exploration_template

April 30, 2020

1 Ford GoBike System Data

2 (January 2019 - December 2019)

2.1 by Nancy Harrington

2.2 Preliminary Wrangling

The data set used for analysis is taken from the Ford GoBike data for the year 2019. The data detailed bike trips taken by riders and the characteristics that were associated with every trip. Those characteristics included the duration of the trip, start & end times, start & end stations, user type, start station latitude & longitude, end station latitude & longitude, bike id, and bike share for all trip.

[72]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import glob
import os
import datetime


%matplotlib inline
```

Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

[7]:
```
# load dataset
path = r'C:\Users\nharr\Documents\Udacity\Visual_project\FordGoBikeData'

all_files=glob.glob(os.path.join(path, "*.csv"))

all_files

list_csv=[]

for file in all_files:
```

```
    list_csv.append(pd.read_csv(file,sep=','))

df_master=pd.concat(list_csv)

df_master.to_csv('ford_master.csv',index=False)
```

```
C:\Users\nharr\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:3063: DtypeWarning: Columns (14) have
mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
C:\Users\nharr\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:3063: DtypeWarning: Columns (13,14)
have mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
C:\Users\nharr\Anaconda3\lib\site-
packages\IPython\core\interactiveshell.py:3063: DtypeWarning: Columns (13) have
mixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

3 Assessing Data

[8]:
```
# read the data
df= pd.read_csv('ford_master.csv')
df.head()
```

[8]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitude	start_station_longitude	end_station_id	end_station_name
0	80825	2019-01-31 17:57:44.6130	2019-02-01 16:24:49.8640	229.0	Foothill Blvd at 42nd Ave	37.775745	-122.213037	196.0	Grand Ave at Perkins St
1	65900	2019-01-31 20:58:33.8860	2019-02-01 15:16:54.1730	4.0	Cyril Magnin St at Ellis St	37.785881	-122.408915	134.0	Valencia St at 24th St
2	62633	2019-01-31 18:06:52.9240	2019-02-01 11:30:46.5300	245.0	Downtown Berkeley BART	37.870139	-122.268422	157.0	65th St at Hollis St
3	44680	2019-01-31 19:46:09.7190	2019-02-01 08:10:50.3180	85.0	Church St at Duboce Ave	37.770083	-122.429156	53.0	Grove St at Divisadero
4	60709	2019-01-31 14:19:01.5410	2019-02-01 07:10:51.0650	16.0	Steuart St at Market St	37.794130	-122.394430	28.0	The Embarcadero at Bryant St

```
   end_station_latitude  end_station_longitude  bike_id   user_type  \
0             37.808894            -122.256460     4861  Subscriber
1             37.752428            -122.420628     5506  Subscriber
2             37.846784            -122.291376     2717    Customer
3             37.775946            -122.437777     4557    Customer
4             37.787168            -122.388098     2100    Customer

  bike_share_for_all_trip rental_access_method
0                      No                  NaN
1                      No                  NaN
2                      No                  NaN
3                      No                  NaN
4                      No                  NaN
```

[10]:
```
# look at how many rows and columns
df.shape
```

[10]:
```
(2506983, 15)
```

[11]:
```
# sample the data to see what needs to be cleaned
df.sample(10)
```

[11]:
```
         duration_sec                start_time                  end_time  \
820810            219  2019-04-06 02:08:33.1230  2019-04-06 02:12:12.9270
2181988           605  2019-11-26 08:16:55.0670  2019-11-26 08:27:00.2930
15185             556  2019-01-30 10:55:21.1740  2019-01-30 11:04:38.1430
200901            619  2019-02-28 08:00:53.1570  2019-02-28 08:11:12.2770
1450379           645       2019-07-22 18:38:06       2019-07-22 18:48:52
1865605          1795  2019-09-10 19:10:27.2710  2019-09-10 19:40:22.3110
2030502           997  2019-10-18 17:47:19.1240  2019-10-18 18:03:56.7640
1598230           978  2019-08-18 14:34:55.5960  2019-08-18 14:51:14.2420
2128857          1630  2019-10-06 13:12:58.5430  2019-10-06 13:40:09.0960
944410            111  2019-05-19 20:03:08.8390  2019-05-19 20:05:00.5160

         start_station_id                          start_station_name  \
820810              240.0                      Haste St at Telegraph Ave
2181988               5.0  Powell St BART Station (Market St at 5th St)
15185               373.0     Potrero del Sol Park (25th St at Utah St)
200901              370.0                           Jones St at Post St
1450379               NaN                                           NaN
1865605             163.0                     Lake Merritt BART Station
2030502              62.0                  Victoria Manalo Draves Park
1598230              75.0                     Market St at Franklin St
2128857               6.0                The Embarcadero at Sansome St
944410              327.0                     5th St at San Salvador St
```

```
         start_station_latitude  start_station_longitude  end_station_id  \
820810                37.866043              -122.258804           247.0
2181988               37.783899              -122.408445           350.0
15185                 37.751792              -122.405216           355.0
200901                37.787327              -122.413278            58.0
1450379               37.775079              -122.444954            96.0
1865605               37.797320              -122.265320           197.0
2030502               37.777791              -122.406432           384.0
1598230               37.773793              -122.421239           109.0
2128857               37.804770              -122.403234            75.0
944410                37.332039              -121.881766           317.0

                  end_station_name  end_station_latitude  \
820810     Fulton St at Bancroft Way             37.867789
2181988         8th St at Brannan St             37.771431
15185        23rd St at Tennessee St             37.755367
200901          Market St at 10th St             37.776619
1450379        Dolores St at 15th St             37.766210
1865605  El Embarcadero at Grand Ave             37.808848
2030502        Jackson St at Polk St             37.794160
1598230       17th St at Valencia St             37.763316
2128857     Market St at Franklin St             37.773793
944410     San Salvador St at 9th St             37.333955

         end_station_longitude  bike_id   user_type bike_share_for_all_trip  \
820810              -122.265896     4502  Subscriber                     Yes
2181988             -122.405787    11612  Subscriber                      No
15185               -122.388795      322  Subscriber                      No
200901              -122.417385     5023  Subscriber                      No
1450379             -122.426614   181696  Subscriber                     NaN
1865605             -122.249680     1497  Subscriber                      No
2030502             -122.421568     1827  Subscriber                      No
1598230             -122.421904     3391    Customer                      No
2128857             -122.421239    10538    Customer                      No
944410              -121.877349     2362  Subscriber                      No

        rental_access_method
820810                   NaN
2181988                  NaN
15185                    NaN
200901                   NaN
1450379                  app
1865605                  NaN
2030502                  NaN
1598230                  NaN
2128857                  NaN
944410                   NaN
```

[13]:
```
# look at the data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2506983 entries, 0 to 2506982
Data columns (total 15 columns):
 #   Column                   Dtype
---  ------                   -----
 0   duration_sec             int64
 1   start_time               object
 2   end_time                 object
 3   start_station_id         float64
 4   start_station_name       object
 5   start_station_latitude   float64
 6   start_station_longitude  float64
 7   end_station_id           float64
 8   end_station_name         object
 9   end_station_latitude     float64
 10  end_station_longitude    float64
 11  bike_id                  int64
 12  user_type                object
 13  bike_share_for_all_trip  object
 14  rental_access_method     object
dtypes: float64(6), int64(2), object(7)
memory usage: 286.9+ MB
```

[16]:
```
# look at the statistics
df.describe()
```

[16]:

	duration_sec	start_station_id	start_station_latitude	\
count	2.506983e+06	2.426249e+06	2.506983e+06	
mean	8.076483e+02	1.465047e+02	3.776506e+01	
std	1.974714e+03	1.223171e+02	1.363698e-01	
min	6.000000e+01	3.000000e+00	0.000000e+00	
25%	3.590000e+02	4.700000e+01	3.776931e+01	
50%	5.710000e+02	1.050000e+02	3.778053e+01	
75%	8.870000e+02	2.430000e+02	3.779539e+01	
max	9.121100e+05	4.980000e+02	4.551000e+01	

	start_station_longitude	end_station_id	end_station_latitude	\
count	2.506983e+06	2.424081e+06	2.506983e+06	
mean	-1.223499e+02	1.427044e+02	3.776422e+01	
std	3.089648e-01	1.214296e+02	2.392885e-01	
min	-1.225143e+02	3.000000e+00	0.000000e+00	
25%	-1.224130e+02	4.300000e+01	3.777003e+01	
50%	-1.223983e+02	1.010000e+02	3.778076e+01	
75%	-1.222914e+02	2.390000e+02	3.779587e+01	

```
max                0.000000e+00    4.980000e+02          4.551000e+01

       end_station_longitude       bike_id
count           2.506983e+06  2.506983e+06
mean           -1.223459e+02  2.789833e+04
std             7.080417e-01  1.146067e+05
min            -1.225143e+02  4.000000e+00
25%            -1.224117e+02  1.952000e+03
50%            -1.223981e+02  4.420000e+03
75%            -1.222934e+02  9.682000e+03
max             0.000000e+00  9.999410e+05
```

[17]:
```
# look for duplicates
df.duplicated().sum()
```

[17]:
```
0
```

[18]:
```
# look for NaN values
df.isna().sum()
```

[18]:
```
duration_sec                0
start_time                  0
end_time                    0
start_station_id        80734
start_station_name      80133
start_station_latitude      0
start_station_longitude     0
end_station_id          82902
end_station_name        82350
end_station_latitude        0
end_station_longitude       0
bike_id                     0
user_type                   0
bike_share_for_all_trip  243259
rental_access_method    2386145
dtype: int64
```

3.0.1 Quality

- Start time and end time are not in timestamp format.
- Missing values for: start_station_id, start_station_name, end_station_id, end_station_name, bike_share_for_all_trip, and rental_access_method.
- Add descriptive columns for the months/weekdays/hours for better analysis.
- duration is in seconds.

4 Cleaning

[35]:
```
# make a copy of the dataframe
df_clean = df.copy()
```

[36]:
```
df_clean.head()
```

[36]:
```
   duration_sec                start_time                  end_time  \
0         80825  2019-01-31 17:57:44.6130  2019-02-01 16:24:49.8640
1         65900  2019-01-31 20:58:33.8860  2019-02-01 15:16:54.1730
2         62633  2019-01-31 18:06:52.9240  2019-02-01 11:30:46.5300
3         44680  2019-01-31 19:46:09.7190  2019-02-01 08:10:50.3180
4         60709  2019-01-31 14:19:01.5410  2019-02-01 07:10:51.0650

   start_station_id           start_station_name  start_station_latitude  \
0             229.0    Foothill Blvd at 42nd Ave               37.775745
1               4.0  Cyril Magnin St at Ellis St               37.785881
2             245.0       Downtown Berkeley BART               37.870139
3              85.0      Church St at Duboce Ave               37.770083
4              16.0      Steuart St at Market St               37.794130

   start_station_longitude  end_station_id             end_station_name  \
0              -122.213037           196.0       Grand Ave at Perkins St
1              -122.408915           134.0        Valencia St at 24th St
2              -122.268422           157.0          65th St at Hollis St
3              -122.429156            53.0        Grove St at Divisadero
4              -122.394430            28.0  The Embarcadero at Bryant St

   end_station_latitude  end_station_longitude  bike_id   user_type  \
0             37.808894            -122.256460     4861  Subscriber
1             37.752428            -122.420628     5506  Subscriber
2             37.846784            -122.291376     2717    Customer
3             37.775946            -122.437777     4557    Customer
4             37.787168            -122.388098     2100    Customer

  bike_share_for_all_trip rental_access_method
0                      No                  NaN
1                      No                  NaN
2                      No                  NaN
3                      No                  NaN
4                      No                  NaN
```

Define

- Change the start time and end time into datetime format.

Code

[37]:
```
df_clean.start_time = pd.to_datetime(df_clean.start_time)
df_clean.end_time = pd.to_datetime(df_clean.end_time)
```

Test

[38]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2506983 entries, 0 to 2506982
Data columns (total 15 columns):
 #   Column                   Dtype
---  ------                   -----
 0   duration_sec             int64
 1   start_time               datetime64[ns]
 2   end_time                 datetime64[ns]
 3   start_station_id         float64
 4   start_station_name       object
 5   start_station_latitude   float64
 6   start_station_longitude  float64
 7   end_station_id           float64
 8   end_station_name         object
 9   end_station_latitude     float64
 10  end_station_longitude    float64
 11  bike_id                  int64
 12  user_type                object
 13  bike_share_for_all_trip  object
 14  rental_access_method     object
dtypes: datetime64[ns](2), float64(6), int64(2), object(5)
memory usage: 286.9+ MB
```

Define

- Add the month name column
- Add the month number column
- Add the weekday column
- Add start and end time hour column
- Add the month date column

Code

[39]:
```
# Start time month (January - December)
df_clean['start_time_month'] = df_clean['start_time'].dt.strftime('%B')
```

[40]:
```
# Start time month (1-12)
df_clean['start_time_month_num'] = df_clean['start_time'].dt.month.astype(int)
```

[41]:
```
# Start time weekday
df_clean['start_time_weekday'] = df_clean['start_time'].dt.strftime('%a')
```

[42]:
```
# Start and end time hour
df_clean['start_time_hour'] = df_clean['start_time'].dt.hour
df_clean['end_time_hour'] = df_clean['end_time'].dt.hour
```

[43]:
```
# Start time date of the month
df_clean['start_time_date']= df_clean['start_time'].dt.day
```

Test

[44]:
```
df_clean.sample(5)
```

[44]:

```
         duration_sec              start_time                end_time  \
316868            518 2019-02-11 08:15:10.415 2019-02-11 08:23:49.152
1652588           734 2019-08-10 10:04:31.287 2019-08-10 10:16:46.187
1384581           504 2019-07-07 07:29:59.574 2019-07-07 07:38:24.550
1520128           512 2019-08-29 08:54:17.531 2019-08-29 09:02:49.578
1397899           615 2019-07-03 14:47:42.364 2019-07-03 14:57:57.494

         start_station_id                                start_station_name  \
316868              120.0                              Mission Dolores Park
1652588             171.0                            Rockridge BART Station
1384581              75.0                         Market St at Franklin St
1520128              30.0     San Francisco Caltrain (Townsend St at 4th St)
1397899              43.0  San Francisco Public Library (Grove St at Hyde…

         start_station_latitude  start_station_longitude  end_station_id  \
316868                37.761420              -122.426435            58.0
1652588               37.844279              -122.251900           267.0
1384581               37.773793              -122.421239            95.0
1520128               37.776598              -122.395282           363.0
1397899               37.778768              -122.415929            86.0

                                     end_station_name  \
316868                           Market St at 10th St
1652588                       Derby St at College Ave
1384581                         Sanchez St at 15th St
1520128  Salesforce Transit Center (Natoma St at 2nd St)
1397899                       Market St at Dolores St

         end_station_latitude  …  bike_id   user_type  \
316868               37.776619  …     4644  Subscriber
1652588              37.861804  …     3191  Subscriber
1384581              37.766219  …      353  Subscriber
1520128              37.787492  …    10220  Subscriber
1397899              37.769305  …      283  Subscriber

        bike_share_for_all_trip rental_access_method start_time_month  \
```

```
316868                       No                  NaN          February
1652588                      No                  NaN            August
1384581                      No                  NaN              July
1520128                      No                  NaN            August
1397899                      No                  NaN              July

        start_time_month_num  start_time_weekday start_time_hour  \
316868                     2                 Mon               8
1652588                    8                 Sat              10
1384581                    7                 Sun               7
1520128                    8                 Thu               8
1397899                    7                 Wed              14

         end_time_hour  start_time_date
316868               8               11
1652588             10               10
1384581              7                7
1520128              9               29
1397899             14                3

[5 rows x 21 columns]
```

Define

- Change the duration column from seconds into minutes.

Code

[46]:
```
# Duration in seconds to duration in minutes
df_clean['duration_min'] = df_clean['duration_sec']/60
df_clean['duration_min'] = df_clean['duration_min'].astype(int)
```

Test

[48]:
```
df_clean.sample()
```

[48]:
```
         duration_sec              start_time                end_time  \
2115052          1063 2019-10-08 08:32:56.953 2019-10-08 08:50:40.136

         start_station_id                      start_station_name  \
2115052              54.0  Alamo Square (Steiner St at Fulton St)

         start_station_latitude  start_station_longitude  end_station_id  \
2115052               37.777547              -122.433274            30.0

                                      end_station_name  end_station_latitude  \
2115052  San Francisco Caltrain (Townsend St at 4th St)             37.776598
```

```
         …   user_type  bike_share_for_all_trip rental_access_method  \
2115052  …  Subscriber                      No                   NaN

        start_time_month start_time_month_num start_time_weekday  \
2115052          October                   10               Tue

         start_time_hour end_time_hour  start_time_date  duration_min
2115052                8             8                8            17

[1 rows x 22 columns]
```

Save cleaned dataframe to a new dataframe

[49]:
```
df_clean.to_csv('ford_master_clean.csv', index = False)
```

4.0.1 What is the structure of your dataset?

For 2019 there was 2,506,983 rides taken in the Bay area with 15 different column characteristics(duration_sec, start_time,end_time,start_station_id,start_station_name,start_station_latitude,start_station_longitude end_station_name, end_station_latitude, end_station_longitude, bike_id, user_type, bike_share_for_all_trip, rental_access_method) The data was then cleaned and columns were added to help with visualiation and understanding of data trends (start_time_month, start_time_month_num, start_time_weekday,start_time_hour, end_time_hour, start_time_date, duration_min)

4.0.2 What is/are the main feature(s) of interest in your dataset?

The main features of interest for the dataset are most popular months and days of usage. Also I would like to see the average duration of the ride and most popular start and end stations. And the user type if they are a member or a casual rider. The bike share for all is for Bay Area residents who qualify for CalFresh, SFMTA Lifeline Pass, or PG&E CARE utility discount are eligible to join our Bike Share for all program and I would like to see how beneficial that program is.

4.0.3 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

The features of the dataset that will help support my investigation will be the months and weekdays and duration columns as well as the user type and bike share for all columns and the stations columns.

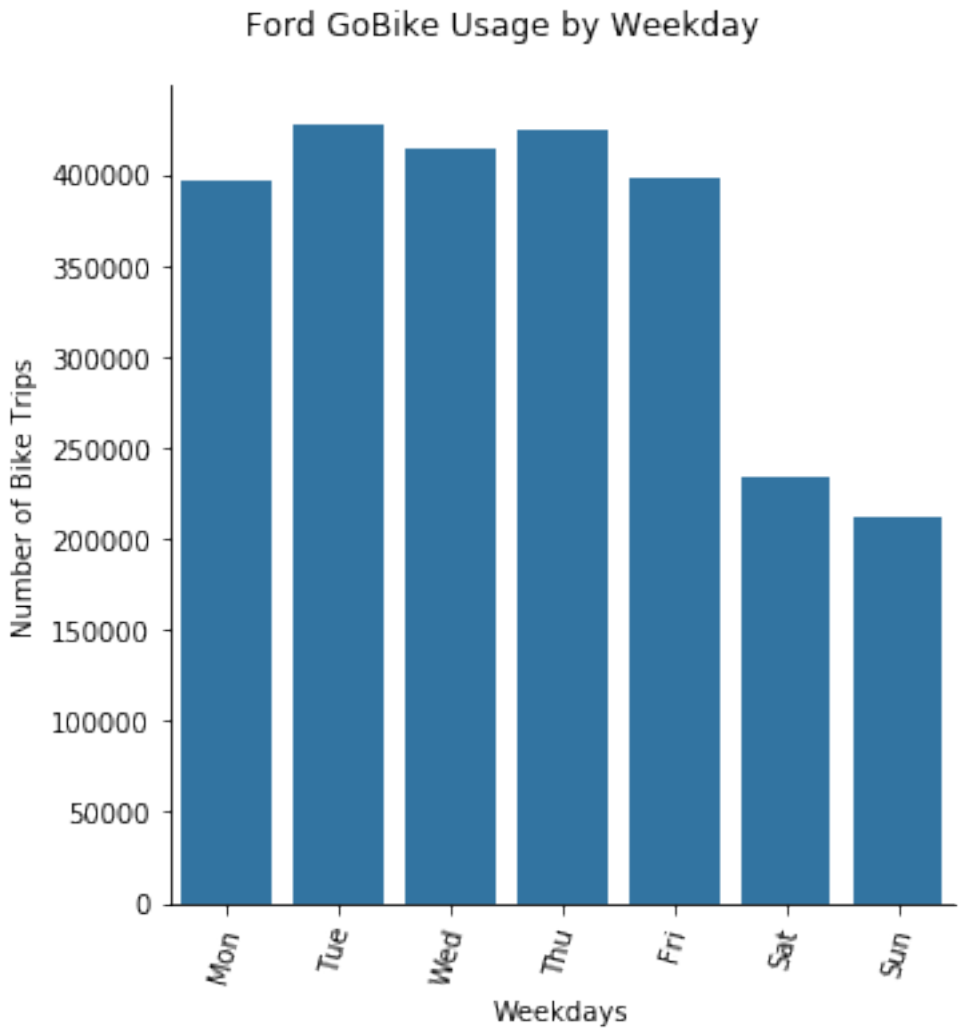
4.1 Univariate Exploration

In this section, investigate distributions of individual variables. If you see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

1.) What is the most popular rental day of the week?

[50]:
```
# remove standard color palette to a plain one
base_color = sb.color_palette()[0]
```

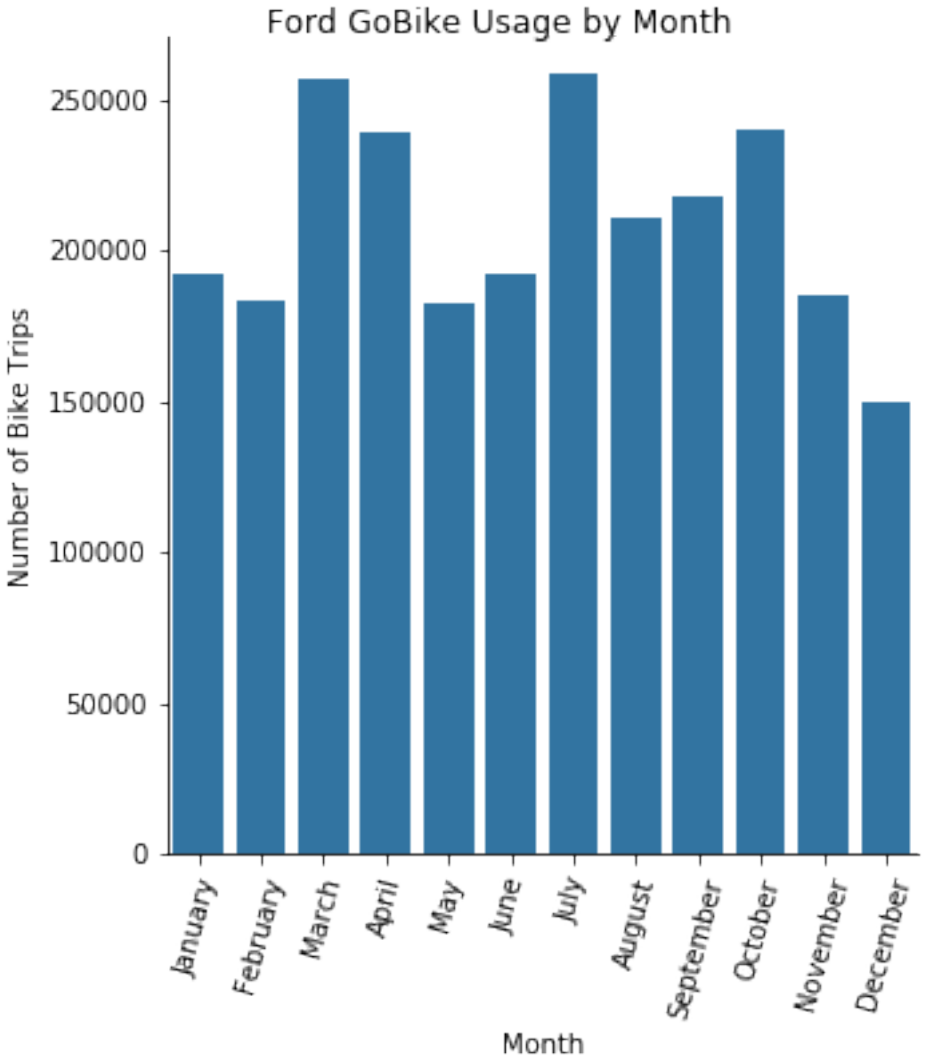
[51]:
```
# weekday usage of the bike share
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']

df = sb.catplot(data=df_clean, x='start_time_weekday', kind='count', color =␣
↪base_color, order = weekday)

df.set_axis_labels('Weekdays', 'Number of Bike Trips')

df.fig.suptitle('Ford GoBike Usage by Weekday', y=1.05);

df.set_xticklabels(rotation=75);
```



1a.) During the week is substansually more popular for bike share riders with Tuesday being the most popular.

2.) What is the most popular rental month?

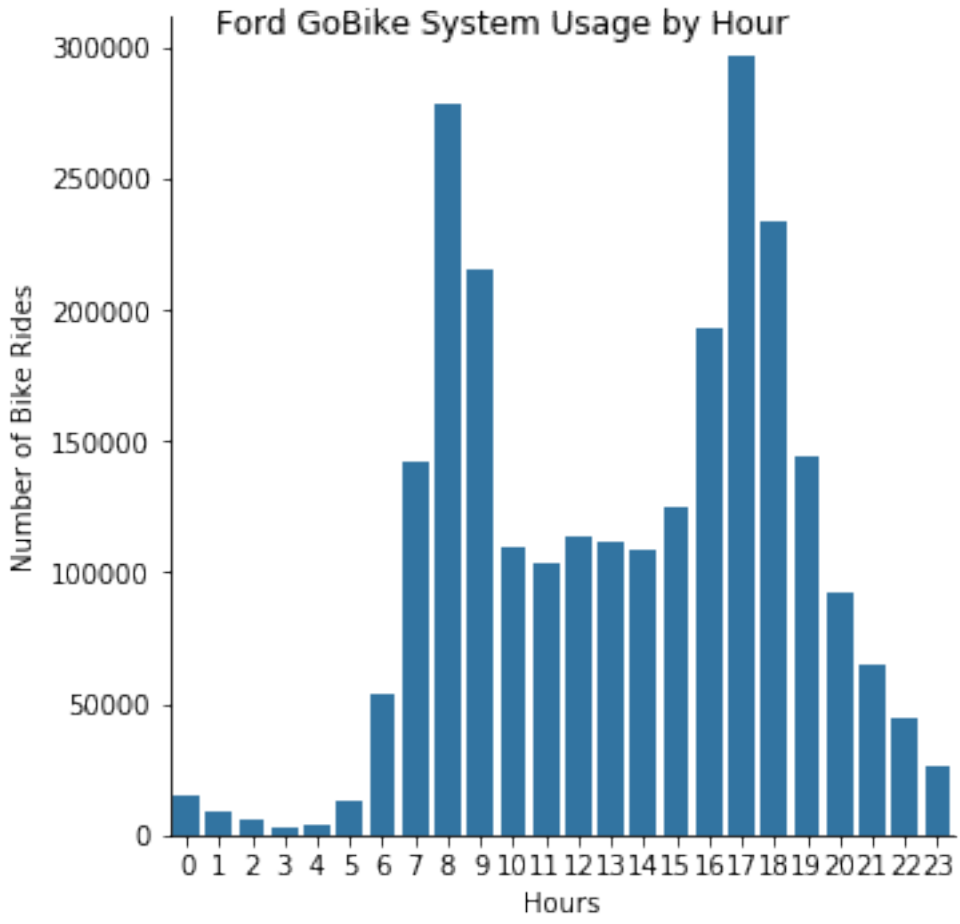
[52]:
```
# monthly usage of bike share
df = sb.catplot(data = df_clean, x = 'start_time_month', kind = 'count', color␣
 ↪= base_color);

df.set_axis_labels('Month', 'Number of Bike Trips'),

df.fig.suptitle('Ford GoBike Usage by Month', y = 1.0);

df.set_xticklabels(rotation=75);
```



2a.) March, April and July are the most popular months. Im guessing the spring months with the good weather and I would be curious to see if July was due to tourism.

3.) What is the most popular rental hour?

[74]:
```
# most popular time of day for bike share
df = sb.catplot(data = df_clean, x='start_time_hour', kind='count', color =␣
 ↪base_color)

df.set_axis_labels('Hours', 'Number of Bike Rides')

