Workshop - Bootstrap

Today we will

- 1. Show the average unique number of observations when bootstrapping
- 2. Estimate the standard deviation on the causal effect from a RANDOMIZED CONTROL TRIAL

Bootstrap Samples

In one code cell:

- import numpy and numpy.random
- set the seed to 490
- create a range from 0 to 10,000
 - hint: start with a smaller size to set up the framework
- create an empty list
- in a 1,000 iteration for loop
 - hint: start with a smaller size to set up the framework
 - randomly sample your range your range with replacement with a size equal to the length of your range using npr.choice()
 - append your empty list with the length of the the number of unique values from the sampling with replacement
- output the average number of unique values over all bootstrapped samples

```
import numpy as np
import numpy.random as npr
npr.seed(490)

x = np.arange(0, 10000)

n_unique = []
for i in range(1000):
    smpl = npr.choice(x, len(x)) # replace = True is default
```

```
n_unique.append(len(np.unique(smpl)))
np.mean(n_unique)/len(x)

Out[1]: 0.6321646

Is this closer to 1/2, 2/3, or 3/4?
2/3
```

Randomize Control Trial

In economics, we call experiments with randomly assigned treatment and control groups *randomized control trials*. In data science, they are called *A-B testing*.

In this application, we will be using a data set from kaggle. We will be using an LPM to estimate the effect of being in a treament group on clicking something. The data is from Audacity, however, there is no information about the experiment specifically. We do not know if this is showing different versions of a website, different versions of an advertisement, or something else entirely.

```
In [2]: import pandas as pd
from tqdm import tqdm
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
Load in the audacity data as ab with index_col = timestamp.Print the head.

In [3]: ab = pd.read_csv('homepage_actions.csv', index_col = 'timestamp')
ab.head()

Out[3]: id group action
timestamp
```

id group action

2016-09-24 17:42:27.839496	804196	experiment	view
2016-09-24 19:19:03.542569	434745	experiment	view
2016-09-24 19:36:00.944135	507599	experiment	view
2016-09-24 19:59:02.646620	671993	control	view
2016-09-24 20:26:14.466886	536734	experiment	view

timestamp

Determine the unique values of group and action

```
In [4]: print(ab['group'].unique())
    print(ab['action'].unique())

['experiment' 'control']
['view' 'click']
```

Create a dummy variable treatment for those in the treatment group. Create a dummy variable click for those that clicked.

```
In [5]: ab['treatment'] = (ab.group == 'experiment')*1
ab['click'] = (ab.action == 'click')*1
```

Create an object x that is the model matrix composed of a constant and the treatment variable. Create an object y that is the click variable.

```
In [6]: x = sm.add_constant(ab.treatment)
y = ab.click
```

In one line, fit a statsmodel OLS and print the summary. Note the estimate and standard error on the treatment variable.

```
In [7]: sm.OLS(y, x).fit().summary2()

Out[7]: Model: OLS Adj. R-squared: 0.000

Dependent Variable: click AIC: 8991.4917

Date: 2021-03-10 12:26 BIC: 9005.5126
```

-4493.7

8188

Log-Likelihood:

No. Observations:

```
Df Model:
                                  1
                                            F-statistic:
                                                           3.738
      Df Residuals:
                               8186 Prob (F-statistic):
                                                          0.0532
                                                         0.17552
        R-squared:
                              0.000
                                               Scale:
            Coef. Std.Err.
                                              [0.025 0.975]
                                       P>|t|
                    0.0064 34.0676 0.0000
                                              0.2060 0.2312
   const 0.2186
treatment 0.0179
                    0.0093
                             1.9335 0.0532 -0.0002 0.0361
     Omnibus: 1459.439
                            Durbin-Watson:
                                               2.566
Prob(Omnibus):
                   0.000 Jarque-Bera (JB): 2342.875
                                 Prob(JB):
        Skew:
                   1.301
                                               0.000
      Kurtosis:
                   2.696
                             Condition No.:
                                                   3
```

Here we will perform the bootstrap in one code cell.

- set the npr seed to 490
- define n equal to the number of rows of ab
- create an empty list beta
- set up a for loop over 2,000 iterations using tqdm
 - use npr.choice() to obtain the bootstrap index
 - fit a LinearRegression()
 - hint: X needs to be a DataFrame, not a Series. Select the treatment variable using ab[['treatment']].iloc[indx]. y needs to be a Series. Select with only single square brackets.
 - append the fit.coef_ to beta
 - Note: the intercept, which we do not need, is contained seperately in fit.intercept_.

```
In [8]: npr.seed(490)
    n = ab.shape[0]
    beta = []
```

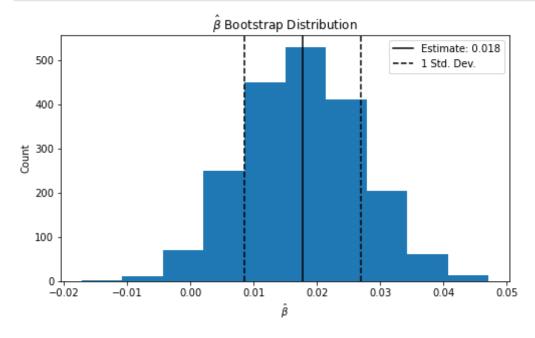
```
for i in tqdm(range(2000)):
               indx = npr.choice(range(n), n)
               fit = LinearRegression().fit(ab[['treatment']].iloc[indx], y = ab['click'].iloc[indx])
               # fit.intercept
               beta.append(fit.coef )
                           | 2000/2000 [00:16<00:00, 121.27it/s]
          100%
         Using one print() statment, print the average beta with 3 decimal places and the standard deviation of beta with 4 decimal places.
          print((np.mean(beta), np.std(beta)))
 In [9]:
          (0.017742494201839362, 0.009154431907603055)
         Up next, we will produce a histogram. However, we need to perform some preprocessing.
         Print the top five observations of beta using a slice. Note the format.
          beta[:5]
In [11]:
Out[11]: [array([0.02343743]),
           array([0.02741371]),
           array([0.00896696]),
           array([0.02451603]),
           array([0.0079953])]
         To convert to a list we can work with
           • use np.concatenate() on beta

    chain the .flat attribute

           wrap the whole thing with list()

    overwrite beta

          beta = list(np.concatenate(beta).flat)
In [12]:
         Finally, use matplotlib to create a histogram of beta.
          plt.figure(figsize = (8, 4.5))
In [13]:
           plt.hist(beta)
```



In []: