: sex, Length: 1309, dtype: bool
```

Notice that the equality operator == is not being used in the usual sense, i.e., to determine whether the object titanic_df.sex is the string "male". This makes no sense, since titanic_df.sex is a Series. Instead, the equality operator is being *broadcast* over the elements of titanic_df.sex. As a result, we end up with a Series of booleans that indicates whether *each* element of titanic_df.sex is equal to "male".

This boolean mask can then be passed into a DataFrame to obtain just the subset of rows where the mask equals True.

```
In [5]: titanic_df[titanic_df.sex == "male"]
```

```
Out[5]:      pclass  survived                             name   sex     age  \
        1         1         1   Allison, Master. Hudson Trevor  male  0.9167
```

```
3           1         0  Allison, Mr. Hudson Joshua Creighton  male  30.0000
...       ...       ...                                   ...   ...       ...
1307        3         0                  Zakarian, Mr. Ortin  male  27.0000
1308        3         0                   Zimmerman, Mr. Leo  male  29.0000

      sibsp  parch  ticket     fare    cabin embarked boat    body  \
1         1      2  113781  151.550  C22 C26        S   11     NaN
3         1      2  113781  151.550  C22 C26        S  NaN   135.0
...     ...    ...     ...      ...      ...      ...  ...     ...
1307      0      0    2670    7.225      NaN        C  NaN     NaN
1308      0      0  315082    7.875      NaN        S  NaN     NaN

                            home.dest
1     Montreal, PQ / Chesterville, ON
3     Montreal, PQ / Chesterville, ON
...                               ...
1307                              NaN
1308                              NaN

[843 rows x 14 columns]
```

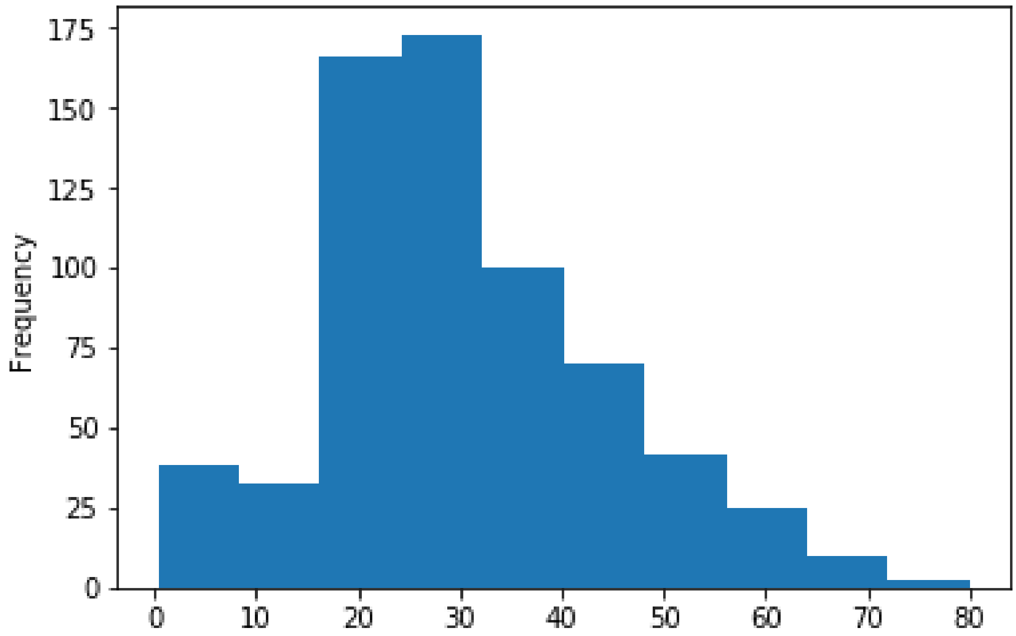
How can we tell that it worked? For one, notice that the index is missing the numbers 0 and 2; that's because passengers 0 and 2 in the original `DataFrame` were female. Also, the index goes up to 1308, but there are only 843 rows in this `DataFrame`.

In this new `DataFrame`, the variable `sex` should only take on one value, `"male"`. Let's check this.