df.fig.suptitle('Ford GoBike System Usage by Hour');
```



3a.) The most popular times of day are at 8-9 in the morning and at 5-6 in the evening which leads me to believe that they are being used to comute to work.

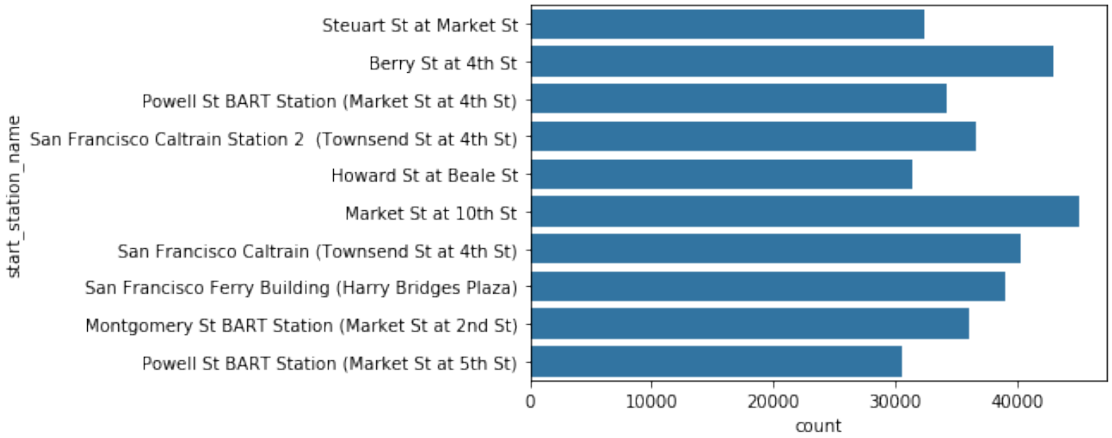
4.) What are the most popular start stations?

[81]:
```
top_start_stations_df = df_clean.start_station_name.value_counts()[:10].index
```

[82]:
```
top_start_stations_df = df_clean[df_clean.start_station_name.
↪isin(top_start_stations)].copy()
```

[84]:
```
# top ten start stations
sb.countplot(data=top_start_stations_df,␣
↪y='start_station_name',color=base_color)
```

[84]: <matplotlib.axes._subplots.AxesSubplot at 0x22c4451d308>



4a.) The most popular start station is Market station at 10th St.

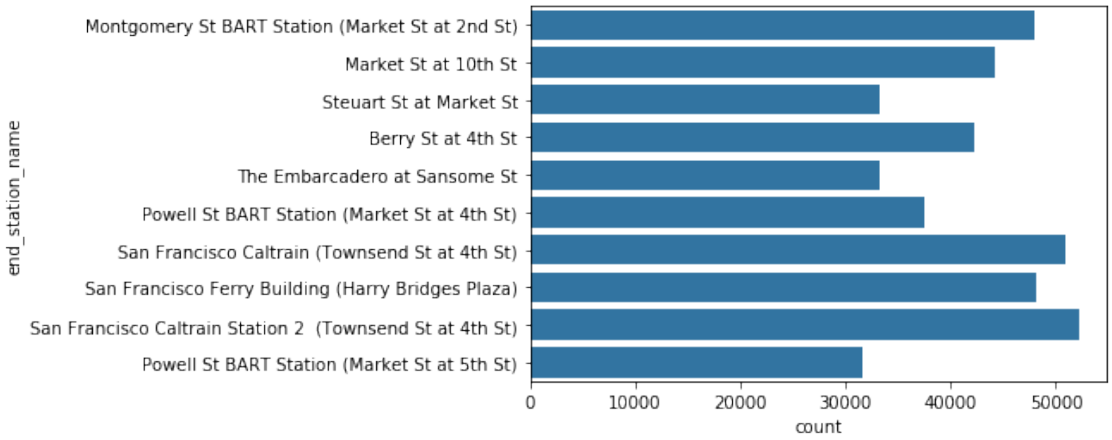
5.) What are the most popular end stations?

[85]:
```
top_end_stations_df = df_clean.end_station_name.value_counts()[:10].index
```

[87]:
```
top_end_stations_df = df_clean[df_clean.end_station_name.
↪isin(top_end_stations)].copy()
```

[88]:
```
# top ten end stations
sb.countplot(data=top_end_stations_df, y='end_station_name',color=base_color)
```

[88]: <matplotlib.axes._subplots.AxesSubplot at 0x22bbf1e0488>



5a.) The most popular end station is the San Francisco Caltrain Station 2.

[90]:
```
df_clean.bike_share_for_all_trip.value_counts()
```

[90]:
```
No     2086152
Yes     177572
Name: bike_share_for_all_trip, dtype: int64
```

[96]:
```
customer = df_clean.query('user_type == "Customer"')['bike_id'].count()
subscriber = df_clean.query('user_type == "Subscriber"')['bike_id'].count()
```

[97]:
```
customer
```

[97]:
```
485817
```

[98]:
```
subscriber
```

[98]:
```
2021166
```

4.1.1 Discuss the distribution(s) of your variable(s) of interest. Were there any unusual points? Did you need to perform any transformations?

My variables of interest being mostly date and time. I would like to see if there is a relationship betweed day of week, time of day and month between user and customer riders. It does seem to show at this point with no other variable involved that during the week is more popular than the weekend, to and from work hours see a surge of riders and the spring time is busier, however there is July that shows a significant amount of riders. The start and end stations I would like to see performance of the station and if there are any distinguishing attributes. And lastly the newer program bike share for all trip and the performance numbers and if it is valuable program.

4.1.2 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

The month column was cleaned added to and extracted from the start time colum. There is a significant jump during July and I need to investigate further. I also extracted the days of the week column from the start date to look at popular day of the week. Again I extracted the hour from the start date column to examine the time of day that gets more usage than other.

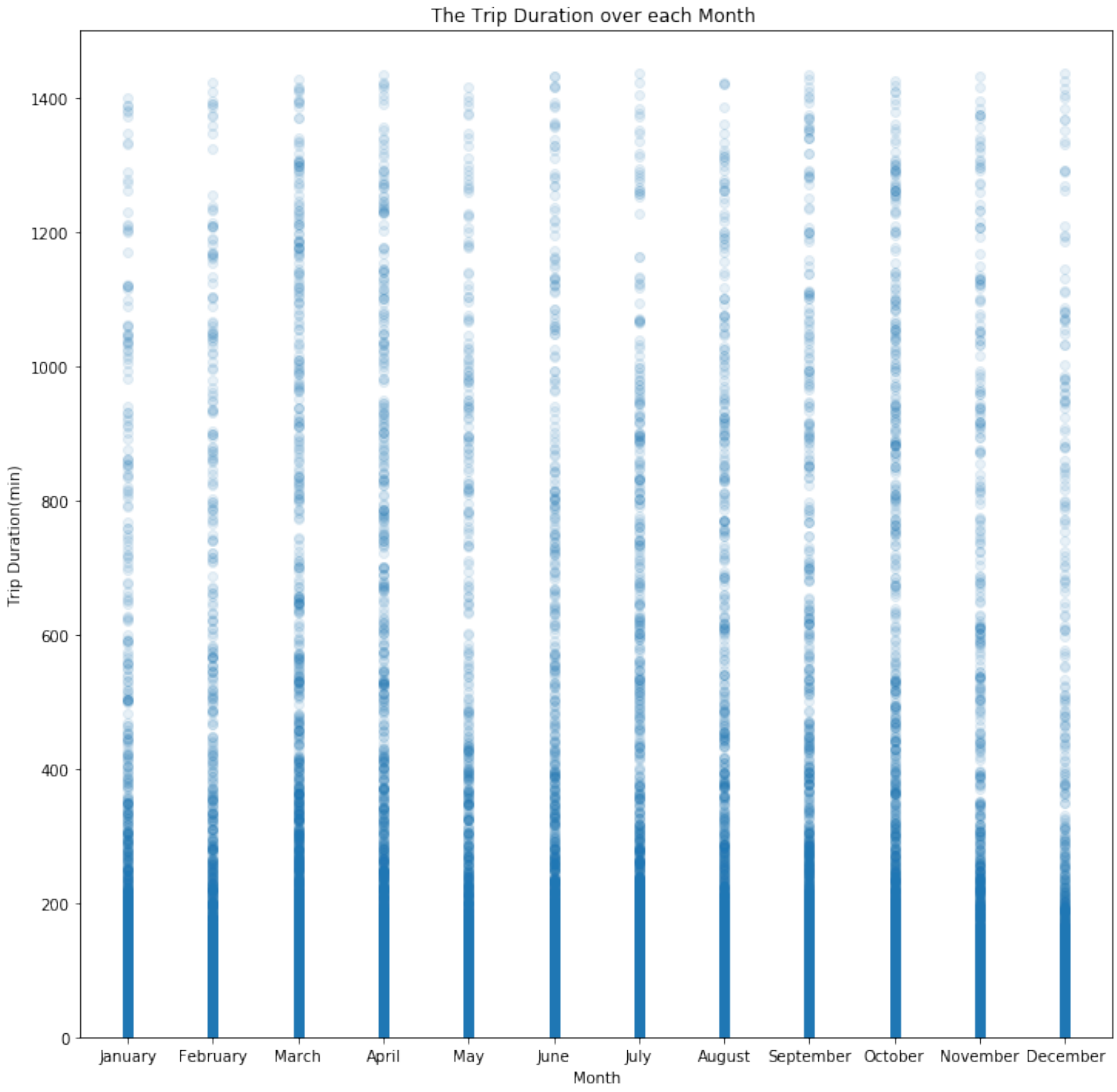
4.2 Bivariate Exploration

In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

6.) What is the average trip duration per month?

[128]:
```
# look and check the trip duration changes over each month.
plt.figure(figsize = [12,12]) # make the whole figure bigger
plt.scatter(data = df_clean , x = 'start_time_month' , y = 'duration_min' ,␣
 ↪alpha = 0.1 )
plt.ylim(0,1500)
plt.title('The Trip Duration over each Month ')
plt.xlabel('Month')
plt.ylabel('Trip Duration(min)')
```

[128]:
```
Text(0, 0.5, 'Trip Duration(min)')
```

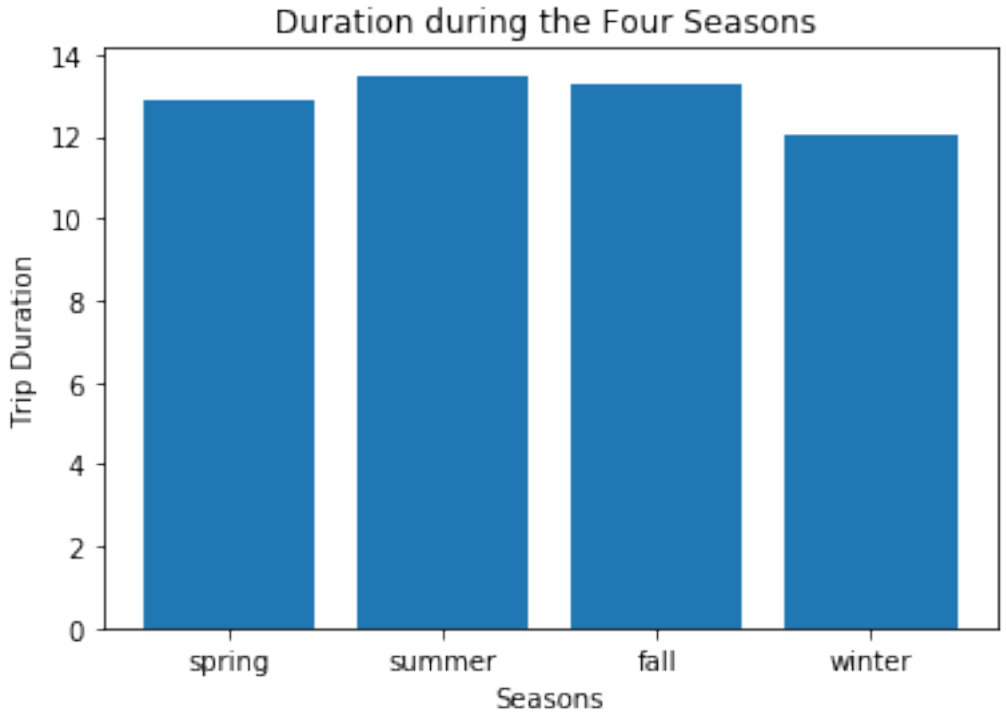


6a.) The trip duration is longer during the spring and summer months.

7.)Is there a distinction between the seasons and the trip durations?

[132]:
```
# lets create 4 season categories
spring_dur = df_clean.query('start_time_month_num in ["3" , "4" , "5"]' ).
 ↪duration_min.mean ()
summer_dur = df_clean.query('start_time_month_num in ["6" , "7" , "8"] ').
 ↪duration_min.mean()
fall_dur = df_clean.query('start_time_month_num in ["9" , "10" , "11"] ').
 ↪duration_min.mean()
winter_dur = df_clean.query('start_time_month_num in ["12" , "1" , "2"]' ).
 ↪duration_min.mean()
```

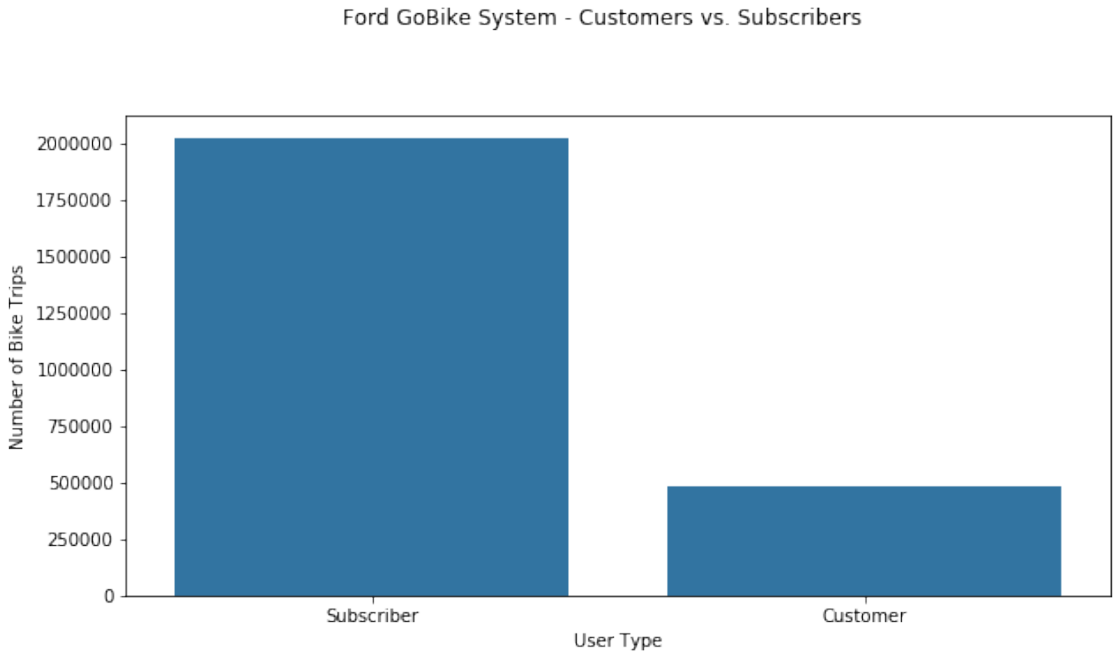
```
plt.bar(['spring','summer','fall','winter'],[spring_dur , summer_dur , fall_dur␣
 ↪, winter_dur] )
plt.title('Duration during the Four Seasons ')
plt.xlabel('Seasons')
plt.ylabel('Trip Duration');
```



7a.)The graph shows that summer and fall have longer duration times.

8.) Is one user type more pevalant than the other?

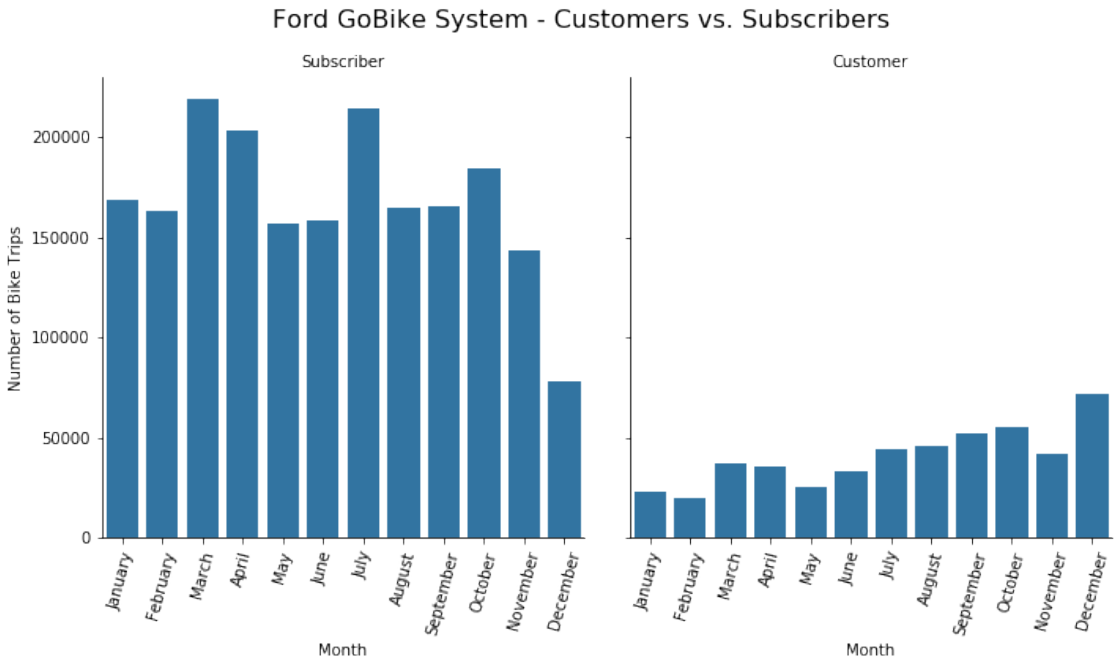
[129]:
```
plt.figure(figsize = [10, 5])

