US_Bike-Share_Analysis

May 26, 2018

1 2016 US Bike Share Activity Snapshot

1.1 Table of Contents

## Posing Questions

Before looking at the bike sharing data, you should start by asking questions you might want to understand about the bike share data. Consider, for example, if you were working for Motivate. What kinds of information would you want to know about in order to make smarter business decisions? If you were a user of the bike-share service, what factors might influence how you would want to use the service?

Question 1: Write at least two questions related to bike sharing that you think could be answered by data.

Answer 1:

- Q1. How many people travel from place A to place B by walking where bicycle-sharing system isn't installed?
- Q2. How many people from them are willing to use our service?
- Q3. How many of our users use subscription service? And how many dont?
- Q4. How many of our users want to Subscribe to our service but is a little bit expensive to them?

## Data Collection and Wrangling

Now it's time to collect and explore our data.

Question 2: However, there is still a lot of data for us to investigate, so it's a good idea to start off by looking at one entry from each of the cities we're going to analyze. Run the first code cell below to load some packages and functions that you'll be using in your analysis. Then, complete the second code cell to print out the first trip recorded from each of the cities (the second line of each data file).

Answer

```
In [1]: #importing necessory modules for analyzing data
        import pandas as pd
        import numpy as np

        #importing graphing modules
        import matplotlib.pyplot as plt
        import seaborn as sns
```

```
In [2]: #assigning city data files to a pandas dataframe variable
        NYC_data = pd.read_csv('data/NYC-CitiBike-2016.csv')
        Chicago_data = pd.read_csv('data/Chicago-Divvy-2016.csv')
        Washington_DC_data = pd.read_csv('data/Washington-CapitalBikeshare-2016.csv')
```

```
In [3]: #printing out the first entry of New York city
        NYC_data.head(1)
```

```
Out[3]:    tripduration          starttime           stoptime  start station id  \
        0           839  1/1/2016 00:09:55  1/1/2016 00:23:54               532

          start station name  start station latitude  start station longitude  \
        0    S 5 Pl & S 4 St               40.710451               -73.960876

           end station id         end station name  end station latitude  \
        0             401  Allen St & Rivington St             40.720196

           end station longitude  bikeid  usertype  birth year  gender
        0             -73.989978   17109  Customer         NaN       0
```

```
In [4]: #printing out the first entry of Chicago city
        Chicago_data.head(1)
```

```
Out[4]:    trip_id        starttime         stoptime  bikeid  tripduration  \
        0  9080545  3/31/2016 23:30  3/31/2016 23:46    2295           926

           from_station_id          from_station_name  to_station_id  \
        0              156  Clark St & Wellington Ave            166

                        to_station_name    usertype gender  birthyear
        0  Ashland Ave & Wrightwood Ave  Subscriber   Male     1990.0
```

```
In [5]: #printing out the first entry of Washington DC city
        Washington_DC_data.head(1)
```

```
Out[5]:    Duration (ms)       Start date         End date  Start station number  \
        0         427387  3/31/2016 22:57  3/31/2016 23:04                 31602
```

```
             Start station  End station number  \
0  Park Rd & Holmead Pl NW               31207

                          End station Bike number Member Type
0  Georgia Ave and Fairmont St NW      W20842  Registered
```

The powerful and flexible pandas module makes acccessing data a lot easier by giving just few words of code.

### Condensing the Trip Data

It should also be observable from the above printout that each city provides different information. Even where the information is the same, the column names and formats are sometimes different. To make things as simple as possible when we get to the actual exploration, we should trim and clean the data. Cleaning the data makes sure that the data formats across the cities are consistent, while trimming focuses only on the parts of the data we are most interested in to make the exploration easier to work with.

You will generate new data files with five values of interest for each trip: trip duration, starting month, starting hour, day of the week, and user type. Each of these may require additional wrangling depending on the city:

- **Duration**: This has been given to us in seconds (New York, Chicago) or milliseconds (Washington). A more natural unit of analysis will be if all the trip durations are given in terms of minutes.
- **Month**, **Hour**, **Day of Week**: Ridership volume is likely to change based on the season, time of day, and whether it is a weekday or weekend. Use the start time of the trip to obtain these values. The New York City data includes the seconds in their timestamps, while Washington and Chicago do not. The datetime package will be very useful here to make the needed conversions.
- **User Type**: It is possible that users who are subscribed to a bike-share system will have different patterns of use compared to users who only have temporary passes. Washington divides its users into two types: 'Registered' for users with annual, monthly, and other longer-term subscriptions, and 'Casual', for users with 24-hour, 3-day, and other short-term passes. The New York and Chicago data uses 'Subscriber' and 'Customer' for these groups, respectively. For consistency, you will convert the Washington labels to match the other two.

Question 3a: Address each of the cleaning tasks described above.
Answer:

```
In [6]: """Converting duration columns to minutes of each files"""

        #since New York & Chicago duration have been given in second, we divide by 60 converti
        NYC_data['tripduration'] = NYC_data['tripduration']/60
        Chicago_data['tripduration'] = Chicago_data['tripduration']/60

        #since Washington has in miliseconds...
        Washington_DC_data['Duration (ms)'] = Washington_DC_data['Duration (ms)']/60000
```

```
In [7]: """Converting Start time of the trip of each file to datetime format"""
```

```
        #converting each file to datetime
        NYC_data['starttime'] = pd.to_datetime(NYC_data['starttime'])
        Chicago_data['starttime'] = pd.to_datetime(Chicago_data['starttime'])
        Washington_DC_data['Start date'] = pd.to_datetime(Washington_DC_data['Start date'])
```

```
In [8]: """Changing User type of Washington DC city to match other city values for convenience

        #chaning member type colum values
        Washington_DC_data['Member Type'].replace(to_replace = 'Registered', value = 'Subscribe
        Washington_DC_data['Member Type'].replace(to_replace = 'Casual', value = 'Customer', i
```

```
In [9]: NYC_data.head(1)
```

```
Out[9]:    tripduration           starttime           stoptime  start station id  \
        0     13.983333 2016-01-01 00:09:55  1/1/2016 00:23:54               532

          start station name  start station latitude  start station longitude  \
        0    S 5 Pl & S 4 St               40.710451               -73.960876

           end station id         end station name  end station latitude  \
        0             401  Allen St & Rivington St             40.720196

           end station longitude  bikeid  usertype  birth year  gender
        0             -73.989978   17109  Customer         NaN       0
```

```
In [10]: Chicago_data.head(1)
```

```
Out[10]:    trip_id           starttime         stoptime  bikeid  tripduration  \
         0  9080545 2016-03-31 23:30:00  3/31/2016 23:46    2295     15.433333

            from_station_id          from_station_name  to_station_id  \
         0              156  Clark St & Wellington Ave            166

                         to_station_name    usertype gender  birthyear
         0  Ashland Ave & Wrightwood Ave  Subscriber   Male     1990.0
```

```
In [11]: Washington_DC_data.head(1)
```

```
Out[11]:    Duration (ms)          Start date          End date  Start station number  \
         0       7.123117 2016-03-31 22:57:00  3/31/2016 23:04                 31602

                      Start station  End station number  \
         0  Park Rd & Holmead Pl NW               31207

                             End station Bike number Member Type
         0  Georgia Ave and Fairmont St NW      W20842  Subscriber
```

Question 3b: Now, create a condensed data file for each city consisting only of the data fields indicated above.

Answer :

```
In [12]: "New York"
         #first lets split datetime values into different columns

         #will display month
         NYC_data['month'] = NYC_data['starttime'].dt.month
         #will display hour
         NYC_data['hour'] = NYC_data['starttime'].dt.hour
         #will display name of the day
         NYC_data['day_of_week'] = NYC_data['starttime'].dt.weekday_name

         #now lets drop unneccesory columns
         NYC_data.drop(['starttime', 'stoptime', 'start station id', 'start station name', 'sta
                        'end station id', 'end station name', 'end station latitude', 'end sta
                        'birth year', 'gender'], axis = 1, inplace = True)

         #dsiplaying first two rows
         NYC_data.head(2)
```

```
Out[12]:    tripduration    usertype  month  hour day_of_week
         0     13.983333    Customer      1     0      Friday
         1     11.433333  Subscriber      1     0      Friday
```

```
In [13]: "Chicago"
         #first lets split datetime values into different columns

         #will display month
         Chicago_data['month'] = Chicago_data['starttime'].dt.month
         #will display hour
         Chicago_data['hour'] = Chicago_data['starttime'].dt.hour
         #will display name of the day
         Chicago_data['day_of_week'] = Chicago_data['starttime'].dt.weekday_name

         #now lets drop unneccesory columns
         Chicago_data.drop(['trip_id', 'starttime', 'stoptime','from_station_id', 'from_statio
                            'bikeid', 'birthyear', 'gender'], axis = 1, inplace = True)

         #dsiplaying first two rows
         Chicago_data.head(2)
```

```
Out[13]:    tripduration    usertype  month  hour day_of_week
         0     15.433333  Subscriber      3    23    Thursday
         1      3.300000  Subscriber      3    22    Thursday
```

```
In [14]: "Washington DC"
         #first lets split datetime values into different columns

         #will display month
         Washington_DC_data['month'] = Washington_DC_data['Start date'].dt.month
         #will display hour
```

```
        Washington_DC_data['hour'] = Washington_DC_data['Start date'].dt.hour
        #will display name of the day
        Washington_DC_data['day_of_week'] = Washington_DC_data['Start date'].dt.weekday_name


        #now lets drop unneccesory columns
        Washington_DC_data.drop(['Start date', 'End date','Start station number', 'Start stati
                                 'End station', 'Bike number'], axis = 1, inplace = True)

        #dsiplaying first two rows
        Washington_DC_data.head(2)
```

```
Out[14]:    Duration (ms) Member Type  month  hour day_of_week
         0       7.123117  Subscriber      3    22    Thursday
         1       9.792517  Subscriber      3    22    Thursday
```

Before converting the above dataframes to csv, let's change the column names of Washington city where it has two columns that don't match with other 2 cities. Having same column names across three cities in a csv file makes our code and life easier a bit!!

```
In [15]: Washington_DC_data.rename(columns = {'Duration (ms)' : 'tripduration', 'Member Type':
         Washington_DC_data.head(1)
```

```
Out[15]:    tripduration    usertype  month  hour day_of_week
         0      7.123117  Subscriber      3    22    Thursday
```

```
In [16]: """Now Converting these dataframes to csv file"""

         #the csv format will be placed in 'output' folder

         #NYC
         NYC_data.to_csv(r'output\NYC.csv', encoding = 'utf-8', index = False, columns = ['trip
                                                                                          'use
         #Chicago
         Chicago_data.to_csv(r'output\Chicago.csv', encoding = 'utf-8', index = False, columns

         #Washington
         Washington_DC_data.to_csv(r'output\Washington_DC.csv', encoding = 'utf-8', index = Fal
```

## Exploratory Data Analysis

Now that you have the data collected and wrangled, you're ready to start exploring the data. In this section you will write some code to compute descriptive statistics from the data. You will also be introduced to the `matplotlib` library to create some basic histograms of the data.

### Statistics

Question 4a: Which city has the highest number of trips? Which city has the highest proportion of trips made by subscribers? Which city has the highest proportion of trips made by short-term customers?

Answer:

```
In [17]: #reading new data files from output folder
         NYC_data = pd.read_csv('output/NYC.csv')
         Chicago_data = pd.read_csv('output/Chicago.csv')
         Washington_DC_data = pd.read_csv('output/Washington_DC.csv')
```

```
In [18]: #giving list of variables which hold datafiles
         cities_data = [NYC_data, Chicago_data, Washington_DC_data]

         #giving a list city names
         city_names = ['NYC', 'Chicago', 'Washington']
```

```
In [19]: #giving a function to calculate statistics
         def total_count(city):

             #this gives us total no. of subscribers and customers from 'usertype' column sinc
             subs, cust = city['usertype'].value_counts()
             #giving total number of datatrips of the city
             total = subs + cust

             return (subs, cust, total)
```

```
In [20]: #for printing city name
         i = 0

         #looping through list of datafiles and calling the function to print each cities stat
         for city in cities_data:

             #will store the return values in these var
             subs, cust, total = total_count(city)
             #displaying statistics of each city
             print('In ' + city_names[i] +' city, the total no. of Subscribers are ' + str(sub

             #will display next city name
             i+=1
```

```
In NYC city, the total no. of Subscribers are 245896, Customers are 30185 and total no. of ride

In Chicago city, the total no. of Subscribers are 54982, Customers are 17149 and total no. of

In Washington city, the total no. of Subscribers are 51753, Customers are 14573 and total no.
```

From the above data computed, now we can answer for the above questions:

- New York has the highest number of trips of 276798.
- New York has the highest proportion of trips made by subscribers.(0.888)
- Chicago has the highest proportion of trips made by short-term customers.(0.237)

Question 4b: Bike-share systems are designed for riders to take short trips. Most of the time, users are allowed to take trips of 30 minutes or less with no additional charges, with overage charges made for trips of longer than that duration. What is the average trip length for each city? What proportion of rides made in each city are longer than 30 minutes?

```
In [21]: #function to calculate avg
         def average_trip_length(city):
             #taking avg of trip duration
             avg = city['tripduration'].mean()
             return avg
```

```
In [22]: #for printing city name
         i = 0

         #looping through list of datafiles and calling the function to print each cities stat
         for city in cities_data:

             #will store the return values of the func to a var
             avg = average_trip_length(city)
             #displaying statistics of each city
             print('For ' + city_names[i] +' city, the average tip length is ' + str(avg) + '\

             #will display next city name
             i+=1
```

```
For NYC city, the average tip length is 15.812592998

For Chicago city, the average tip length is 16.5636293688

For Washington city, the average tip length is 18.9328735591
```

```
In [23]: def lenght_more_30min(city):
             #gives total no.of trip rides of the city
             total_trip_rides = city.shape[0]

             #gives boolean values if greater
             no_trips = city['tripduration'] >= 30.0

             #return no. of True boolean values and total rides
             return no_trips.sum() , total_trip_rides
```

```
In [24]: #for printing city name
         i = 0

         #looping through list of datafiles and calling the function to print each cities stat
         for city in cities_data:
```

```
    #saves the value returned by a function to respective var
    yes, total = lenght_more_30min(city)
    #calculates proportion
    prop = (yes/total)*100

    #displays output
    print('Proportion of trips longer than 30 min in ' + city_names[i] + ': ' + str(p

    i+=1
```

```
Proportion of trips longer than 30 min in NYC: 7.3168881278

Proportion of trips longer than 30 min in Chicago: 8.34731252859

Proportion of trips longer than 30 min in Washington: 10.8388867111
```

Question 4c: Dig deeper into the question of trip duration based on ridership. Choose one city. Within that city, which type of user takes longer rides on average: Subscribers or Customers?

Answer:

```
In [25]: #function for calculating mean duration of subscribers and customers and who travels
         def avg_length_sub_cust(city):

             #this will calculate the mean of trip duration for subscribers and customers
             sub_length_mean = city.loc[city['usertype'] == 'Subscriber', 'tripduration'].mean
             cust_length_mean = city.loc[city['usertype'] == 'Customer', 'tripduration'].mean(

             #who rides the most? subscribers or customers
             if sub_length_mean > cust_length_mean:
                 best = 'Subscribers'
             else:
                 best = 'Customers'

             return sub_length_mean, cust_length_mean, best
```

```
In [26]: #for printing city name
         i = 0

         #looping through list of datafiles and calling the function to print each cities stat
         for city in cities_data:

             #saves the value returned by a function to respective var
             sub_length_mean, cust_length_mean, best = avg_length_sub_cust(city)

             #displays output
             print('The avarage trip of Subscribers:' + str(sub_length_mean) + ', The average
             print('Type of users took longer rides: ' +  best + '\n\n')
             i+=1
```

```
The avarage trip of Subscribers:13.6807905239, The average trip of customers: 32.9820043068

Type of users took longer rides: Customers


The avarage trip of Subscribers:12.0672016903, The average trip of customers: 30.979781134

Type of users took longer rides: Customers


The avarage trip of Subscribers:12.5281204993, The average trip of customers: 41.6780313925

Type of users took longer rides: Customers
```

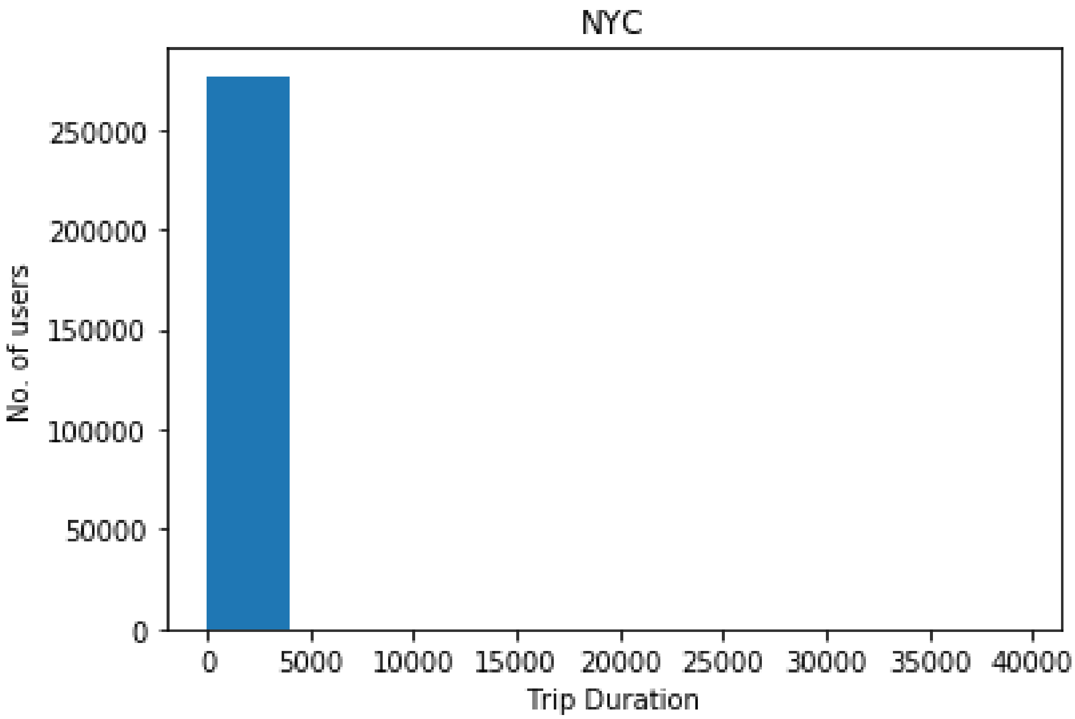
### Visualizations

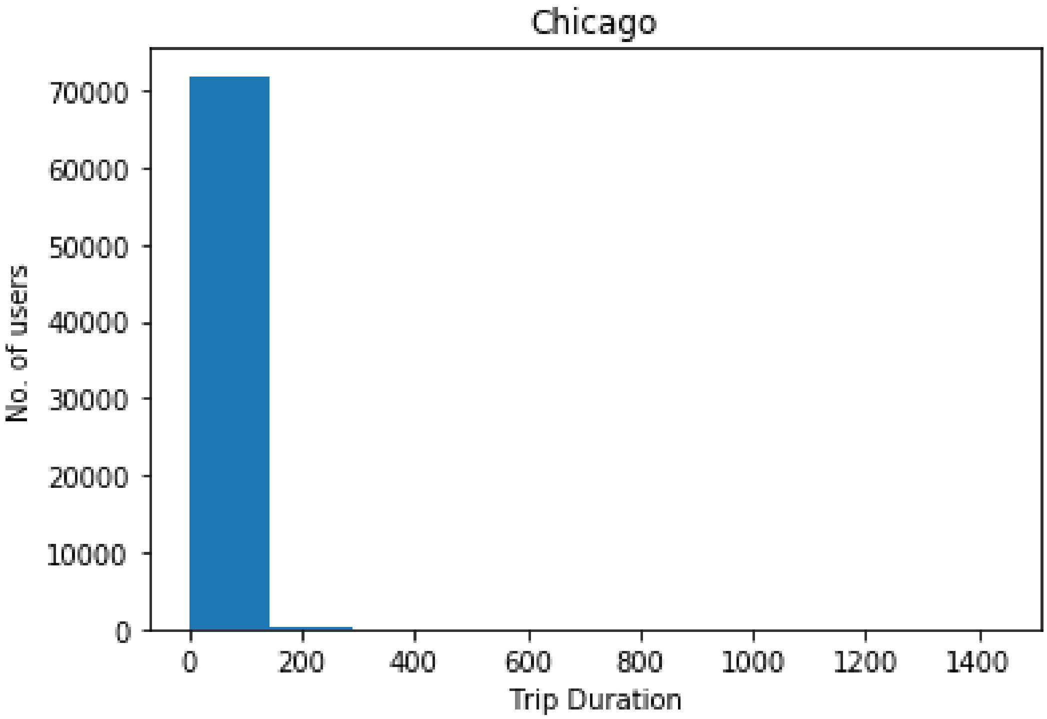
The last set of values that you computed should have pulled up an interesting result. While the mean trip time for Subscribers is well under 30 minutes, the mean trip time for Customers is actually *above* 30 minutes! It will be interesting for us to look at how the trip times are distributed. In order to do this, a new library will be introduced here, `matplotlib`.