```
In [6]: titanic_df[titanic_df.sex == "male"]["sex"].value_counts()

Out[6]: male    843
        Name: sex, dtype: int64
```

Now we can analyze this subsetted `DataFrame` using the techniques we learned in Chapter 1. For example, the following code produces a histogram of the ages of the male passengers on the Titanic:

```
In [7]: titanic_df[titanic_df.sex == "male"].age.plot.hist()

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0e2da2630>
```



Boolean masks are also compatible with `.loc` and `.iloc`:

```
In [8]: titanic_df.loc[titanic_df.sex == "male"]
```

```
Out[8]:      pclass  survived                             name   sex      age  \
        1         1         1      Allison, Master. Hudson Trevor  male   0.9167
        3         1         0  Allison, Mr. Hudson Joshua Creighton  male  30.0000
        ...     ...       ...                              ...   ...      ...
        1307      3         0               Zakarian, Mr. Ortin  male  27.0000
        1308      3         0                Zimmerman, Mr. Leo  male  29.0000

              sibsp  parch  ticket     fare    cabin embarked boat   body  \
        1         1      2  113781  151.550  C22 C26        S   11    NaN
        3         1      2  113781  151.550  C22 C26        S  NaN  135.0
        ...     ...    ...     ...      ...      ...      ...  ...    ...
        1307      0      0    2670    7.225      NaN        C  NaN    NaN
        1308      0      0  315082    7.875      NaN        S  NaN    NaN

                                home.dest
        1     Montreal, PQ / Chesterville, ON
        3     Montreal, PQ / Chesterville, ON
        ...                               ...
        1307                              NaN
        1308                              NaN

        [843 rows x 14 columns]
```

The ability to pass a boolean mask into `.loc` or `.iloc` is useful if we want to select columns at the same time that we are filtering rows. For example, the following code returns the ages of the male passengers:

```
In [9]: titanic_df.loc[titanic_df.sex == "male", "age"]
```

```
Out[9]: 1        0.9167
        3       30.0000
                 ...
        1307    27.0000
        1308    29.0000
        Name: age, Length: 843, dtype: float64
```

Of course, this result could be obtained another way; we could first apply the boolean mask and then select the column from the subsetted `DataFrame`, the same way we would select a column from any other `DataFrame`:

```
In [10]: titanic_df[titanic_df.sex == "male"]["age"]
```

```
Out[10]: 1        0.9167
         3       30.0000
                  ...
         1307    27.0000
         1308    29.0000
         Name: age, Length: 843, dtype: float64
```

2.1.1 Speed Comparison

We've just seen two ways to filter a `DataFrame`. Which is better?

One consideration is that the first method forces you to set the index of your `DataFrame` to the variable you want to filter on. If your `DataFrame` already has a natural index, you might not want to replace that index just to be able to filter the data.

Another consideration is speed. Let's test the runtimes of the two options by using the `%timeit` magic. (**Warning:** The cell below will take a while to run, since `timeit` will run each command multiple times and report the mean and standard deviation of the runtimes.)

```
In [11]: %timeit titanic_df.set_index("sex").loc["male"].age.mean()
         %timeit titanic_df[titanic_df.sex == "male"].age.mean()
```

```
3.43 ms ś 255 ţs per loop (mean ś std. dev. of 7 runs, 100 loops each)
2.3 ms ś 239 ţs per loop (mean ś std. dev. of 7 runs, 100 loops each)
```

So boolean masking is also significantly faster than re-indexing and selecting. All things considered, boolean masking is the best way to filter your data.

2.1.2 Working with Boolean Series

Remember that a boolean mask is a `Series` of booleans. A boolean variable is usually regarded as categorical, but it can also be regarded as quantitative, where `True`s are 1s and `False`s are 0s. For example, the following command actually produces a `Series` of 0s and 3s.

```
In [12]: (titanic_df.sex == "male") * 3

Out[12]: 0       0
         1       3
                ..
         1307    3
         1308    3
         Name: sex, Length: 1309, dtype: int64
```

How can we use the dimorphic nature of booleans to our advantage? In Chapter 1.2, we saw how we functions like `.sum()` and `.mean()` could be applied to a binary categorical variable whose categories are coded as 0 and 1, such as the `survived` variable in the Titanic data set. The sum tells us the *number* of observations in category 1, while the mean tells us the *proportion* in category 1.

Since boolean `Series` are essentially variables of 0s and 1s, the command

```
In [13]: (titanic_df.sex == "male").sum()

Out[13]: 843
```

returns the *number* of observations where `sex == "male"` and

```
In [14]: (titanic_df.sex == "male").mean()

Out[14]: 0.6440030557677616
```

returns the *proportion* of observations where `sex == "male"`. Check that these answers are correct by some other method.

2.2 Filtering on Multiple Criteria

What if we want to visualize the age distribution of male *survivors* on the Titanic?" To answer this question, we have to filter the `DataFrame` on two variables, `sex` and `survived`.

We can filter on two or more criteria by combining boolean masks using logical operators. First, let's get the boolean masks for the two filters of interest:

```
In [15]: titanic_df.sex == "male"

Out[15]: 0       False
         1        True
                 ...
         1307     True
         1308     True
         Name: sex, Length: 1309, dtype: bool

In [16]: titanic_df.survived == 1
```

```
Out[16]: 0        True
         1        True
                  ...
         1307    False
         1308    False
         Name: survived, Length: 1309, dtype: bool
```

Now, we want to combine these two boolean masks into a single mask that is `True` only when *both* masks are `True`. This can be accomplished with the logical operator `&`.

```
In [17]: (titanic_df.sex == "male") & (titanic_df.survived == 1)
```

```
Out[17]: 0       False
         1        True
                  ...
         1307    False
         1308    False
         Length: 1309, dtype: bool
```

Verify for yourself that the `True` values in this `Series` correspond to observations where *both* masks were True.

Warning: Notice the parentheses around each boolean mask above. These parentheses are necessary because of operator precedence. In Python, the logical operator `&` has higher precedence than the comparison operator `==`, so the command

`titanic_df.sex == "male" & titanic_df.survived == 1`

will be interpreted as

`titanic_df.sex == ("male" & titanic_df.survived) == 1`

and result in an error. Python does not know how to evaluate `("male" & titanic_df.survived)`, since the logical operator `&` is not defined between a `str` and a `Series`.

The parentheses ensure that Python evaluates the boolean masks first and the logical operator second:

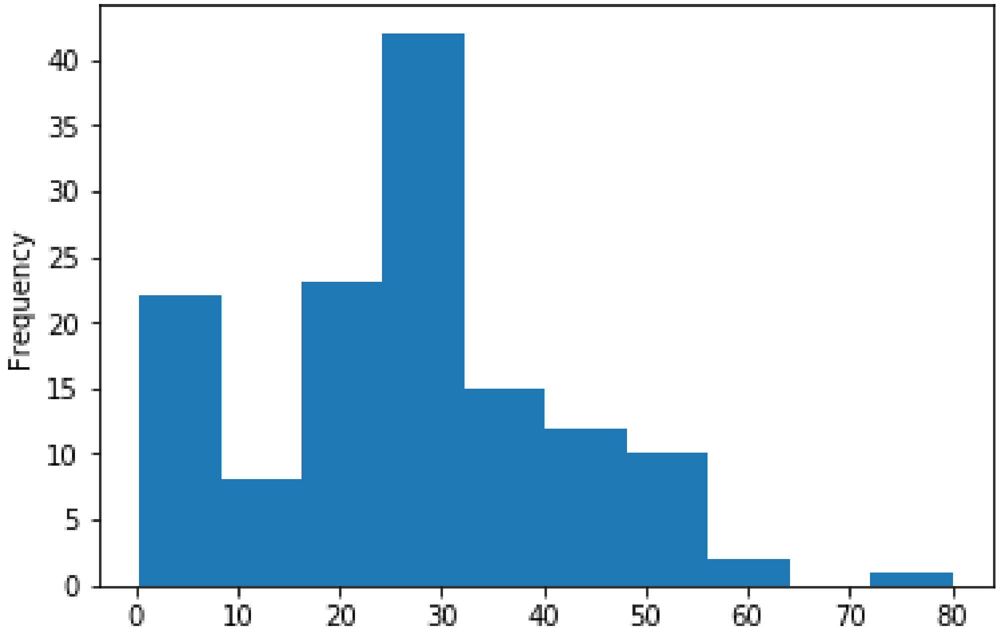
`(titanic_df.sex == "male") & (titanic_df.survived == 1)`.

It is very easy to forget these parentheses. Unfortunately, the error message that you get is not particularly helpful for debugging the code. If you don't believe me, just try running the offending command (without parentheses)!

Now with the boolean mask in hand, we can plot the age distribution of male survivors on the Titanic:

```
In [18]: titanic_df[(titanic_df.sex == "male") & (titanic_df.survived == 1)].age.plot.hist()
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0e2c5a748>
```



Notice the peak between 0 and 10. A disproportionate number of young children survived because they were given priority to board the lifeboats.

Besides `&`, there are two other logical operators, `|` and `~`, that can be used to modify and combine boolean masks.

- `&` means "and"
- `|` means "or"
- `~` means "not"

Like `&`, `|` and `~` operate elementwise on boolean `Series`. Examples are provided below.