graph = sb.countplot(data = df_clean, x = "user_type", order = df_clean.
 ↪user_type.value_counts().index, color=base_color);
graph.set_xlabel('User Type');
graph.set_ylabel('Number of Bike Trips');
plt.suptitle('Ford GoBike System - Customers vs. Subscribers', y=1.05);
```



8a.) There are more subscribers than customers.

9.) What is the average number of bike trips by user time every month?

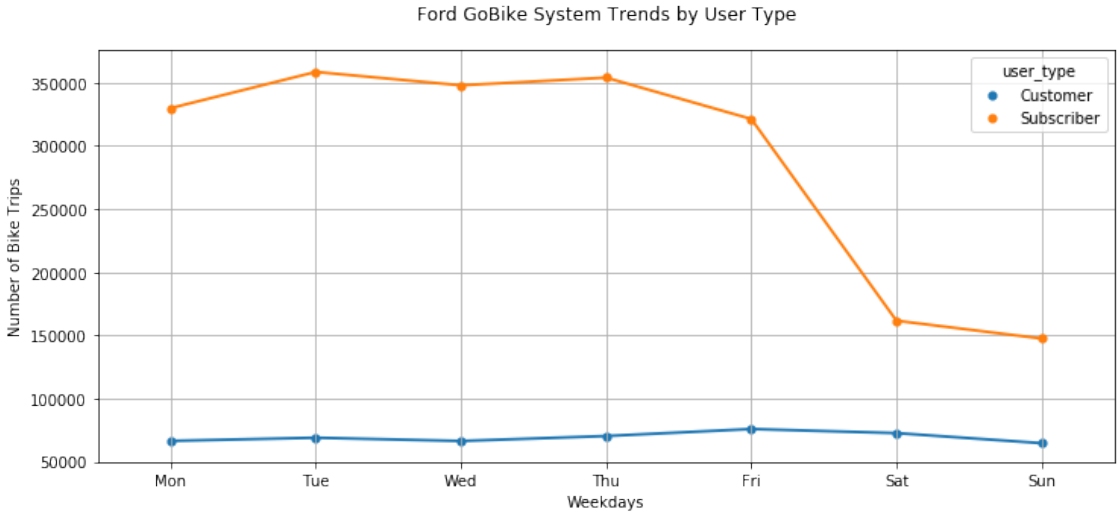
[118]:
```
# Customer Usage by Month vs. Subscriber Usage by Month
#plt.figure(figsize = [12, 5])
graph = sb.catplot(data=df_clean, x='start_time_month', col="user_type",␣
 ↪kind='count', color = base_color);