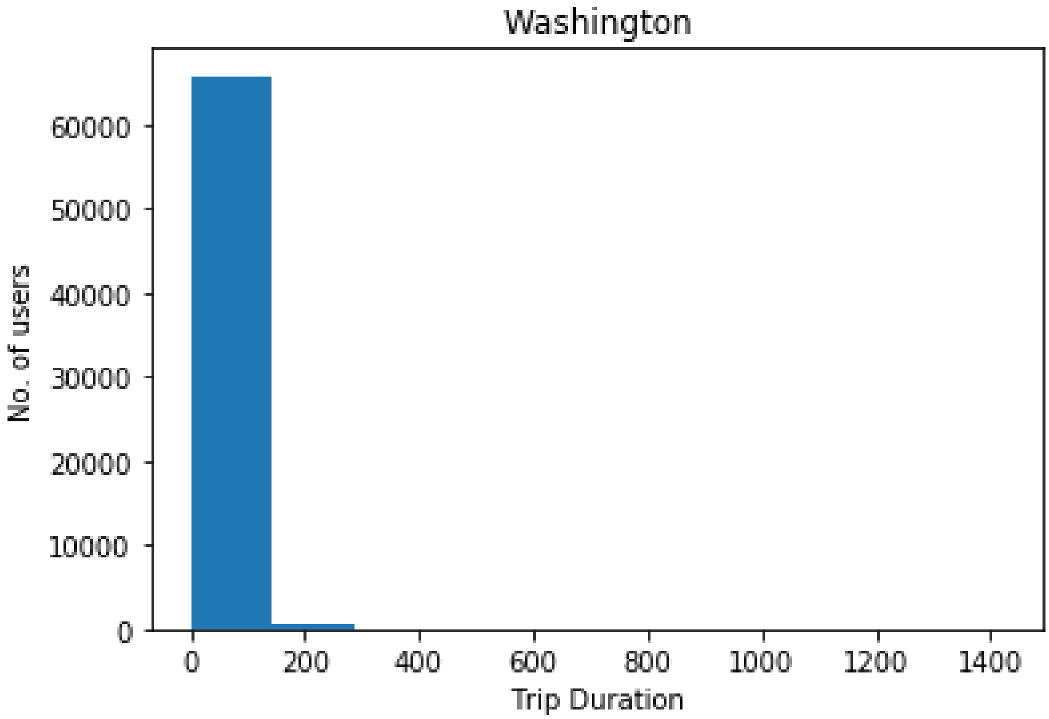
Create a histogram of the trip times for these cities. Don't separate the Subscribers and Customers for now: just collect all of the trip times and plot them.

```
In [27]: #function for graphing trip duration for each cities
         def plot_trip_duration(city):

             #plotting hist of tripduration
             plot = plt.hist(city["tripduration"])
             plt.xlabel('Trip Duration')
             plt.ylabel('No. of users')
             plt.title(city_names[i])
             plt.show()
```

```
In [28]: #loop through cities list
         i=0
         for city in cities_data:
             plot_trip_duration(city)
             i+=1
```


NYC
No. of users
0
50000
100000
150000
200000
250000
0
5000
10000
15000
20000
25000
30000
35000
40000
Trip Duration


Chicago
No. of users
0
10000
20000
30000
40000
50000
60000
70000
0
200
400
600
800
1000
1200
1400
Trip Duration



