Exploration_Ford_GoBike

February 19, 2020

1 Analysis of the "Ford GoBike" Data

1.1 Introduction

> Ford GoBike, currently "Bay Wheels" is a regional public bicycle sharing system in the San Francisco Bay Area. Bay Wheels is the first regional and large-scale bicycle sharing system deployed in California. After Motivate's acquisition by Lyft, the system was subsequently renamed to Bay Wheels in June 2019. The system is expected to expand to 7,000 bicycles around 540 stations.

In this project, I will performing an exploratory analysis on data provided by Ford GoBike.

1.2 Part I - Data Wrangling

In this project, we will focus on the record of individual trips taken in from 2017 to April, 2019.

Ford GoBike Data: https://s3.amazonaws.com/fordgobike-data/index.html

[1]:
```
# import all packages and set plots to be embedded inline
from requests import get
from os import path, getcwd, makedirs, listdir
from io import BytesIO
from zipfile import ZipFile
import pandas as pd
import numpy as np
import matplotlib
from matplotlib import pyplot as plt
import matplotlib.ticker as tick
import seaborn as sns
import datetime
import math
import calendar
import warnings
warnings.filterwarnings('ignore')
from IPython.display import Image
%matplotlib inline
```

[2]:
```python
# download the dataset with pandas
folder_name_of_csvs = 'trip_data_files'
```

[3]:
```python
makedirs(folder_name_of_csvs)
pd.read_csv('https://s3.amazonaws.com/fordgobike-data/2017-fordgobike-tripdata.
 ↪csv').to_csv('{}/2017-forgobike-tripdata.csv'.format(folder_name_of_csvs))
for month in range(1,12):
    month_string = str(month)
    month_leading_zero = month_string.zfill(2)

    bike_data_url = 'https://s3.amazonaws.com/fordgobike-data/2018' +␣
 ↪month_leading_zero + '-fordgobike-tripdata.csv.zip'
    response = get(bike_data_url)

    # code below opens zip file; BytesIO returns a readable and writeable view␣
 ↪of the contents;
    unzipped_file = ZipFile(BytesIO(response.content))

    # puts extracted zip file into folder trip_data_files
    unzipped_file.extractall(folder_name_of_csvs)

for month in range(1,4):
    month_string = str(month)
    month_leading_zero = month_string.zfill(2)

    bike_data_url = 'https://s3.amazonaws.com/fordgobike-data/2019' +␣
 ↪month_leading_zero + '-fordgobike-tripdata.csv.zip'
    response = get(bike_data_url)

    # code below opens zip file; BytesIO returns a readable and writeable view␣
 ↪of the contents;
    unzipped_file = ZipFile(BytesIO(response.content))

    # puts extracted zip file into folder trip_data_files
    unzipped_file.extractall(folder_name_of_csvs)
```

[3]:
```python
# Combine All Locally Saved CSVs into One DataFrame
list_csvs = []
for file_name in listdir(folder_name_of_csvs):
    list_csvs.append(pd.read_csv(folder_name_of_csvs+'/'+file_name))
df = pd.concat(list_csvs)
```

[4]:
```python
#saving this combined dataframe to a csv file
df.to_csv('data.csv')
```

1.3 Part II - Assesement of Data

[36]:
```python
# Examine DataFrame
df = pd.read_csv('data.csv')
```

[37]:
```python
df.sample(5)
```

[37]:
```
         Unnamed: 0  Unnamed: 0.1  bike_id bike_share_for_all_trip  \
779559       192869           NaN      306                      No
182004       182004           NaN     2432                      No
172687       172687           NaN     2752                      No
3026255       89510           NaN     4419                      No
227418        28196           NaN     5665                      No

         duration_sec  end_station_id  end_station_latitude  \
779559            372            50.0             37.780526
182004            723           263.0             37.862827
172687            552           349.0             37.781010
3026255           445            58.0             37.776619
227418            842           315.0             37.834174

         end_station_longitude               end_station_name  \
779559             -122.390288          2nd St at Townsend St
182004             -122.290231  Channing Way at San Pablo Ave
172687             -122.405666           Howard St at Mary St
3026255            -122.417385           Market St at 10th St
227418             -122.272968           Market St at 45th St

                         end_time  member_birth_year member_gender  \
779559   2018-10-02 09:00:00.8890             1980.0          Male
182004   2018-07-04 08:32:53.6690             1996.0          Male
172687   2018-07-05 19:45:30.3970             1979.0          Male
3026255  2018-09-17 11:18:46.0950             1977.0          Male
227418   2019-03-28 15:47:08.0610             1966.0          Male

         start_station_id  start_station_latitude  start_station_longitude  \
779559               16.0               37.794130              -122.394430
182004              253.0               37.866418              -122.253799
172687               17.0               37.792251              -122.397086
3026255               3.0               37.786375              -122.404904
227418              265.0               37.858868              -122.291209

                                    start_station_name  \
779559                             Steuart St at Market St
182004                             Haste St at College Ave
172687   Embarcadero BART Station (Beale St at Market St)
3026255      Powell St BART Station (Market St at 4th St)
```

```
227418                              Ninth St at Parker St

                        start_time   user_type
779559   2018-10-02 08:53:48.6450  Subscriber
182004   2018-07-04 08:20:49.9490  Subscriber
172687   2018-07-05 19:36:17.6060  Subscriber
3026255  2018-09-17 11:11:20.7120  Subscriber
227418   2019-03-28 15:33:05.2620  Subscriber
```

[38]:
```python
#duplicate check
df.duplicated().sum()
```

[38]: 0

[39]:
```python
#to get a general feel for the data
df.describe().round(decimals = 3)
```

[39]:

	Unnamed: 0	Unnamed: 0.1	bike_id	duration_sec	end_station_id
count	3122962.000	519700.000	3122962.000	3122962.000	3110653.000
mean	120691.548	259849.500	2710.282	878.682	118.739
std	102631.872	150024.612	1722.985	2494.130	102.619
min	0.000	0.000	10.000	61.000	3.000
25%	48796.000	129924.750	1322.000	352.000	30.000
50%	97778.000	259849.500	2559.000	558.000	86.000
75%	160364.750	389774.250	3782.000	875.000	185.000
max	519699.000	519699.000	7108.000	86369.000	420.000

	end_station_latitude	end_station_longitude	member_birth_year
count	3122962.000	3122962.000	2909807.000
mean	37.769	-122.352	1983.113
std	0.135	0.328	10.435
min	0.000	-122.474	1878.000
25%	37.771	-122.411	1978.000
50%	37.781	-122.397	1985.000
75%	37.796	-122.295	1991.000
max	45.510	0.000	2001.000

	start_station_id	start_station_latitude	start_station_longitude
count	3110653.000	3122962.000	3122962.000
mean	120.445	37.769	-122.353
std	102.699	0.103	0.161
min	3.000	0.000	-122.474
25%	31.000	37.771	-122.412
50%	88.000	37.781	-122.398
75%	186.000	37.795	-122.293
max	420.000	45.510	0.000