graph.set_axis_labels("Month", "Number of Bike Trips");
graph.set_titles("{col_name}");

graph.fig.suptitle('Ford GoBike System - Customers vs. Subscribers', y=1.05,␣
 ↪fontsize=16);
graph.set_xticklabels(rotation=75);
```



9a.) The number of subscriber riders is more during the spring and July. And the number or customer riders is higher during December.

10.) What is the average number of bike trips per user type during the week?

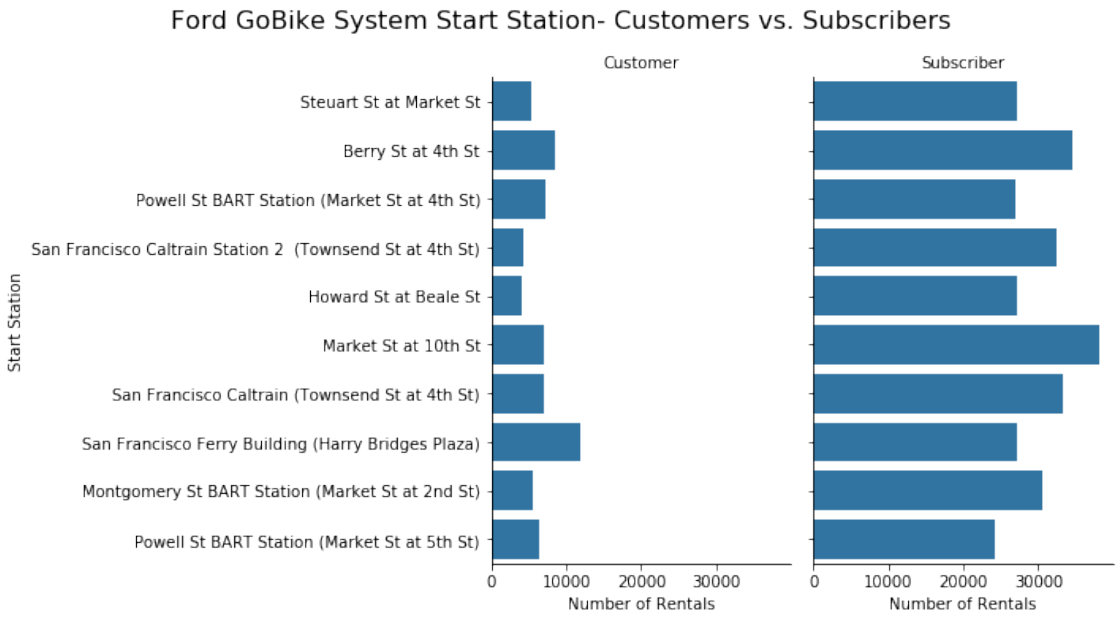
[119]:
```
plt.figure(figsize=(12, 5))

df_clean_user_week = df_clean.groupby(['start_time_weekday', 'user_type']).
 ↪size().reset_index()
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']

ax = sb.pointplot(data=df_clean_user_week, x='start_time_weekday', y=0, hue =␣
 ↪'user_type', scale=.7, order = weekday);

plt.title('Ford GoBike System Trends by User Type', y=1.05)
plt.xlabel('Weekdays')
plt.ylabel('Number of Bike Trips');
plt.grid()
```



10a.) The number of subscriber riders is way lower during the weekend and the customer is around the same during the week with a slight uptick on the weekend.

11.) What is the most popular start station per user?

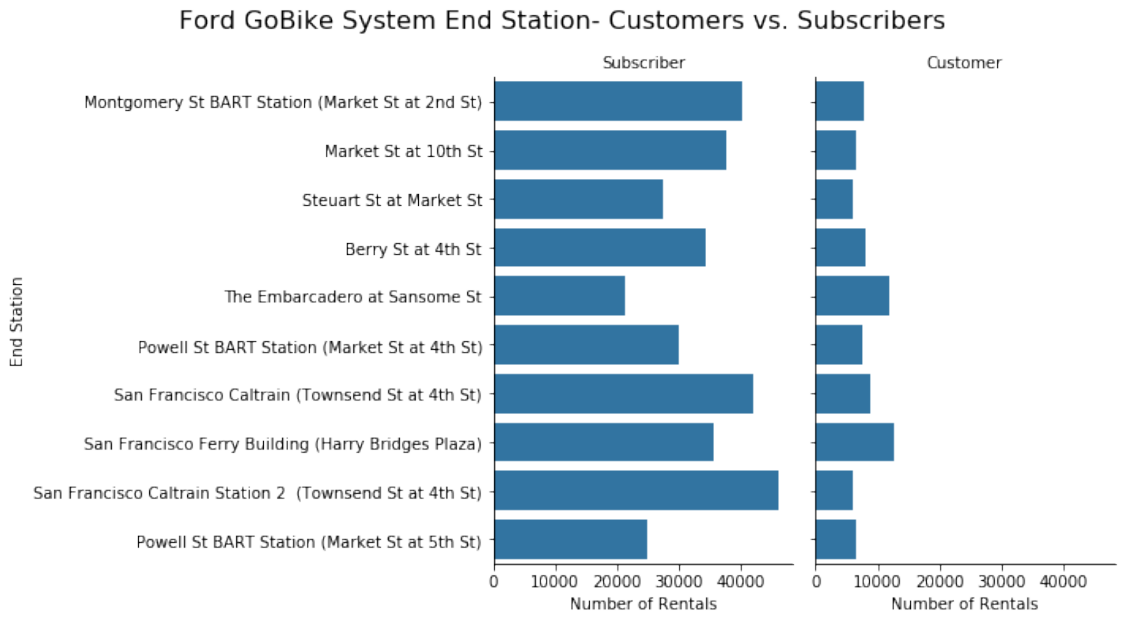
[140]:
```
# Customer Usage by Start Station vs. Subscriber Usage by Start Station
#plt.figure(figsize = [12, 5])
graph = sb.catplot(data=top_start_stations_df, y='start_station_name',␣
 ↪col="user_type", kind='count', color = base_color);

graph.set_axis_labels("Number of Rentals", "Start Station");
graph.set_titles("{col_name}");

graph.fig.suptitle('Ford GoBike System Start Station- Customers vs.␣
 ↪Subscribers', y=1.05, fontsize=16);
```



11a.) The most popular start station for a customer is the San Fransico Ferry Building. And the most popular End station for subscribers is the Market station at 10th st.

12.) What is the most popular end station per user?

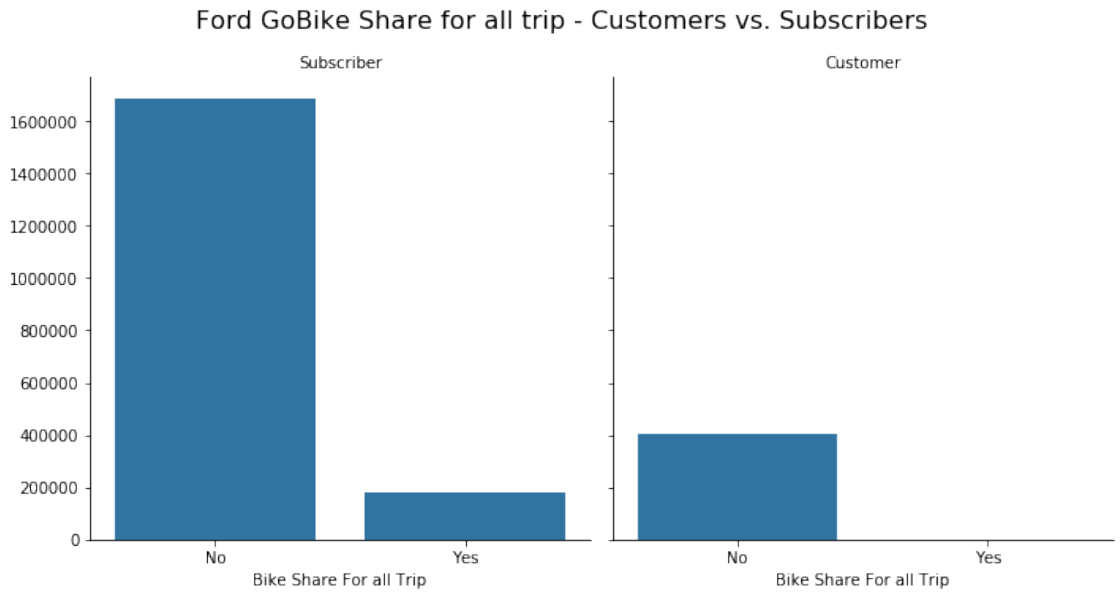
[141]:
```
# Customer Usage by End Station vs. Subscriber Usage by End Station
#plt.figure(figsize = [12, 5])
graph = sb.catplot(data=top_end_stations_df, y='end_station_name',␣
↪col="user_type", kind='count', color = base_color);

graph.set_axis_labels("Number of Rentals", "End Station");
graph.set_titles("{col_name}");

graph.fig.suptitle('Ford GoBike System End Station- Customers vs. Subscribers',␣
↪y=1.05, fontsize=16);
```



12a.) The most popular end station for subscribers is San Francisco Caltrain Station 2. And the most popular end station for customers is the San Francisco Ferry Building.

13.) How popular is the bike share for all trip?

[142]:
```
# bike_share_for_all_trip vs. user_type
#plt.figure(figsize = [12, 5])
graph = sb.catplot(data=df_clean, x='bike_share_for_all_trip', col="user_type",␣
↪kind='count', color = base_color);

graph.set_axis_labels("Bike Share For all Trip", "");
graph.set_titles("{col_name}");

graph.fig.suptitle('Ford GoBike Share for all trip - Customers vs.␣
↪Subscribers', y=1.05, fontsize=16);
```



13a.)The bike share for all trip is non-existant for customers and not as utilized as subscriber rentals.

4.2.1 Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

There is a relationship with the rider user type and the amounts of rentals and certain times of year and days of the week. The customers seem to be touristy with the times of day, day of the week, and what stations are more popular they all stay about the same through out the year. The subscribers utilize the bike rentals for working comute during the week and working hours.

4.2.2 Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

I was interested to see the the bike share for all trip data was not as stand out as I thought it would have been. Also it does not apply to a customer only to subscribers.

4.3 Multivariate Exploration

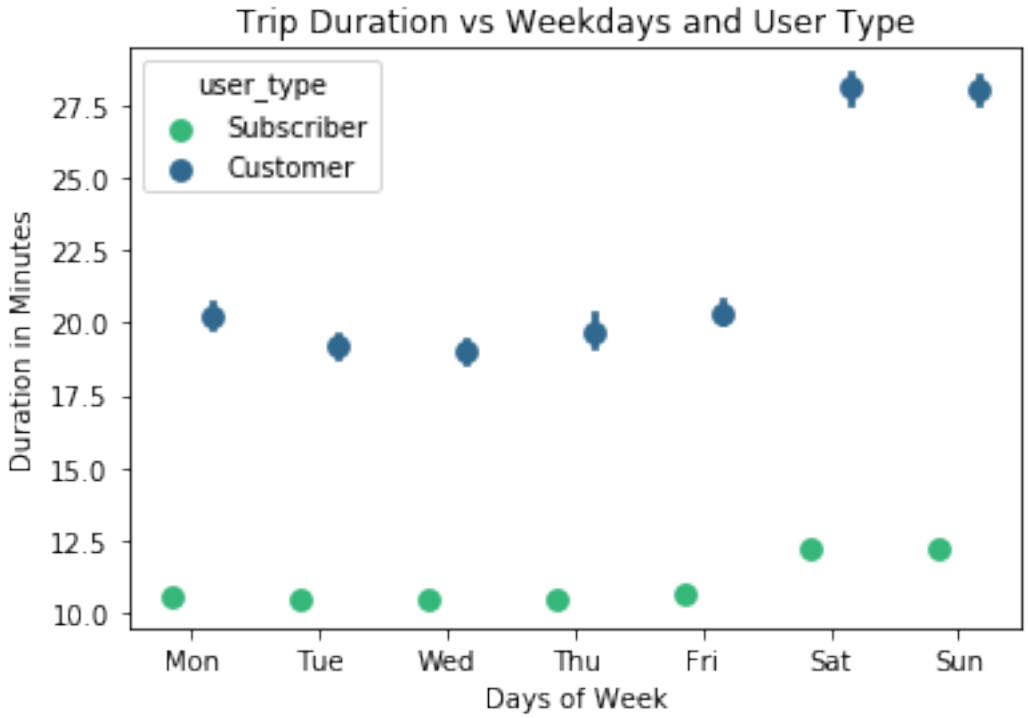
Create plots of three or more variables to investigate your data even further. Make sure that your investigations are justified, and follow from your work in the previous sections.

14.) How does the duration change per user during the week?

[151]:

```
sb.pointplot(data = df_clean, x = 'start_time_weekday', y = 'duration_min', hue␣
 ↪= 'user_type' , palette = 'viridis_r', dodge = 0.3, linestyles = "",␣
 ↪order=['Mon','Tue','Wed','Thu','Fri','Sat','Sun'])
plt.title('Trip Duration vs Weekdays and User Type')
plt.xlabel('Days of Week')
plt.ylabel('Duration in Minutes')
```

[151]:
```
Text(0, 0.5, 'Duration in Minutes')
```

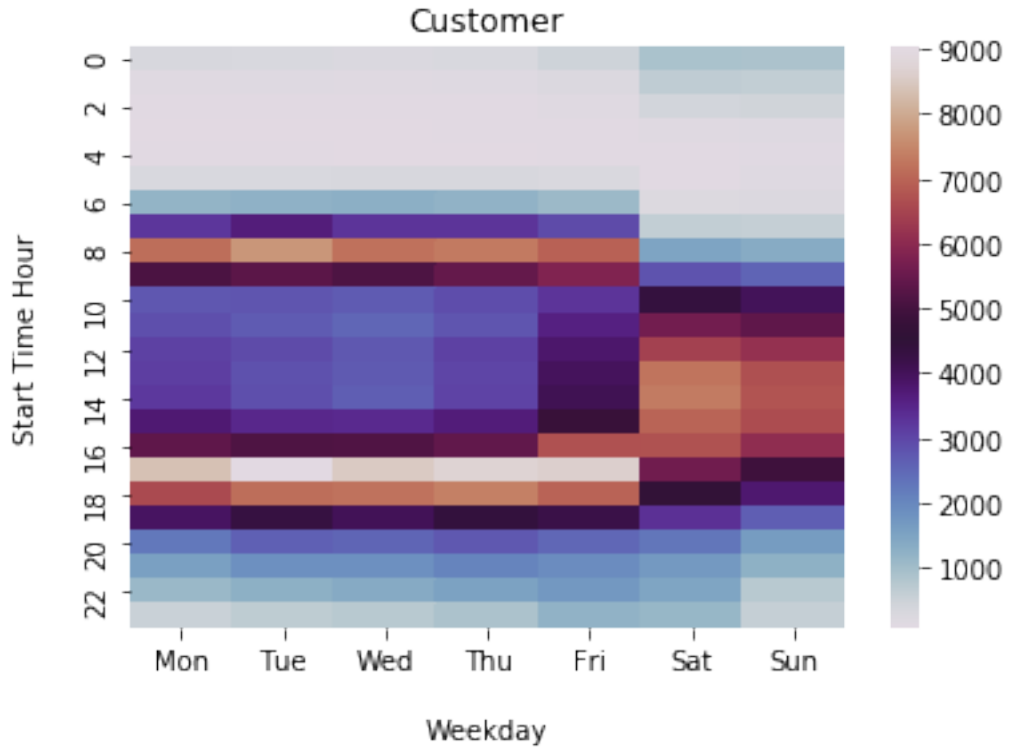


14a.)The subscriber has shorter duration times during the week and longer times during the weekend. The customer has higher duration times over the subscriber with the longest times being on the weekend.

15.) How does the start time hour change per user during the week?

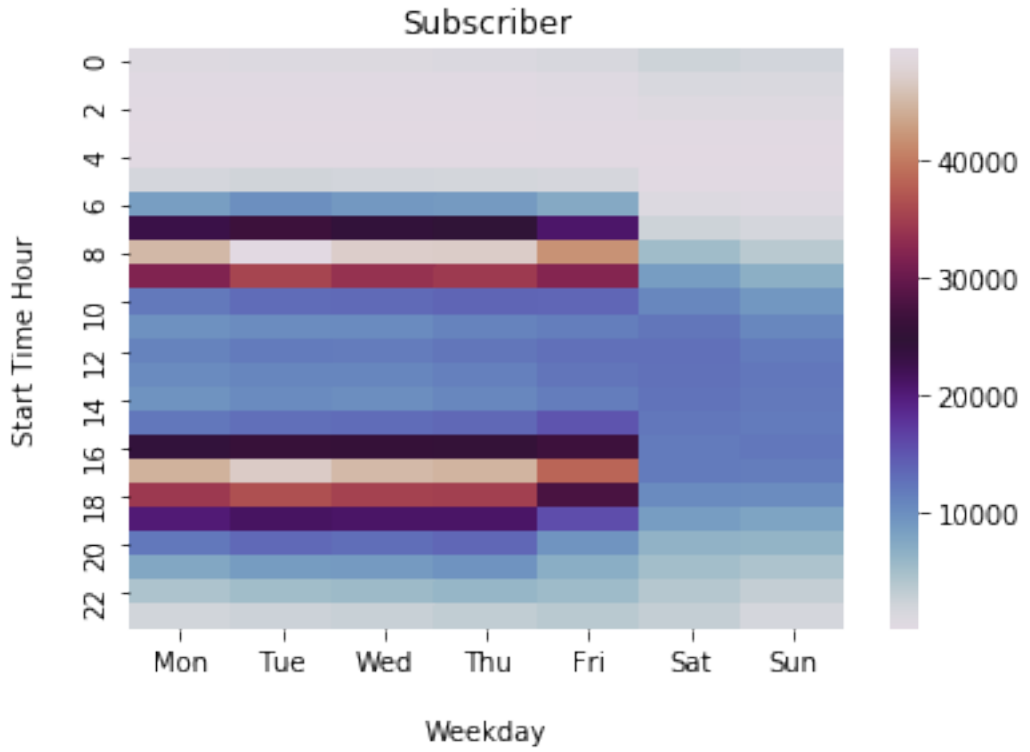
[160]:
```
# Weekday order
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
df_clean['start_time_weekday'] = pd.Categorical(df_clean['start_time_weekday'],␣
 ↪categories= ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun'], ordered=True);

