2.2 The Split-Apply-Combine Strategy

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```
In [1]: %matplotlib inline
        import pandas as pd
```

In the previous section, we discussed how to restrict our analysis to a particular subset of observations using boolean masks. So, for example, if we wanted to calculate the survival rate for passengers in third class, we would write:

```
In [2]: titanic_df = pd.read_csv("https://raw.githubusercontent.com/dlsun/data-science-book/ma
        titanic_df[titanic_df.pclass == 3].survived.mean()
```

```
Out[2]: 0.25528913963328631
```

But what if we wanted to calculate the survival rate by class? We could slice the data set three times, once for each class:

```
In [3]: (titanic_df[titanic_df.pclass == 1].survived.mean(),
         titanic_df[titanic_df.pclass == 2].survived.mean(),
         titanic_df[titanic_df.pclass == 3].survived.mean())
```

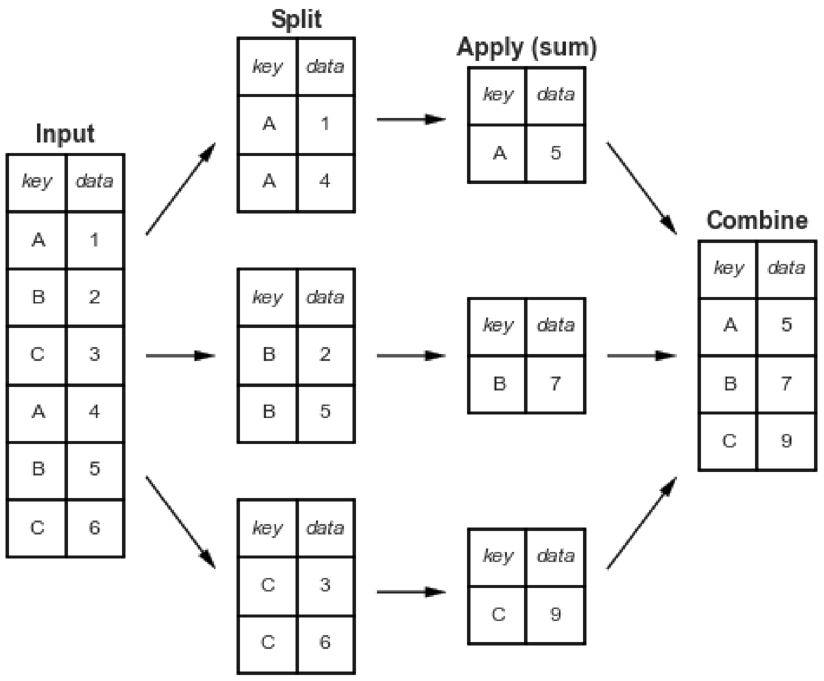
```
Out[3]: (0.61919504643962853, 0.4296028880866426, 0.25528913963328631)
```

But this code is inefficient and repetitive. It also does not generalize well to variables with hundreds of possible categories.

The problem of calculating the survival rate by class is an example of a problem that can be solved using the **split-apply-combine strategy**. The key insight here is that many data analyses follow the same basic pattern:

- First, a data set is **split** into several subsets based on some variable.
- Next, some analysis is **applied** to each subset.
- Finally, the results from each analysis are **combined**.

The three steps are diagrammed in the figure below:



source

Applying this strategy to our working example above, we should first *split* up the Titanic data according to the value of `pclass`, *apply* `.survived.mean()` to each subset, and finally *combine* the results into one `Series`.

[*Note:* The term "split-apply-combine" was coined by Hadley Wickham in a 2011 paper, but the idea is not new. It should already be familiar to you if you know SQL or MapReduce.]

1.1 Split-Apply-Combine in `pandas`: the `.groupby()` method

To implement the split-apply-combine strategy in `pandas`, we use the `.groupby()` method. First, we specify one or more variables to split on in the argument to `.groupby()`. Then, we specify our analysis as usual. Pandas will handle splitting the data, applying the analysis to each subset, and combining the results at the end.