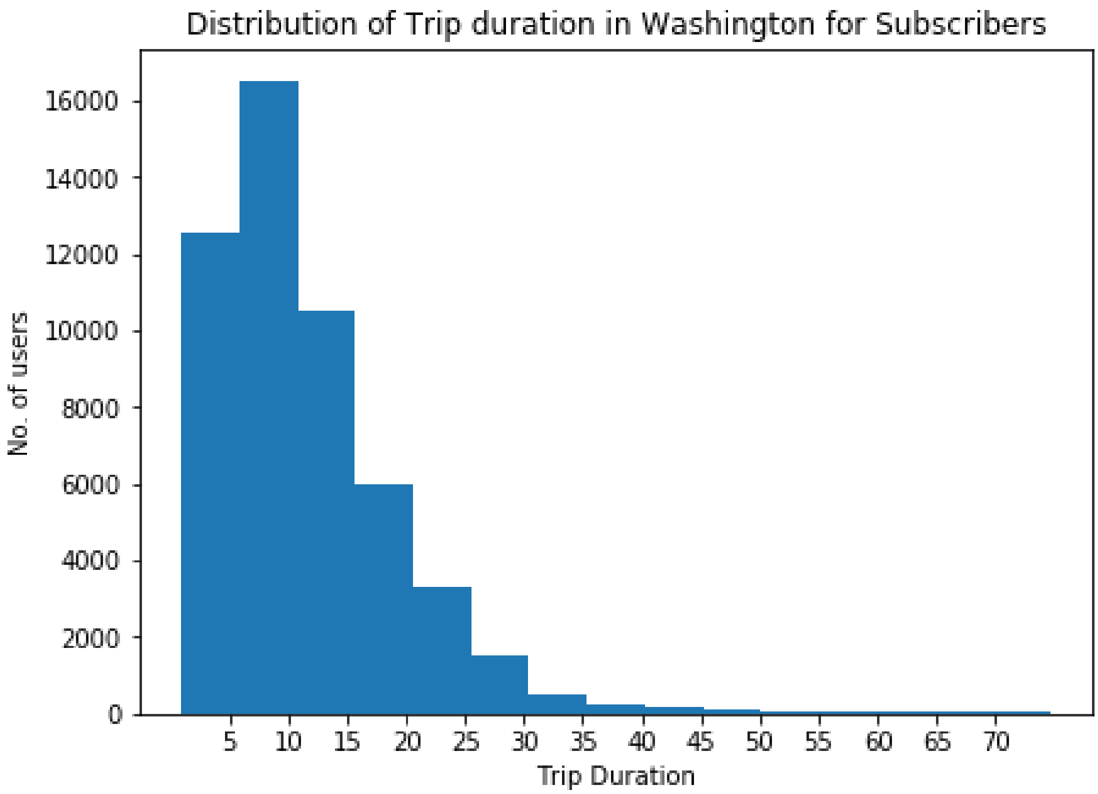
You're probably looking at a plot that's completely unexpected. The plot consists of one extremely tall bar on the left, maybe a very short second bar, and a whole lot of empty space in the center and right. Take a look at the duration values on the x-axis. This suggests that there are some highly infrequent outliers in the data.

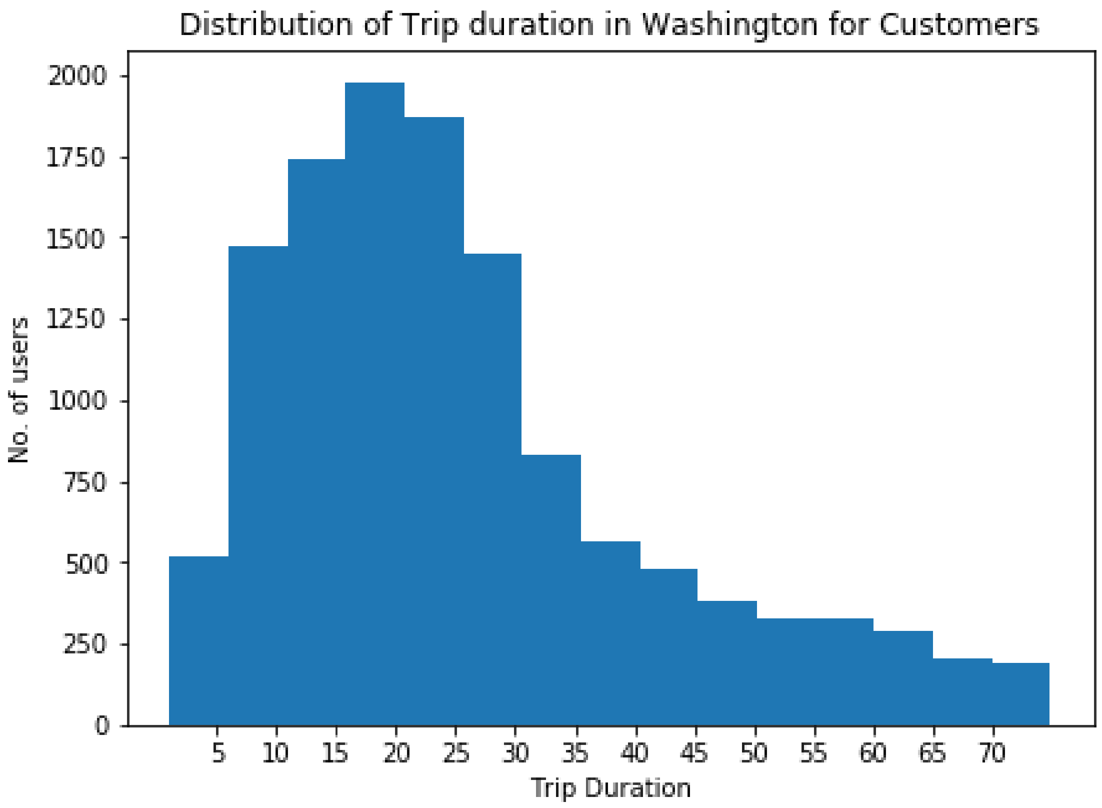
Question 5: Plot the distribution of trip times for the Subscribers in your selected city. Do the same thing for only the Customers. Add limits to the plots so that only trips of duration less than 75 minutes are plotted. As a bonus, set the plots up so that bars are in five-minute wide intervals. For each group, where is the peak of each distribution? How would you describe the shape of each distribution?

Answer: Since we have to plot for any one city, I choose to plot of Washington DC city.

```
In [29]: #copying the data of subscribers and customers to different variables since we have t
         Washington_DC_subs = Washington_DC_data.loc[Washington_DC_data['usertype'] == 'Subscri
         Washington_DC_cust = Washington_DC_data.loc[Washington_DC_data['usertype'] == 'Custom

         #now from these data we want only the duration time whoo traveled 75 min or less
         Washington_DC_subs_75 = Washington_DC_subs.loc[Washington_DC_data['tripduration'] <=
         Washington_DC_cust_75 = Washington_DC_cust.loc[Washington_DC_data['tripduration'] <=

         #graph size
         plt.figure(figsize=(7,5))

         #graph type with no. of bins
         plt.hist(Washington_DC_subs_75, bins = 15)
```

```
#lables
plt.xlabel('Trip Duration')
plt.ylabel('No. of users')

#start, end, difference - x ticks
plt.xticks(np.arange(5,75,5))

#title
plt.title('Distribution of Trip duration in Washington for Subscribers')
#displaying of subscribers
plt.show()

#graph size
plt.figure(figsize=(7,5))

#graph type with no. of bins
plt.hist(Washington_DC_cust_75, bins = 15)

#lables
plt.xlabel('Trip Duration')
plt.ylabel('No. of users')

#start, end, difference - x ticks
plt.xticks(np.arange(5,75,5))

#title
plt.title('Distribution of Trip duration in Washington for Customers')
#displaying of customers
plt.show()
```


Distribution of Trip duration in Washington for Subscribers
No. of users
16000
14000
12000
10000
8000
6000
4000
2000
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
Trip Duration



- As you can see the distribution of trip duration in Washington city of 'Subscribed' members is positively skewed (skewed right). Not lot of subscribed members ride more than 25 mins. The mode of this distribituon is between 5-10 min, means the proportion of the no. of subscribed users who ride between 5-10 min is highest than any duration of travel time span. The mean in such distribution is pulled to the tails while the median is always between the mode and mean in such distributiions.
- The same distribution is also seen for customer users in Washington city. Its peaky to the left(kind of) and has tail to the right making it positively skewed or skewed right distribution. If you visualize this distribution from 5-30 on x-axis(duration) you will see that it has a normal distribution which includes highest no. of customers who ride beteween these time spans. The most number of users in the distribution compared to all other time spans (duration), ride between 15-20 min, making the mode of the distribution.

## Performing Your Own Analysis
So far, you've performed an initial exploration into the data available. You have compared the relative volume of trips made between three U.S. cities and the ratio of trips made by Subscribers and Customers. For one of these cities, you have investigated differences between Subscribers and Customers in terms of how long a typical trip lasts. Now it is your turn to continue the exploration in a direction that you choose. Here are a few suggestions for questions to explore:

- How does ridership differ by month or season? Which month / season has the highest ridership? Does the ratio of Subscriber trips to Customer trips change depending on the month or season?
- Is the pattern of ridership different on the weekends versus weekdays? On what days are Subscribers most likely to use the system? What about Customers? Does the average duration of rides change depending on the day of the week?
- During what time of day is the system used the most? Is there a difference in usage patterns for Subscribers and Customers?

If any of the questions you posed in your answer to question 1 align with the bullet points above, this is a good opportunity to investigate one of them. As part of your investigation, you will need to create a visualization. If you want to create something other than a histogram, then you might want to consult the Pyplot documentation. In particular, if you are plotting values across a categorical variable (e.g. city, user type), a bar chart will be useful. The documentation page for `.bar()` includes links at the bottom of the page with examples for you to build off of for your own use.

Question 6: Continue the investigation by exploring another question that could be answered by the data available. Document the question you want to explore below. Your investigation should involve at least two variables and should compare at least two groups. You should also use at least one visualization as part of your explorations.

Answer:

My Q: During what time of day is the system used the most? Is there a difference in usage patterns for Subscribers and Customers?

Let's explore.

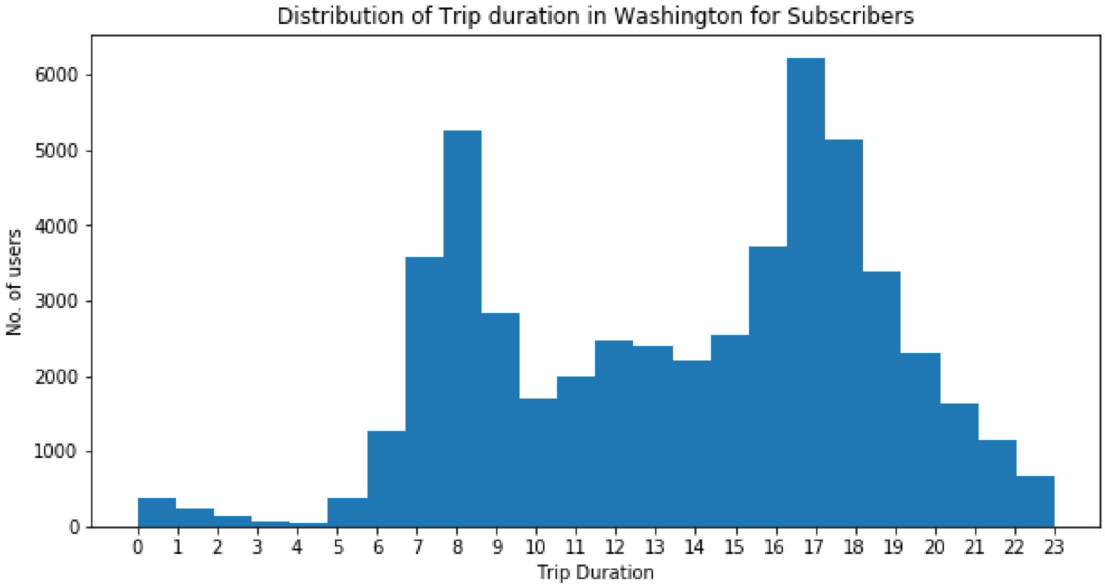
```
In [30]: #returns rides of every hour
         Washington_DC_data['hour'].value_counts()
```