[40]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3122962 entries, 0 to 3122961
Data columns (total 18 columns):
Unnamed: 0                  int64
Unnamed: 0.1                float64
bike_id                     int64
bike_share_for_all_trip     object
duration_sec                int64
end_station_id              float64
end_station_latitude        float64
end_station_longitude       float64
end_station_name            object
end_time                    object
member_birth_year           float64
member_gender               object
start_station_id            float64
start_station_latitude      float64
start_station_longitude     float64
start_station_name          object
start_time                  object
user_type                   object
dtypes: float64(8), int64(3), object(7)
memory usage: 428.9+ MB
```

Issues - 2 unamed columns - start time and end time are not timestamps - bike id, start_station_id, end_station_id can be set to object type - birth years having dates less than 1900 - there is a need for ride distance column - user type, gender and bike_share_for_all_trip can be set to category

1.4 Part III - Cleaning

[41]:
```
# Create copies of original DataFrames
df_copy = df.copy()
```

1.4.1 Setting appropriate data types

[42]:
```
#settings the time related flields to datetime data_type
df.start_time = pd.to_datetime(df.start_time)
df.end_time = pd.to_datetime(df.end_time)
#setting objects to categorical data_type
df.user_type = df.user_type.astype('category')
df.member_gender = df.member_gender.astype('category')
df.bike_share_for_all_trip = df.bike_share_for_all_trip.astype('category')
```

```python
#setting names to string data_type
df.bike_id = df.bike_id.astype(str)
df.start_station_id = df.bike_id.astype(str)
df.end_station_id = df.bike_id.astype(str)
```

[43]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3122962 entries, 0 to 3122961
Data columns (total 18 columns):
Unnamed: 0                  int64
Unnamed: 0.1                float64
bike_id                     object
bike_share_for_all_trip     category
duration_sec                int64
end_station_id              object
end_station_latitude        float64
end_station_longitude       float64
end_station_name            object
end_time                    datetime64[ns]
member_birth_year           float64
member_gender               category
start_station_id            object
start_station_latitude      float64
start_station_longitude     float64
start_station_name          object
start_time                  datetime64[ns]
user_type                   category
dtypes: category(3), datetime64[ns](2), float64(6), int64(2), object(5)
memory usage: 366.3+ MB
```

1.4.2 Dropping unnecessary columns

[44]:
```python
#dropping the columns
df.drop(['Unnamed: 0', 'Unnamed: 0.1'], axis=1, inplace=True)
```

1.4.3 Generation of Age Column

[45]:
```python
#Filter data to include reasonable member age range
df['member_age'] = 2019-df['member_birth_year']
```

1.4.4 Enhancing the current data table with date related fields

[46]:
```
#s_ prefix would be used for start time and e_ shall be used for end time values
#extracting date
df['s_date']=df['start_time'].dt.date
df['e_date']=df['end_time'].dt.date
#extracting year
df['s_year']=df['start_time'].dt.year.astype(int)
df['e_year']=df['end_time'].dt.year.astype(int)
#extracting month
df['s_month']=df['start_time'].dt.month.astype(int)
df['e_month']=df['end_time'].dt.month.astype(int)
#extracting hour
df['s_hour']=df['start_time'].dt.hour
df['e_hour']=df['end_time'].dt.hour
#extracting weekday
df['s_weekday']=df['start_time'].dt.weekday.apply(lambda x: calendar.
 ↪day_abbr[x])
df['e_weekday']=df['end_time'].dt.weekday.apply(lambda x: calendar.day_abbr[x])
```

[47]:
```
#dropping start_time and end_time data since we have extracted the required␣
 ↪data from them
df.drop(['start_time', 'end_time'], axis = 1, inplace = True)
```

[48]:
```
df.columns
```

[48]:
```
Index(['bike_id', 'bike_share_for_all_trip', 'duration_sec', 'end_station_id',
       'end_station_latitude', 'end_station_longitude', 'end_station_name',
       'member_birth_year', 'member_gender', 'start_station_id',
       'start_station_latitude', 'start_station_longitude',
       'start_station_name', 'user_type', 'member_age', 's_date', 'e_date',
       's_year', 'e_year', 's_month', 'e_month', 's_hour', 'e_hour',
       's_weekday', 'e_weekday'],
      dtype='object')
```

[49]:
```
df.shape
```

[49]:
```
(3122962, 25)
```

1.4.5 What is the structure of your dataset?

There are 3122962 rides in the dataset with 25 features. Most variables are numeric in the dataset.

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

We will focus on users' behaviors and personal details like;
Average riding duration
Average riding distance
Age groups of users
Genders
Weekly day distrubition

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

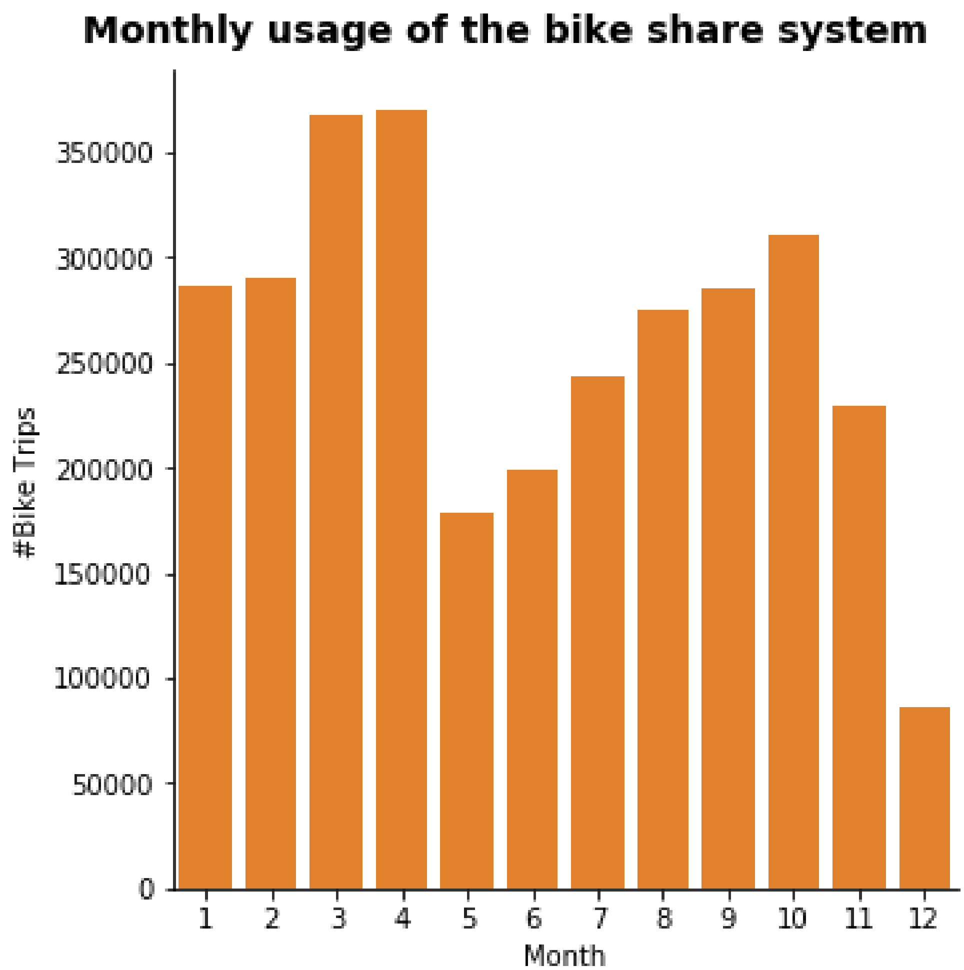
I expect the member_age feature to play a major role