```
In [4]: titanic_df.groupby("pclass").survived.mean()
```

```
Out[4]: pclass
        1    0.619195
        2    0.429603
        3    0.255289
        Name: survived, dtype: float64
```

Compare this line of code with the code to calculate the overall survival rate:
`titanic_df.survived.mean()`.

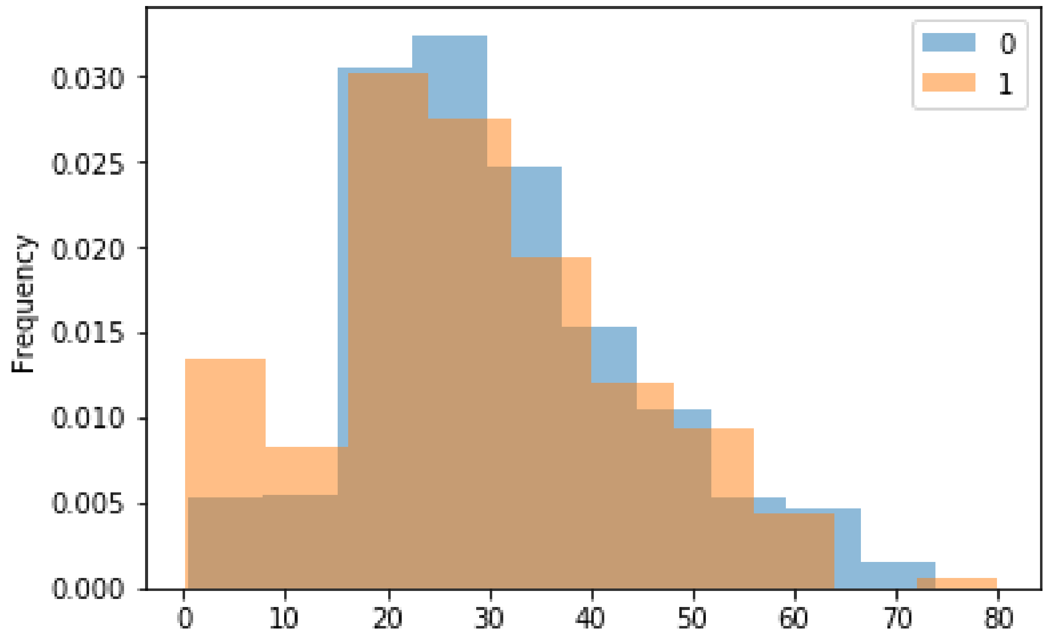
The only difference is `.groupby("pclass")`. This turns a `DataFrame` into a `DataFrameGroupBy` object, which behaves like a `DataFrame`, except that any analysis that we specify will be applied to subsets of the `DataFrame` instead of the whole `DataFrame`.

You can even make visualizations with `.groupby()`! To plot the age distribution of the survivors and non-survivors, we can group by the `survived` variable and then ask for a histogram of age. Behind the scenes, pandas will do this once for the survivors and again for the non-survivors and then combine them into one histogram.

```
In [5]: titanic_df.groupby("survived").age.plot.hist(alpha=.5, normed=True, legend=True)
```

```
/opt/conda/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: The 'normed
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
Out[5]: survived
        0    AxesSubplot(0.125,0.125;0.775x0.755)
        1    AxesSubplot(0.125,0.125;0.775x0.755)
        Name: age, dtype: object
```



It is also possible to group by more than one variable. Simply pass in a list of variable names to .groupby(). For example, the following code calculates the survival rate by class and sex:

```
In [6]: survival_rates = titanic_df.groupby(["pclass", "sex"])["survived"].mean()
        survival_rates
```

```
Out[6]: pclass  sex
        1       female    0.965278
                male      0.340782
        2       female    0.886792
                male      0.146199
        3       female    0.490741
                male      0.152130
        Name: survived, dtype: float64
```

It's clear that survival rates on the Titanic varied drastically by class and by sex.

Notice that when we use `.groupby()`, the resulting index is whatever variable(s) we grouped by. Since we grouped by two variables, this index actually has two levels. An index with more than one level is called a `MultiIndex` in `pandas`. To access a particular row in a `DataFrame` that is indexed by a `MultiIndex`, we pass in a tuple of the values we want from each level.

So, for example, to get female passengers in 2nd class, we would do:

```
In [7]: survival_rates.loc[(2, "female")]
```

```
Out[7]: 0.8867924528301887
```

If we pass in fewer values than there are levels in the index, `pandas` will return everything from the remaining levels.

```
In [8]: survival_rates.loc[2]
```

```
Out[8]: sex
        female    0.886792
        male      0.146199
        Name: survived, dtype: float64
```

survival_rates.loc["female"] will not work because sex is not the outermost variable

2 Exercises

Exercises 1-5 work with the Tips data set (`https://raw.githubusercontent.com/dlsun/data-science-book/ma` The following code reads in 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 percentage tip paid (as a number between 0 and 1).

```
In [9]: tips_df = pd.read_csv("/data301/data/tips.csv")
        tips_df["tip_percent"] = tips_df.tip / tips_df.total_bill
```

Exercise 1. On which day of the week does the waiter serve the largest parties, on average? (You did this exercise in the previous section. See how much easier it is to do using `.groupby()`.)

```
In [10]: tips_df.groupby("day")["size"].mean()
```

```
Out[10]: day
         Fri     2.105263
         Sat     2.517241
         Sun     2.842105
         Thur    2.451613
         Name: size, dtype: float64
```

Exercise 2. Calculate the average bill by day and time. What day-time combination has the highest average bill?

```
In [11]: avg_bill_by_day_time = tips_df.groupby(["day", "time"])["total_bill"].mean()
         avg_bill_by_day_time
```

```
Out[11]: day   time
         Fri   Dinner    19.663333
               Lunch     12.845714
         Sat   Dinner    20.441379
         Sun   Dinner    21.410000
         Thur  Dinner    18.780000
               Lunch     17.664754
         Name: total_bill, dtype: float64
```

Exercise 3. Extract the average bill for Friday lunch from the result of Exercise 2.

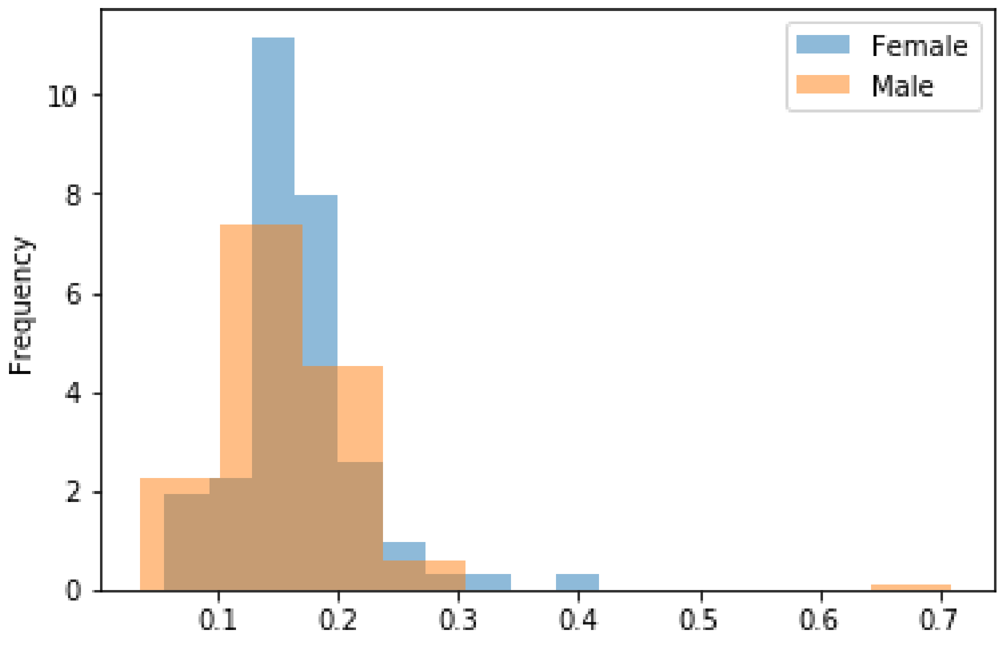
```
In [12]: tips_df[(tips_df.day == "Fri") & (tips_df.time == "Lunch")]["total_bill"].mean()

         avg_bill_by_day_time.loc["Fri", "Lunch"]
```

```
Out[12]: 12.845714285714285
```

Exercise 4. Use `.groupby()` to make a visualization comparing the distribution of tip percentages left by males and females. How do they compare?

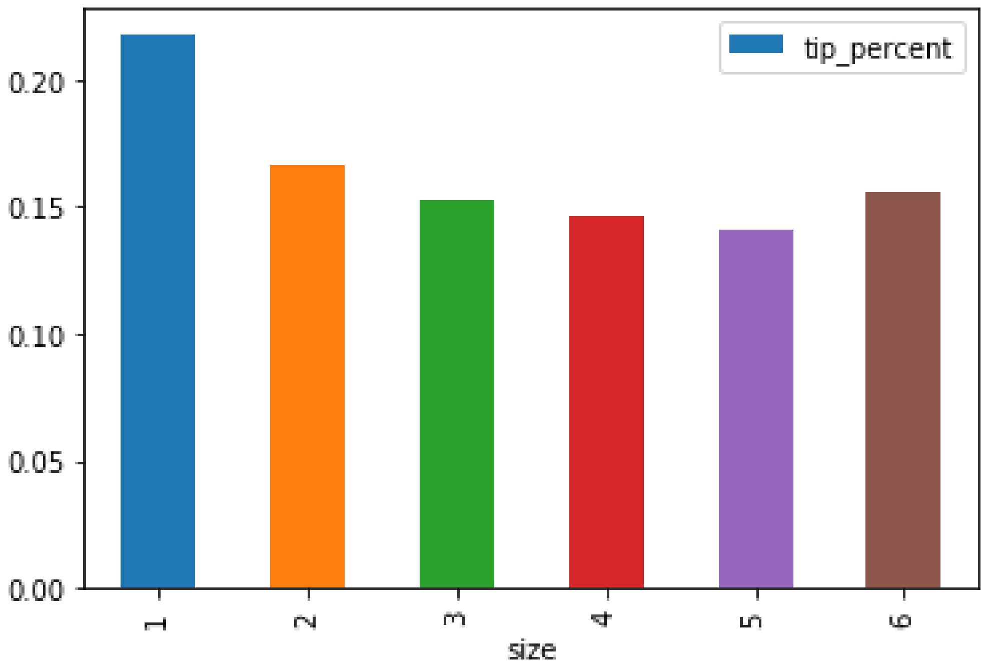
```
In [13]: tips_df.groupby("sex")["tip_percent"].plot.hist(density=True, alpha=0.5, legend=True)
```

```
Out[13]: sex
         Female    AxesSubplot(0.125,0.125;0.775x0.755)
         Male      AxesSubplot(0.125,0.125;0.775x0.755)
         Name: tip_percent, dtype: object
```



Exercise 5. Make a visualization that shows the average tip percentage as a function of table size.

```
In [14]: tips_df.groupby("size").tip_percent.mean().plot.bar(legend=True)

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d9aa25b38>
```


tip_percent
size