```
In [19]: # male OR survived
         (titanic_df.sex == "male") | (titanic_df.survived == 1)

Out[19]: 0        True
         1        True
                  ...
         1307     True
         1308     True
         Length: 1309, dtype: bool

In [20]: # equivalent to (titanic_df.sex != "male")
         ~(titanic_df.sex == "male")

Out[20]: 0         True
         1        False
                  ...
```

```
1307    False
1308    False
Name: sex, Length: 1309, dtype: bool
```

Notice how we use parentheses to ensure that the boolean mask is evaluated before the logical operators.

3 Exercises

Exercises 1-3 deal with the Titanic data set.

Exercise 1. Is there any advantage to selecting the column at the same time you apply the boolean mask? In other words, is the second option below any faster than the first?

1. `titanic_df[titanic_df.sex == "female"].age`
2. `titanic_df.loc[titanic_df.sex == "female", "age"]`

Use the `%timeit` magic to compare the runtimes of these two options.

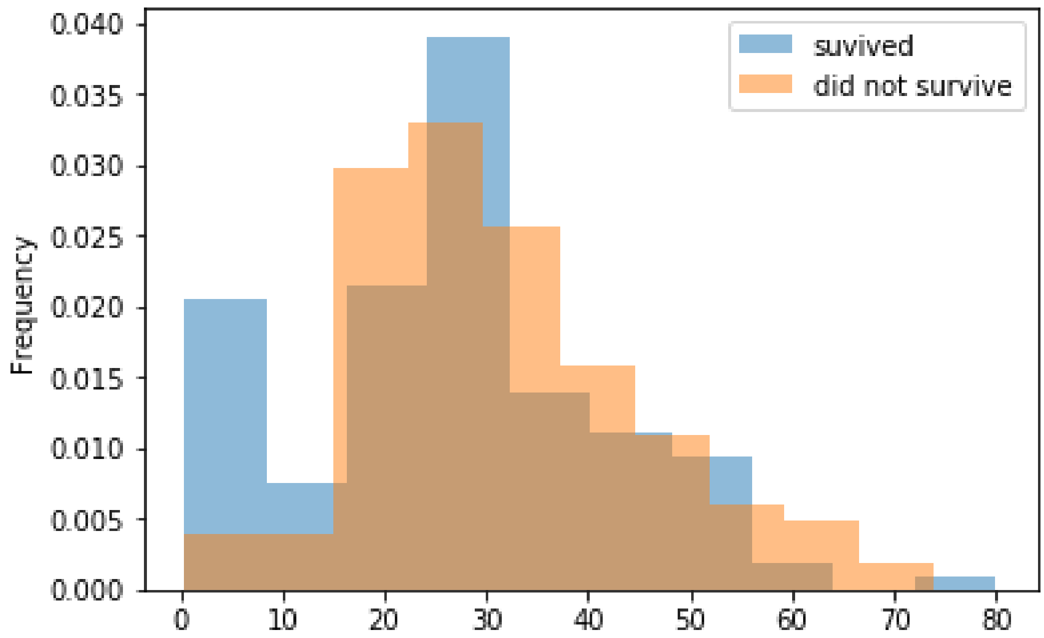
```
In [80]: %timeit titanic_df[titanic_df.sex == "female"].age
         %timeit titanic_df.loc[titanic_df.sex == "female", "age"]
```

```
1.87 ms ś 31.5 ţs per loop (mean ś std. dev. of 7 runs, 1000 loops each)
1.14 ms ś 29.6 ţs per loop (mean ś std. dev. of 7 runs, 1000 loops each)
```

Exercise 2. Produce a graphic that compares the age distribution of the males who survived with the age distribution of the males who did not.

```
In [89]: (titanic_df[(titanic_df.sex == "male")&(titanic_df.survived==1)
                    ].age.plot.hist(legend=True, alpha=0.5, label="suvived", density= True))

         (titanic_df[(titanic_df.sex == "male")&(titanic_df.survived == 0)
                    ].age.plot.hist(legend=True, alpha=0.5, label="did not survive", density =
```

```
Out[89]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0d5cee4a8>
```



Exercise 3. What proportion of 1st class passengers survived? What proportion of 3rd class passengers survived? See if you can use boolean masks to do this.

```
In [95]: survived_pclass_counts = (
             titanic_df[titanic_df.survived == 1].pclass.value_counts())

         pclass_counts = titanic_df.pclass.value_counts()
         survived_pclass_counts/pclass_counts

Out[95]: 1    0.619195
         2    0.429603
         3    0.255289
         Name: pclass, dtype: float64
```

Exercises 4-7 ask you to analyze the Tips data set (`https://raw.githubusercontent.com/dlsun/data-scienc`
The following code reads the data into a `DataFrame` called `tips_df` and creates a new column called `tip_percent` out of the `tip` and `total_bill` columns. This new column represents the tip as a percentage of the total bill (as a number between 0 and 1).

```
In [41]: tips_df = pd.read_csv("https://raw.githubusercontent.com/dlsun/data-science-book/maste
         tips_df["tip_percent"] = tips_df.tip / tips_df.total_bill
         tips_df

Out[41]:      total_bill   tip     sex smoker   day    time  size  tip_percent
         0         16.99  1.01  Female     No   Sun  Dinner     2     0.059447
         1         10.34  1.66    Male     No   Sun  Dinner     3     0.160542
         ..          ...   ...     ...    ...   ...     ...   ...          ...
```

```
242        17.82  1.75    Male     No    Sat  Dinner     2     0.098204
243        18.78  3.00  Female     No   Thur  Dinner     2     0.159744

[244 rows x 8 columns]
```

Exercise 4. Calculate the average tip percentage paid by parties of 4 or more.

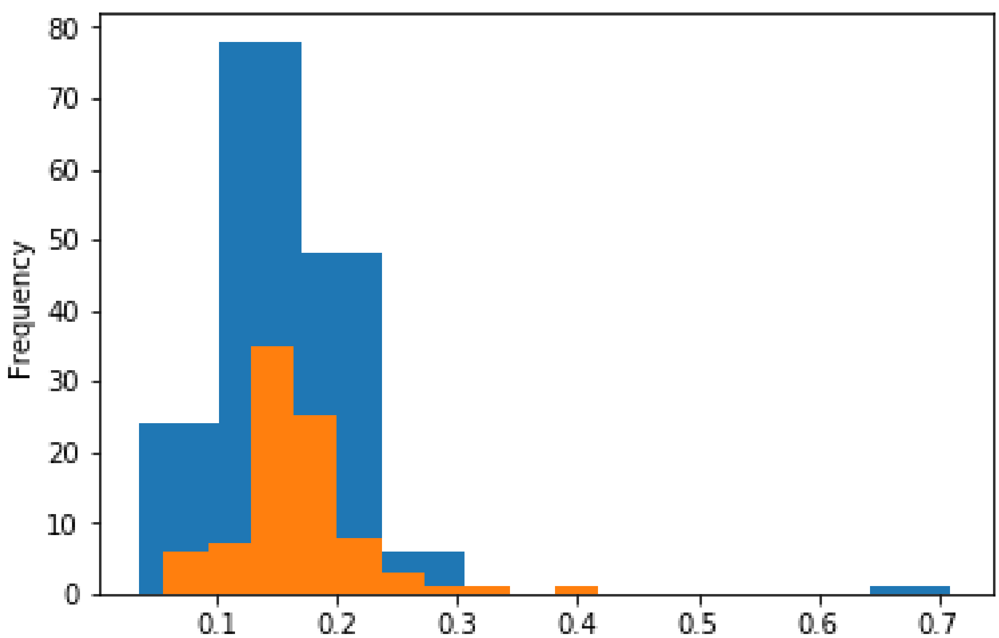
```
In [51]: tips_df[tips_df["size"] >= 4].tip_percent.mean()
```

```
Out[51]: 0.14635885842822238
```

Exercise 5. Make a visualization comparing the distribution of tip percentages left by males and females. How do they compare?

```
In [64]: tips_df[tips_df.sex == "Male"].tip_percent.plot.hist()
         tips_df[tips_df.sex == "Female"].tip_percent.plot.hist()
```

```
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc0de6c0550>
```



Exercise 6. What is the average table size on weekdays? (*Hint:* There are at least two ways to create the appropriate boolean mask: using the `|` logical operator and using the `.isin()` method. See if you can do it both ways.)

```
In [100]: tips_df[(tips_df.day == "Thur")|(tips_df.day == "Fri")]["size"].mean()

          tips_df[tips_df.day.isin(["Thur", "Fri"])]["size"].mean()
```

```
Out[100]: 2.3703703703703702
```

Exercise 7. Calculate the average table size for each day of the week. On which day of the week does the waiter serve the largest parties, on average?

```
In [79]: tips_df[tips_df.day == "Thur"]["size"].mean()

Out[79]: 2.4516129032258065

In [75]: tips_df[tips_df.day == "Fri"]["size"].mean()

Out[75]: 2.1052631578947367

In [76]: tips_df[tips_df.day == "Sat"]["size"].mean()

Out[76]: 2.5172413793103448

In [78]: tips_df[tips_df.day == "Sun"]["size"].mean()

Out[78]: 2.8421052631578947

In [101]: for day in ["Sun", "Thur", "Fri", "Sat"]:
              print(day, tips_df[tips_df.day == day]["size"].mean())

Sun 2.84210526316
Thur 2.45161290323
Fri 2.10526315789
Sat 2.51724137931
```