[19]:
```
# Saving the modified data into csv for the slide
df.to_csv('ppt_data.csv')
```

1.5 Part IV - Univariate Exploration

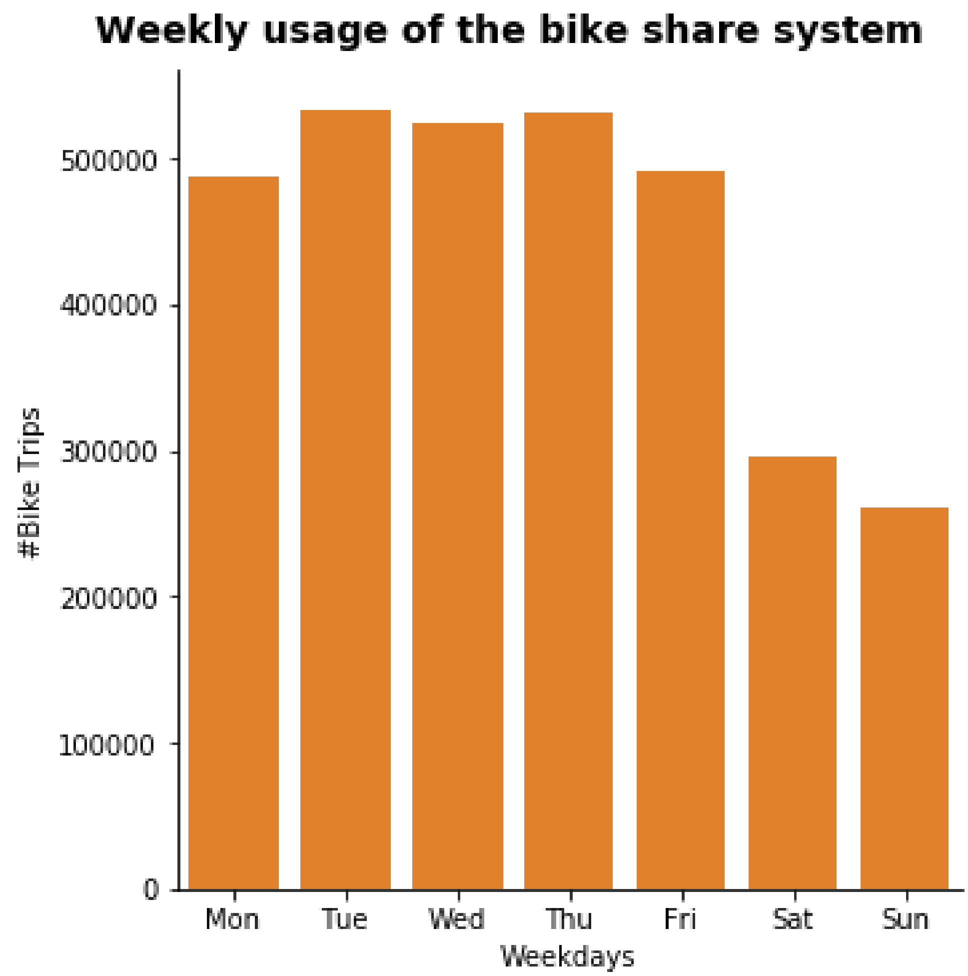
Now, we will try and explore the usage data for the bike rental service. I will plot the graphs to understand the patterns in usage on monthly, weekday and hourly basis. I will also try and see the average duration of these bike trips and explore the member ages to check for any discrepancies.

[50]:
```
# monthly usage of the bike sharing system
basic = sns.color_palette()[1]
p1 = sns.catplot(data=df, x='s_month', kind='count', color = basic)
p1.set_axis_labels("Month", "#Bike Trips")
p1.fig.suptitle('Monthly usage of the bike share system', y=1.03, fontsize=14,␣
↪fontweight='semibold');
p1.savefig('image01.png');
```



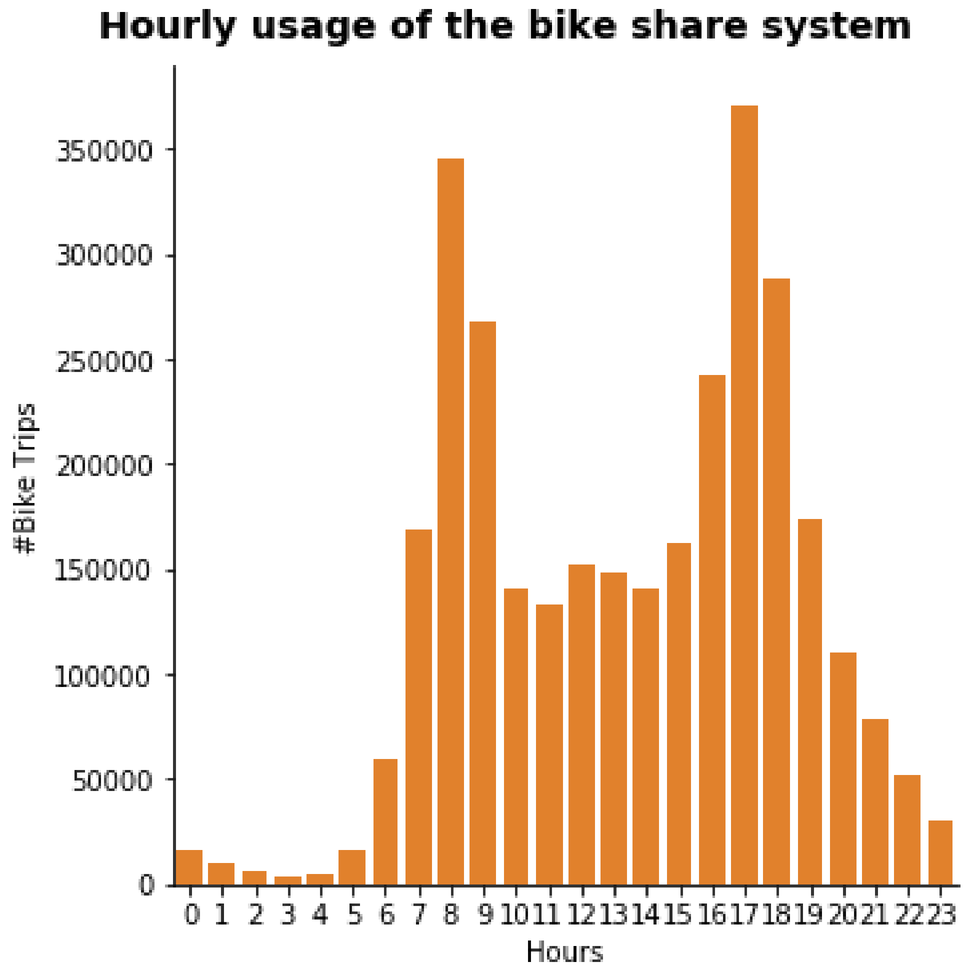
During winter months, we can see that there is decrease in bike rides

[51]:
```
# weekday usage of the bike sharing system
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
p2 = sns.catplot(data=df, x='s_weekday', kind='count', color = basic, order =␣
↪weekday)
p2.set_axis_labels("Weekdays", "#Bike Trips")
p2.fig.suptitle('Weekly usage of the bike share system', y=1.03, fontsize=14,␣
↪fontweight='semibold');
p2.savefig('image02.png');
```



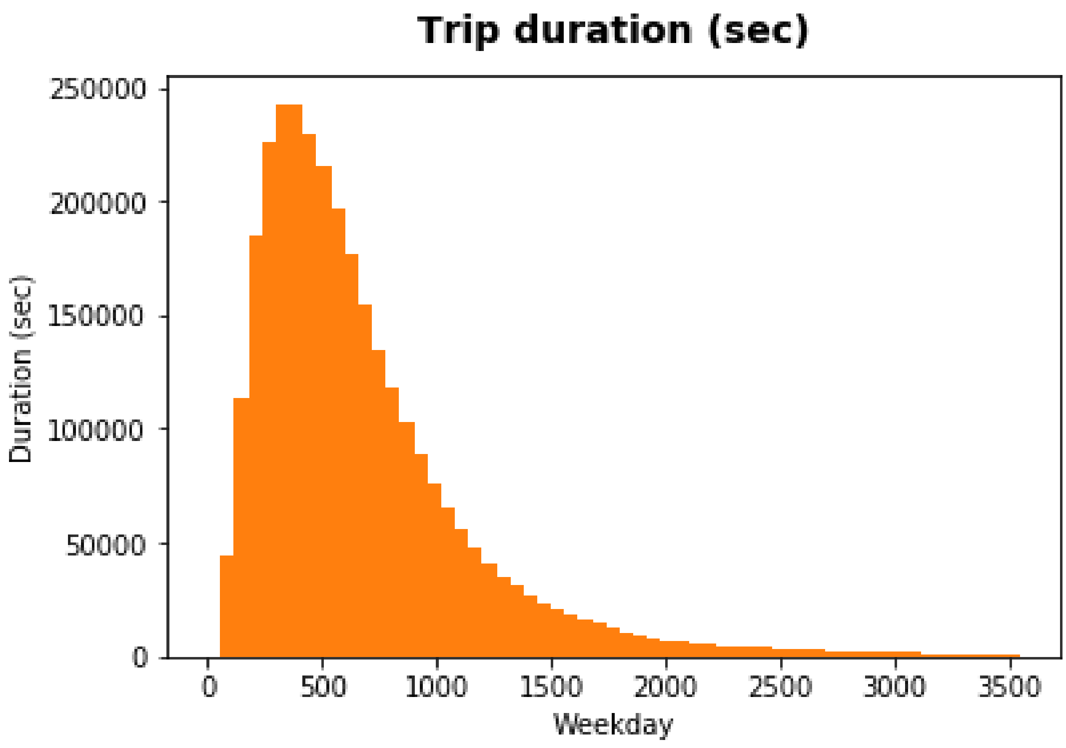
It is observed that there is maximum usage on weekdays

[52]:
```
# hourly usage of the bike sharing system
p3 = sns.catplot(data=df, x='s_hour', kind='count', color = basic)
p3.set_axis_labels("Hours", "#Bike Trips")
p3.fig.suptitle('Hourly usage of the bike share system', y=1.03, fontsize=14,␣
 ↪fontweight='semibold');
p3.savefig('image03.png');
```



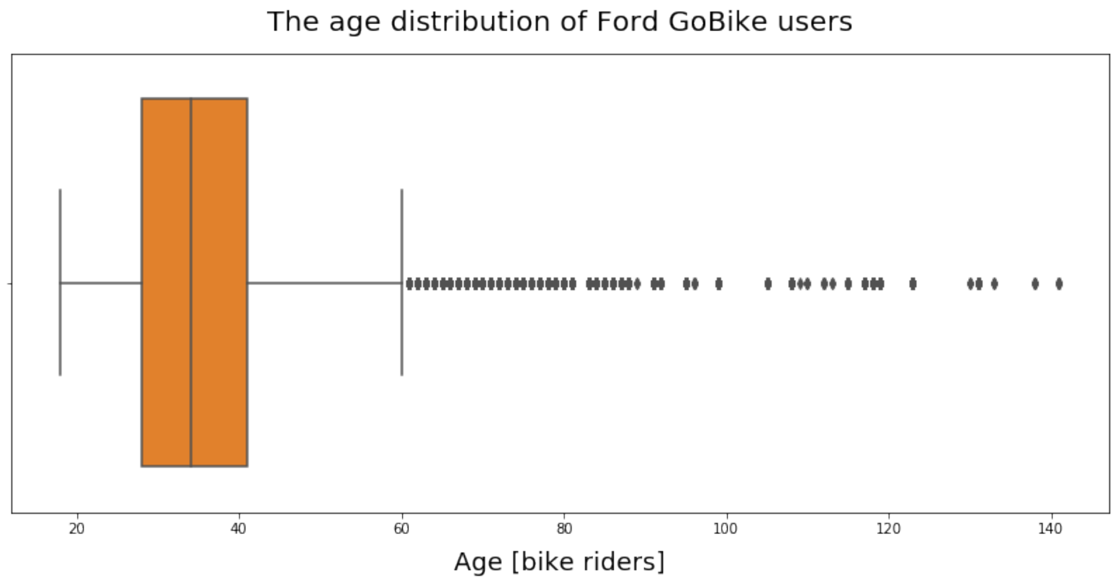
The hourly distribution is bimodal, the system is used mainly around 8-9am and 5-6pm

[53]:
```
# trip duration in seconds per user
bin_edges = np.arange(0, 3600, 60)
plt.hist(data = df, x = 'duration_sec', bins = bin_edges, color = basic)
plt.title("Trip duration (sec)", y=1.03, fontsize=14, fontweight='semibold')
plt.xlabel('Weekday')
plt.ylabel('Duration (sec)');
plt.savefig('image04.png');
```



I will try to analyse the spread of age data using a box plot. It will help in clearly seeing the outliers present in our dataset

[54]:
```
plt.figure(figsize=(14,6))
sns.boxplot(x='member_age', data=df, color = basic, orient='h')
plt.title("The age distribution of Ford GoBike users", fontsize=20, y=1.03)
plt.xlabel("Age [bike riders]", fontsize=18, labelpad=10)
plt.savefig('image05.png');
```



[55]:
```
df.member_age.describe(percentiles = [ .95]).round(decimals = 2)
```

[55]:
```
count    2909807.00
mean          35.89
std           10.43
min           18.00
50%           34.00
95%           56.00
max          141.00
Name: member_age, dtype: float64
```

[56]:
```
#Keeping age below 56 since 95% of the users lie in that range
df = df[df['member_age']<=56]
```

[57]:
```
df.member_age = df.member_age.astype(int)
df.drop(['member_birth_year'], axis=1, inplace=True)
```

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

During winter months, there is decrease in bike rides. The bikes are used mostly on weekdays and around 8-9 am and 5-6 pm. If we consider the duration of trips, its unusual that some of the trips stretch upto 50 hours.

1.5.2 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?

There was one unusal distribution for the member birth year, which in some cases was dated before 1900 and customers having age of 141. This surely should be an entry error. Since 95% of the members are between 17 and 56 years, I removed users older than 56.

1.6 Part V - Bivariate Exploration

I will add in the user_type and see if the usage varies based on the type of user

1.6.1 Percentage of bike rides of subscribers vs customers

[58]:
```
count_of_rides_per_user_type = df.groupby('user_type').size().
↪reset_index(name='count')
```

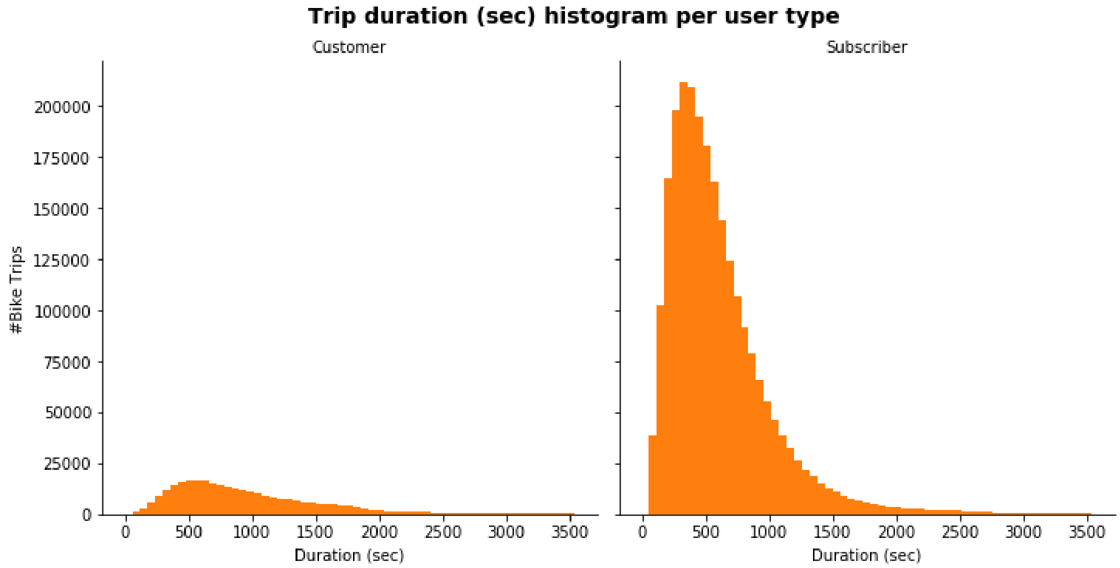
[59]:
```
count_of_rides_per_user_type['count']/len(df)*100
```

[59]:
```
0    11.648905
1    88.351095
Name: count, dtype: float64
```

Percentage of subscribers is almost 88.35%
Percentage of customers is almost 11.64%

1.6.2 User trends of bike rides of subscribers vs customers

[60]:
```
# trip duration in seconds per usertype
g = sns.FacetGrid(df, col="user_type", margin_titles=True, size=5)
bin_edges = np.arange(0, 3600,60)
g.map(plt.hist, "duration_sec", color=basic, bins=bin_edges)
g.set_axis_labels("Duration (sec)", "#Bike Trips")
g.set_titles(col_template = '{col_name}')
g.fig.suptitle('Trip duration (sec) histogram per user type', y=1.03,␣
↪fontsize=14, fontweight='semibold');
g.savefig('image05.png');
```



Subscribers' average trip duration is around 6 minutes.
Customers' average trip duration is around 26 minutes.

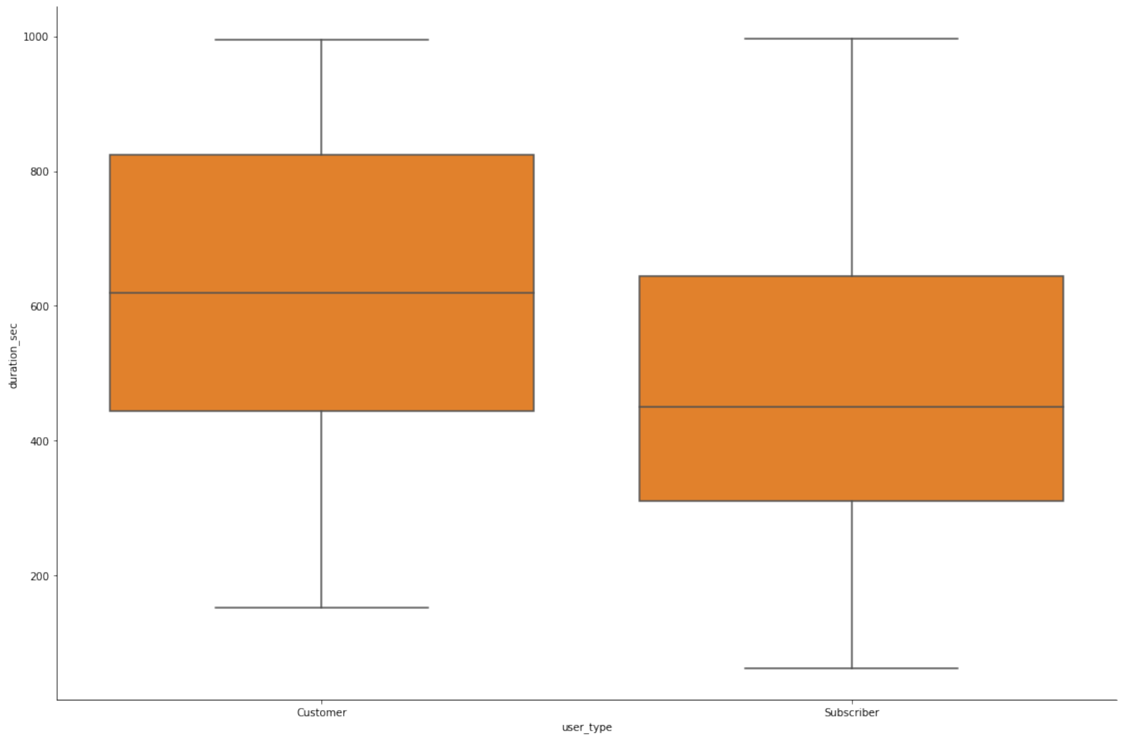
broad view of bike ride durations where I have excluded outliers to get a feel for the distribution above

[61]:
```
#code to chart the comparision using boxplots
np.random.seed(2018)
samples = np.random.choice(df.shape[0], 2000, replace = False)
bike_data_samp = df.reindex(samples)
bike_data_samp=bike_data_samp[bike_data_samp['duration_sec']<1000]

def boxgrid(x, y, **kwargs):
    sns.boxplot(x, y, color = basic)

plt.figure(figsize = [10, 10])
g = sns.PairGrid(data = bike_data_samp, y_vars = 'duration_sec', x_vars =␣
 ↪'user_type',
                size = 10, aspect = 1.5)
plt.xlim(0, 1000)
g.map(boxgrid)
plt.show();
plt.savefig('image06.png');
```

```
<Figure size 720x720 with 0 Axes>
```

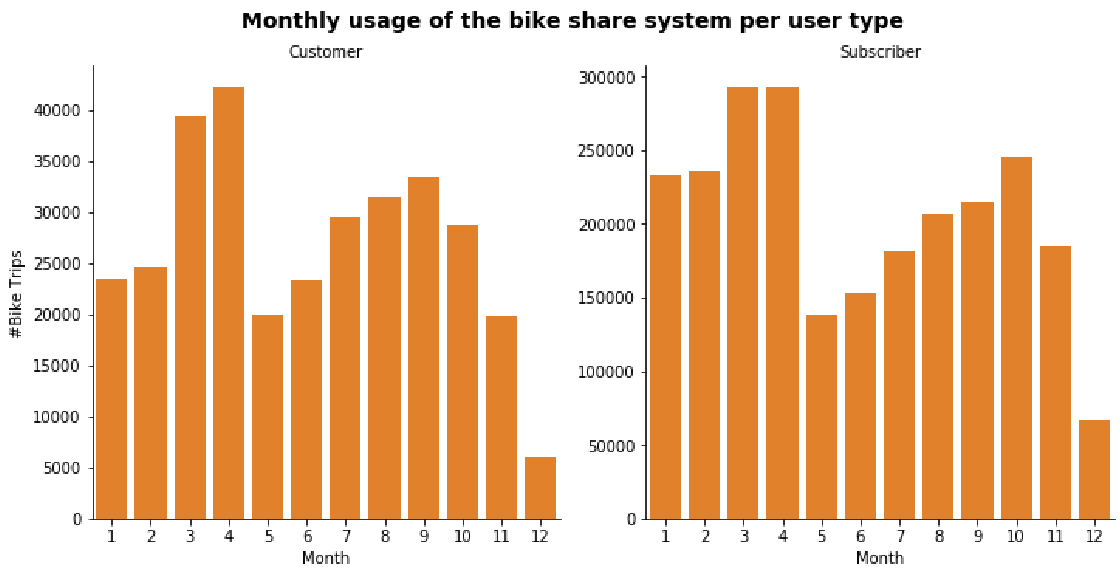



```
<Figure size 432x288 with 0 Axes>
```

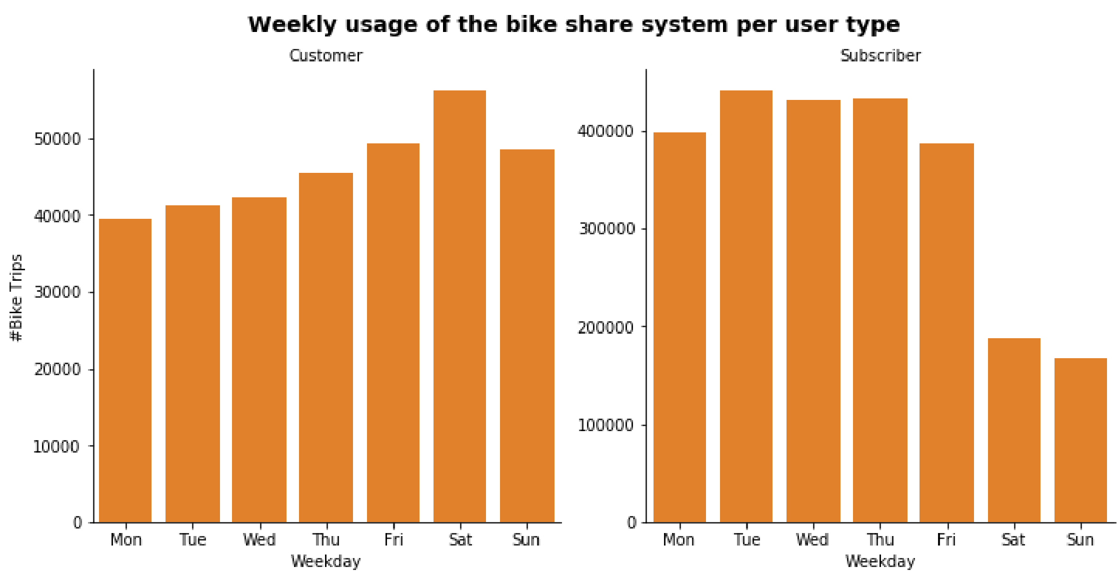
Customers seem to avail longer bike rides

1.6.3 Average trip duration of subscribers vs customers

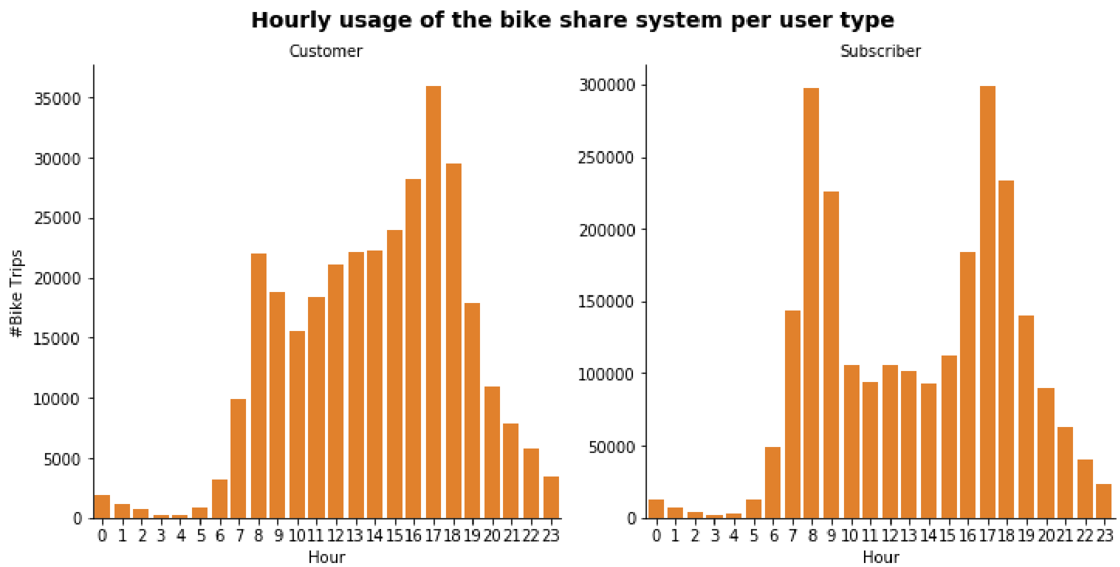
[62]:
```
# monthly usage of the bike sharing system per user type
g = sns.catplot(data=df, x='s_month', col="user_type", kind='count', sharey =␣
↪False,
                color = basic)
g.set_axis_labels("Month", "#Bike Trips")
g.set_titles("{col_name}")
g.fig.suptitle('Monthly usage of the bike share system per user type', y=1.03,␣
↪fontsize=14, fontweight='semibold');
g.savefig('image07.png');
```



[63]:
```
# weekday usage of the bike sharing system per user type
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
g = sns.catplot(data=df, x='s_weekday', col="user_type", kind='count', sharey =
↪False,
            color = basic, order = weekday)
g.set_axis_labels("Weekday", "#Bike Trips")
g.set_titles("{col_name}")
g.fig.suptitle('Weekly usage of the bike share system per user type', y=1.03,
↪fontsize=14, fontweight='semibold');
g.savefig('image08.png');
```



[64]:
```python
# hourly usage of the bike sharing system per user type
g = sns.catplot(data=df, x='s_hour', col="user_type", kind='count', sharey =␣
↪False,
            color = basic)
g.set_axis_labels("Hour", "#Bike Trips")
g.set_titles("{col_name}")
g.fig.suptitle('Hourly usage of the bike share system per user type', y=1.03,␣
↪fontsize=14, fontweight='semibold');
g.savefig('image09.png');
```



1.6.4 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?

We can say that in the univariate exploration, the number of subscribers who used bikes were more than customers. However, in the bivariate exploration, the avearge time spent by customers were more than subscribers Another interesting feature, is the duration (in min) spent on the bike gradually reduces over the months

Adding user type in the mix showed different usage patterns between the two types of users. I believe the customers are users that rent the bike when absoutely necessary, as tourists or for leisure purpose whereas subscribers mostly use this service for their daily commute which should generally be a short distance and therefore less lengthy.

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

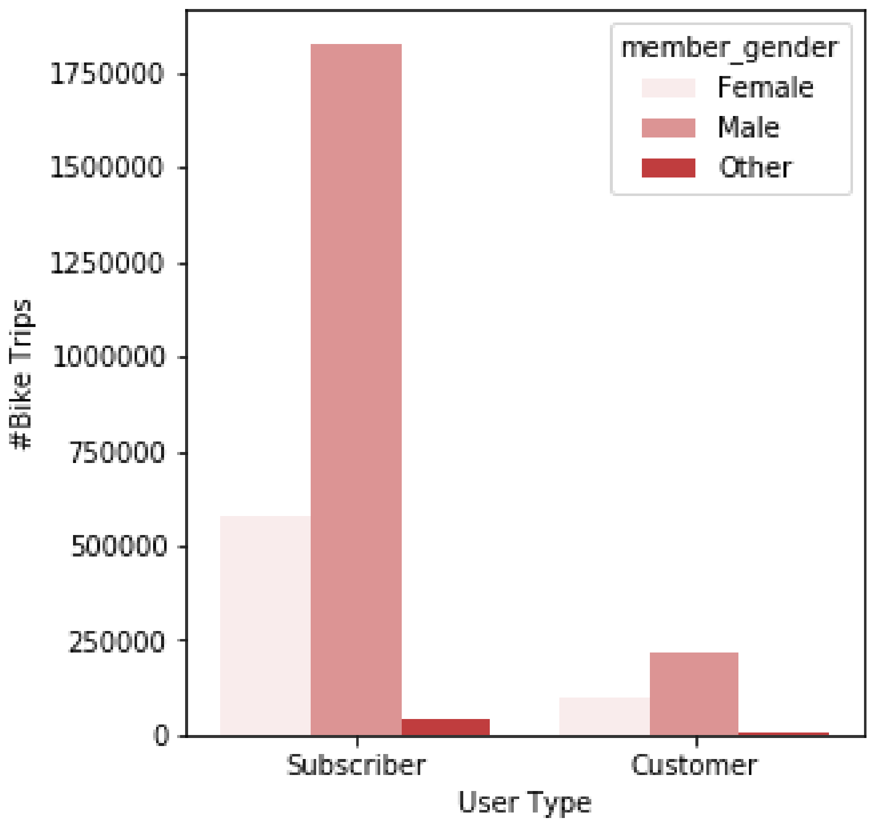
Duration of trip varies based on the type of user

1.7 Multivariate Exploration

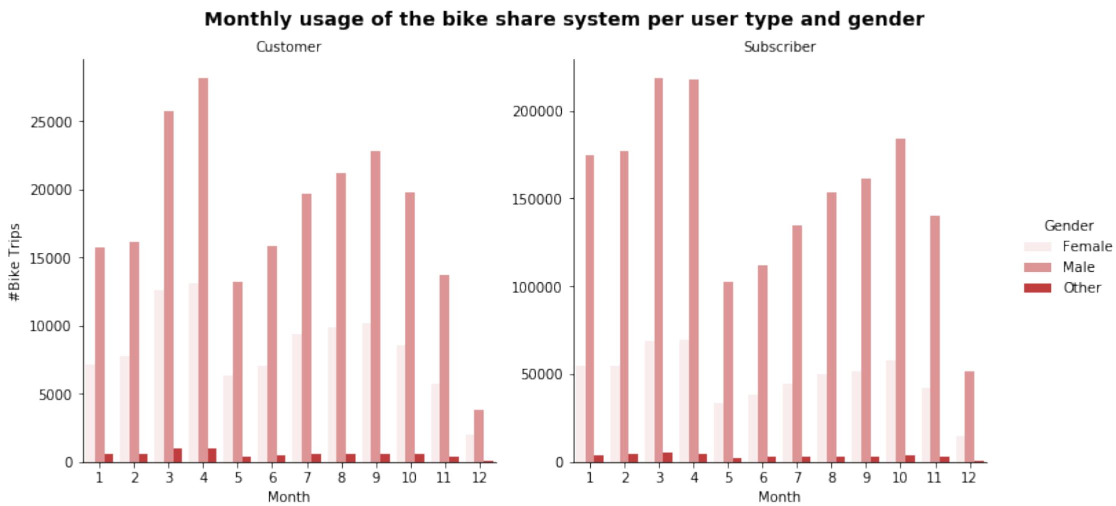
Lets bring in the gender for analysis!

[65]:
```
# we will take a new color theme for this one
basic2 = sns.color_palette()[3]
```

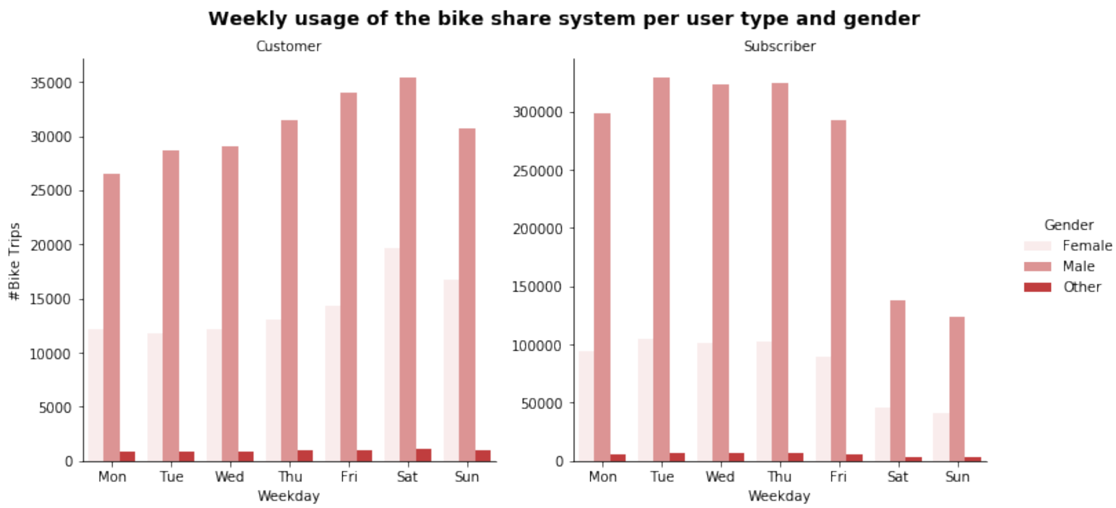
[66]:
```
#segregation of user trips based on gender
plt.figure(figsize = [10, 5])
plt.subplot(1, 2, 1)
g = sns.countplot(data=df, x="user_type", hue="member_gender", order=df.
 ↪user_type.value_counts().index, color = basic2)
g.set_xlabel('User Type')
g.set_ylabel('#Bike Trips');
plt.savefig('image10.png');
```



[67]:
```python
# monthly usage of the bike sharing system per user type and gender
g = sns.catplot(data=df, x='s_month', col="user_type", hue="member_gender",␣
↪kind='count',
                sharey = False, color = basic2)
g.set_axis_labels("Month", "#Bike Trips")
g._legend.set_title('Gender')
g.set_titles("{col_name}")
g.fig.suptitle('Monthly usage of the bike share system per user type and␣
↪gender', y=1.03, fontsize=14, fontweight='semibold');
g.savefig('image11.png');
```



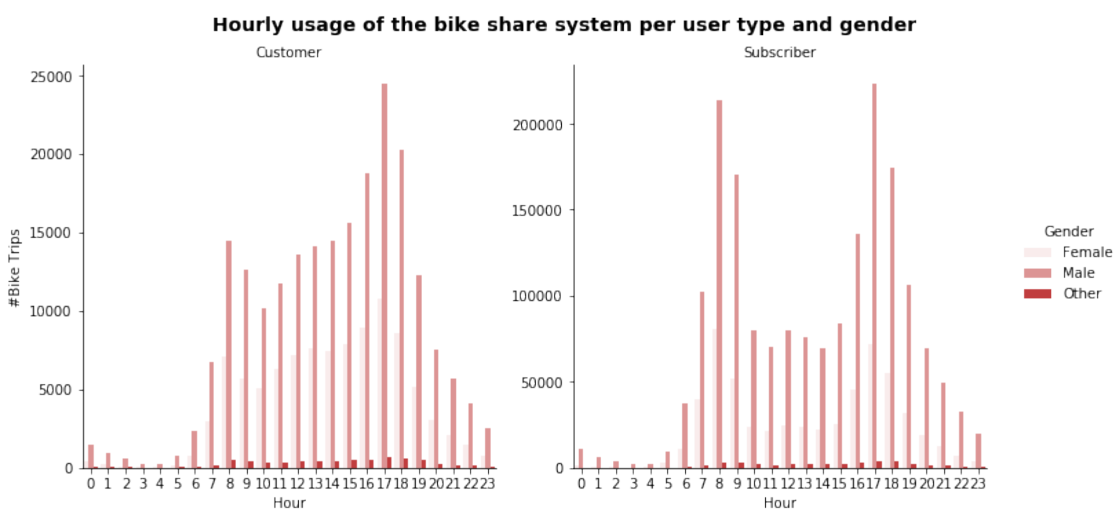
[68]:
```python
#weekday usage of the bike sharing system per user type and gender
weekday = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
g = sns.catplot(data=df, x='s_weekday', col="user_type", hue='member_gender',␣
↪kind='count', sharey = False,
                order = weekday, color = basic2)
g.set_axis_labels("Weekday", "#Bike Trips")
g._legend.set_title('Gender')
g.set_titles("{col_name}")
g.fig.suptitle('Weekly usage of the bike share system per user type and␣
↪gender', y=1.03, fontsize=14, fontweight='semibold');
g.savefig('image12.png');
```



[69]:

```python
# hourly usage of the bike sharing system per user type and gender
plt.figure(figsize = [15, 10])
g = sns.catplot(data=df, x='s_hour', col="user_type", hue='member_gender',
    kind='count', sharey = False, color = basic2)
g.set_axis_labels("Hour", "#Bike Trips")
g._legend.set_title('Gender')
g.set_titles("{col_name}")
g.fig.suptitle('Hourly usage of the bike share system per user type and
    gender', y=1.03, fontsize=14, fontweight='semibold');
g.savefig('image13.png');
```

```
<Figure size 1080x720 with 0 Axes>
```



[70]:

```
# Setting the weekday order
df['s_weekday'] = pd.Categorical(df['s_weekday'],
                                  ␣
 ↪categories=['Mon','Tue','Wed','Thu','Fri','Sat', 'Sun'],
                                  ordered=True)
plt.figure(figsize=(9,8))
plt.suptitle('Hourly usage during the weekday for customers and subscribers',␣
 ↪fontsize=14, fontweight='semibold')

# heatmap for customers
plt.subplot(1, 2, 1)
df_customer = df.query('user_type == "Customer"').groupby(["s_hour",␣
 ↪"s_weekday"])["bike_id"].size().reset_index()
df_customer = df_customer.pivot("s_hour", "s_weekday", "bike_id")
sns.heatmap(df_customer)

plt.title("Customer", y=1.015)
plt.xlabel('Weekday')
plt.ylabel('Start Time Hour')

# heatmap for subscribers
plt.subplot(1, 2, 2)
df_subscriber = df.query('user_type == "Subscriber"').groupby(["s_hour",␣
 ↪"s_weekday"])["bike_id"].size().reset_index()
df_subscriber = df_subscriber.pivot("s_hour", "s_weekday", "bike_id")
sns.heatmap(df_subscriber)

plt.title("Subscriber", y=1.015)
plt.xlabel('Weekday')
plt.ylabel('');
plt.savefig('image14.png');
```

1.8 Conclusion

Plotting a heatmap of when bikes are high in demand throughout the day on each weekday shed a new light on the customers behaviour. People use this service on weekdays more than weekends and 8am to 5pm are the peak hours.

Percentage of subscribers is almost 88.35% and customers is almost 11.65%. Subscribers' average trip duration is around 6 minutes. Customers' average trip duration is around 26 minutes. 90% of bike rides take place on weekday. The peak bike rides time for all members is around commute time.

[71]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Exploration_Ford_GoBike.ipynb'])
```

[71]: 1

```
[ ]:
```