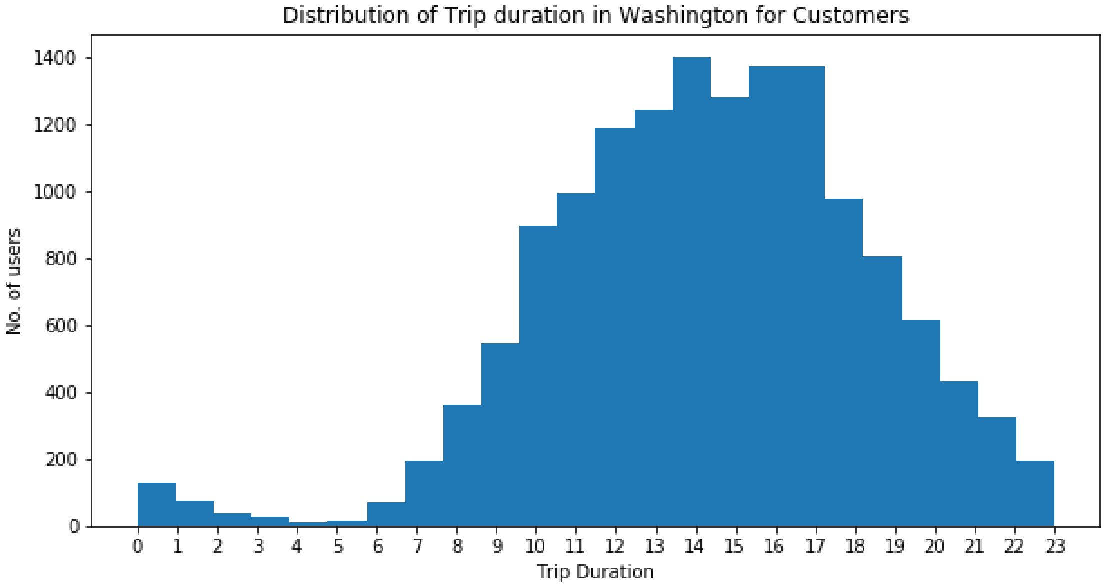
```
Out[30]: 17    7600
         18    6111
         8     5615
         16    5104
         19    4188
         15    3829
         7     3779
         12    3667
         13    3638
         14    3620
         9     3375
         11    2984
         20    2911
         10    2608
         21    2072
         22    1459
         6     1347
         23     858
         0      515
         5      407
```

```
1      299
2      184
3       89
4       67
Name: hour, dtype: int64
```

We have got the first half of our question answering the hour '17' has most rides compared to any hour of the day. Now lets visualize this for Subscribers and Customers.

```
In [31]: #graph size
         plt.figure(figsize=(10,5))

         #graph type with no. of bins
         plt.hist(Washington_DC_subs['hour'], bins = 24)

         #lables
         plt.xlabel('Trip Duration')
         plt.ylabel('No. of users')

         plt.xticks(np.arange(0,24,1))

         #title
         plt.title('Distribution of Trip duration in Washington for Subscribers')
         #displaying of subscribers
         plt.show()

         #graph size
         plt.figure(figsize=(10,5))

         #graph type with no. of bins
         plt.hist(Washington_DC_cust['hour'], bins = 24)

         #lables
         plt.xlabel('Trip Duration')
         plt.ylabel('No. of users')

         plt.xticks(np.arange(0,24,1))

         #title
         plt.title('Distribution of Trip duration in Washington for Customers')
         #displaying of customers
         plt.show()
```





- Subcribers graph shows bimodal type of distributions, which means subscribers choose to ride bikes a lot somewhere between 7 hours to 9 hours and a lot between 17 hours to 19 hours. The bike rides are really low at time between 0 - 5 hours. Rest of the day the use is steady.

- Customers graph has a somewhat normal distribution. This means Customers use lots of bikes in between daytime as you can see between 12-17. The only similarity in the graph of subscribers and customers is that there's less alot less use of bikes between 0-5 hours.

## Conclusions

Congratulations on completing the project! This is only a sampling of the data analysis process: from generating questions, wrangling the data, and to exploring the data. Normally, at this point in the data analysis process, you might want to draw conclusions about the data by performing a statistical test or fitting the data to a model for making predictions. There are also a lot of potential analyses that could be performed on the data which are not possible with only the data provided. For example, detailed location data has not been investigated. Where are the most commonly used docks? What are the most common routes? As another example, weather has potential to have a large impact on daily ridership. How much is ridership impacted when there is rain or snow? Are subscribers or customers affected more by changes in weather?

Question 7: Putting the bike share data aside, think of a topic or field of interest where you would like to be able to apply the techniques of data science. What would you like to be able to learn from your chosen subject?

Answer: I would actually use this in the field of finance. Capturing and analyzing new sources of data, building predictive models.