#plt.figure(figsize=(15,8))

# Heatmap - Customers
#plt.subplot(1, 2, 1)
```

```
df_customer = df_clean.query('user_type == "Customer"').
 ↪groupby(['start_time_hour', 'start_time_weekday'])['bike_id'].size().
 ↪reset_index();
df_customer = df_customer.pivot('start_time_hour', 'start_time_weekday',␣
 ↪'bike_id')

heat_map = sb.heatmap(df_customer, cmap = 'twilight')

plt.title('Customer', y=1.05)
plt.xlabel('Weekday', labelpad = 16)
plt.ylabel('Start Time Hour',  labelpad = 16)

plt.show()
```



[153]:
```
# Heatmap - Subscribers
#plt.subplot(1, 2, 2)
df_subscriber = df_clean.query('user_type == "Subscriber"').
 ↪groupby(['start_time_hour', 'start_time_weekday'])['bike_id'].size().
 ↪reset_index();
df_subscriber = df_subscriber.pivot('start_time_hour', 'start_time_weekday',␣
 ↪'bike_id')
hot_map = sb.heatmap(df_subscriber, cmap = 'twilight')
```

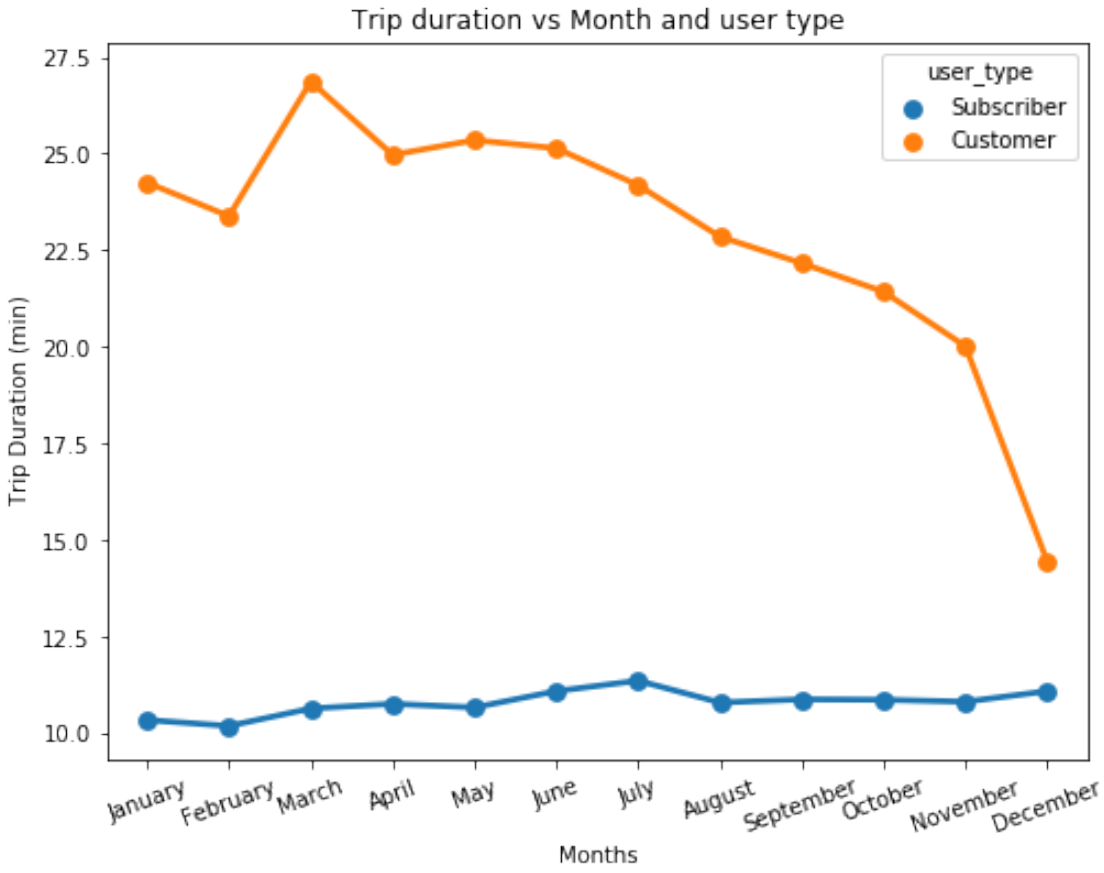
```
plt.title("Subscriber", y=1.05)
plt.xlabel('Weekday', labelpad = 16)
plt.ylabel('Start Time Hour', labelpad = 16);

plt.show()
```



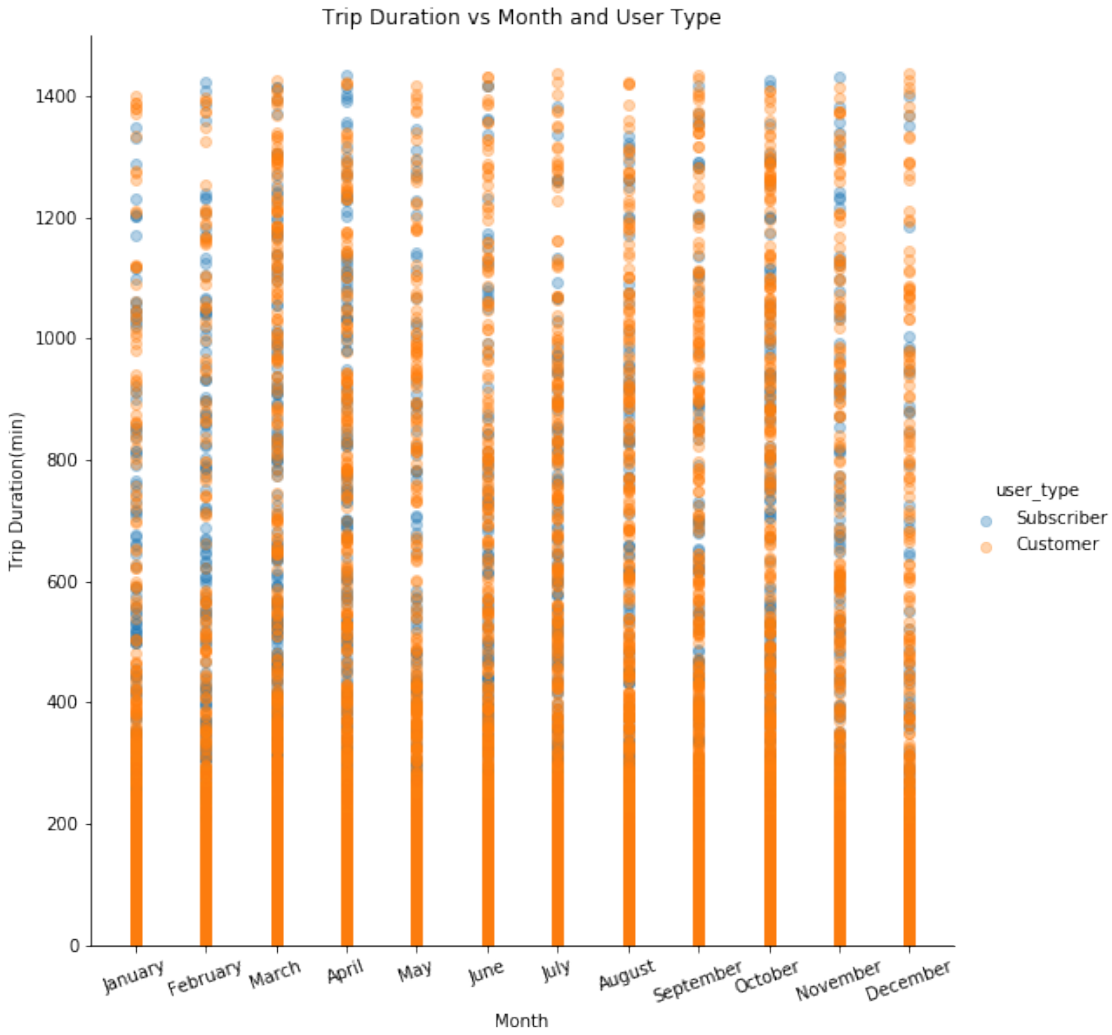
15a.) The heat maps show a good description of popular times of day for specific users during the week. With subscribers using moring and evening comute hours and customers using during the day more on the weekends

16.)How does the trip duration change per user per month?

[159]:
```
fig = plt.figure(figsize = [8,6])
sb.pointplot(data = df_clean, x = 'start_time_month', y = 'duration_min', hue =␣
↪'user_type', ci=None)
plt.title('Trip duration vs Month and user type')
plt.ylabel(' Trip Duration (min)')
plt.xlabel('Months')
plt.xticks(rotation=20)
plt.show();
```



[155]:
```
g = sb.FacetGrid(data =  df_clean, hue = 'user_type', height = 8)
g.map(plt.scatter, 'start_time_month','duration_min', alpha = 1/3)
g.add_legend()
plt.ylim(0, 1500)
plt.title('Trip Duration vs Month and User Type')
plt.xlabel('Month')
plt.ylabel('Trip Duration(min)')
plt.xticks(rotation=20);
```



16a.) The trip duration for the subscriber is shorter all throuhout the year, which helps confirm that most subscribers use the service for work commute. The average trip duration is significantlly longer for customers and dives to shorter trips during December.

4.3.1 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

On average customers had a longer trip duration during the different months.

On average customers had longer trip duration during the days of the week over the subscribers.

The heat map showed that the subscribers utilized the bike share during going to and coming from work while the customers utilized it mostly in the afternoon and all throughout the day during the weekend.

4.3.2 Were there any interesting or surprising interactions between features?

I was suprised to see that even thought the subscribers have higher numbers of rentals they duration times were significantally lower and was not used even on the weekend.

[ ]: