Cyclist Bike-Share

August 9, 2022

1 Cyclist Bike-Share Case Study (Google Data Analytics Capstone Project 1)

```
[1]: from google.colab import drive
     drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

1.1 Introduction

BikeShare Cyclist a bike transportation company based in Chicago, Illinois is faced with the issue of converting customer (casual) bike riders into members. I received a data set which includes subscriber and customer (casual) riders transport details for four quarters in the year 2019, the stakeholders at Cyclist Bikeshare have asked me to use data to inform decisions on turning customer riders into subscribers. For this project I will be using the six phases of data analysis according to Google, which are; 1. Ask 2. Prepare 3. Process 4. Analyze 5. Share 6. Act

1.2 Ask

There are 3 main questions which my immediate stakeholder wants me to answer using this data 1. How do customer and subscriber riders differ in bike usage? 2. Why would customer riders buy a subscription? 3. How can the company use digital media to influence customer riders to become subscribers?

To find answers to the questions, I would first have to come up with a statement of the business task.

1.2.1 Business Task

The main objective of this project is to examine behaviors of customer riders and provide data informed suggestions that can turn them into subscriber riders.

1.3 Prepare

For the prepare phase, a data set has been provided by the company's data team, this clears up the question of the data sets integrity. I can examine the data and perform cleaning before I start my analysis.

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set
```

[2]:
```
<function seaborn.rcmod.set>
```

[3]:
```
df = pd.read_csv('/content/drive/MyDrive/Divvy_Trips_2013.csv')
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2882:
DtypeWarning: Columns (10) have mixed types.Specify dtype option on import or
set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[4]:
```
df.head()
```

[4]:
```
   trip_id         starttime          stoptime  bikeid  tripduration  \
0     4118  2013-06-27 12:11  2013-06-27 12:16     480           316
1     4275  2013-06-27 14:44  2013-06-27 14:45      77            64
2     4291  2013-06-27 14:58  2013-06-27 15:05      77           433
3     4316  2013-06-27 15:06  2013-06-27 15:09      77           123
4     4342  2013-06-27 15:13  2013-06-27 15:27      77           852

   from_station_id           from_station_name  to_station_id  \
0               85         Michigan Ave & Oak St             28
1               32    Racine Ave & Congress Pkwy             32
2               32    Racine Ave & Congress Pkwy             19
3               19         Loomis St & Taylor St             19
4               19         Loomis St & Taylor St             55

                   to_station_name  usertype gender  birthday
0       Larrabee St & Menomonee St  Customer    NaN       NaN
1       Racine Ave & Congress Pkwy  Customer    NaN       NaN
2            Loomis St & Taylor St  Customer    NaN       NaN
3            Loomis St & Taylor St  Customer    NaN       NaN
4  Halsted St & James M Rochford St  Customer    NaN       NaN
```

[5]:
```
df.dtypes
```

[5]:

```
trip_id                int64
starttime             object
stoptime              object
bikeid                 int64
tripduration           int64
from_station_id        int64
from_station_name     object
to_station_id          int64
to_station_name       object
usertype              object
gender                object
birthday             float64
dtype: object
```

The `starttime` and `stoptime` columns are in string format. This has to be changed to datetime in the Process phase.

[6]:

```
for i, column in enumerate(['usertype', 'gender']):
  i = i+1
  print('unique values for ', column,df[column].unique())
```

```
unique values for  usertype ['Customer' 'Subscriber']
unique values for  gender [nan 'Male' 'Female']
```

According to my immediate stakeholder, the `gender` and `birthday` contain null values, because those columns don't contain data from customer (casual) riders.

1.4 Process

The Process phase deals with data cleaning, which is basically making the data more useful for analyses.

[7]:

```
df['starttime'] = pd.to_datetime(df['starttime'])
df['stoptime'] = pd.to_datetime(df['stoptime'])
```

[8]:

```
df['month'] = df['starttime'].dt.month_name()
df['day_of_week'] = df['starttime'].dt.day_name()
df['time_of_day'] = df['starttime'].dt.time
df['hour'] = df['starttime'].dt.hour
```

[9]:

```
df.dtypes
```

[9]:

```
trip_id                       int64
starttime            datetime64[ns]
stoptime             datetime64[ns]
bikeid                        int64
tripduration                  int64
from_station_id               int64
```

```
from_station_name            object
to_station_id                 int64
to_station_name              object
usertype                     object
gender                       object
birthday                    float64
month                        object
day_of_week                  object
time_of_day                  object
hour                          int64
dtype: object
```

I set an order for months and day of week to follow, if this is not done Python would arrange any aggregations done in alphabetic order, which will lead to confusing visuals.

[10]:

```
from pandas.api.types import CategoricalDtype
cats_day = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
 ↪'Sunday']
cat_type = CategoricalDtype(categories=cats_day, ordered=True)
df['day_of_week'] = df['day_of_week'].astype(cat_type)
```

[11]:

```
cats_month = ['June', 'July', 'August', 'September', 'October', 'November',␣
 ↪'December']
cat_type2 = CategoricalDtype(categories=cats_month, ordered=True)
df['month'] = df['month'].astype(cat_type2)
```

[12]:

```
df.head()
```

[12]:

```
   trip_id           starttime            stoptime  bikeid  tripduration  \
0     4118 2013-06-27 12:11:00 2013-06-27 12:16:00     480           316
1     4275 2013-06-27 14:44:00 2013-06-27 14:45:00      77            64
2     4291 2013-06-27 14:58:00 2013-06-27 15:05:00      77           433
3     4316 2013-06-27 15:06:00 2013-06-27 15:09:00      77           123
4     4342 2013-06-27 15:13:00 2013-06-27 15:27:00      77           852

   from_station_id           from_station_name  to_station_id  \
0               85       Michigan Ave & Oak St             28
1               32  Racine Ave & Congress Pkwy             32
2               32  Racine Ave & Congress Pkwy             19
3               19       Loomis St & Taylor St             19
4               19       Loomis St & Taylor St             55

                to_station_name  usertype gender  birthday month  \
0        Larrabee St & Menomonee St  Customer    NaN       NaN  June
1        Racine Ave & Congress Pkwy  Customer    NaN       NaN  June
2             Loomis St & Taylor St  Customer    NaN       NaN  June
3             Loomis St & Taylor St  Customer    NaN       NaN  June
```

```
4  Halsted St & James M Rochford St  Customer    NaN       NaN  June

  day_of_week time_of_day  hour
0    Thursday    12:11:00    12
1    Thursday    14:44:00    14
2    Thursday    14:58:00    14
3    Thursday    15:06:00    15
4    Thursday    15:13:00    15
```

The data set was relatively clean, after changing some columns to datetime format and setting standards for our month and day of week columns, it is time to go into the Analysis phase of the project.

1.5 Analysis

For this phase of the project, I tried to find relationships by aggregating columns in the data set, which I will visualize in the Share phase of this project.

[13]:

```
df_1 = df.groupby(['usertype'])['trip_id'].count().to_frame()
df_1
```

[13]:

```
            trip_id
usertype
Customer     356752
Subscriber   403036
```

[14]:

```
df_2 = df.groupby(['usertype'])['tripduration'].mean().to_frame()
df_2
```

[14]:

```
            tripduration
usertype
Customer     1824.054727
Subscriber    722.018892
```

[15]:

```
df_3 = df.groupby(['month', 'usertype'])['trip_id'].count().to_frame()
df_3.reset_index(inplace=True)
df_3
```

[15]:

```
       month    usertype  trip_id
0       June    Customer     3120
1       June  Subscriber      885
2       July    Customer    51548
3       July  Subscriber    23319
4     August    Customer   110101
5     August  Subscriber    60407
6  September    Customer   105335
7  September  Subscriber    95695
```

```
8     October    Customer    64201
9     October  Subscriber   110494
10   November    Customer    18065
11   November  Subscriber    71945
12   December    Customer     4382
13   December  Subscriber    40291
```

[16]:

```
df_4 = df.groupby(['day_of_week', 'usertype'])['trip_id'].count().to_frame()
df_4.reset_index(inplace=True)
df_4
```

[16]:

```
   day_of_week    usertype  trip_id
0       Monday    Customer    41866
1       Monday  Subscriber    64042
2      Tuesday    Customer    32807
3      Tuesday  Subscriber    69896
4    Wednesday    Customer    30221
5    Wednesday  Subscriber    66828
6     Thursday    Customer    33599
7     Thursday  Subscriber    63272
8       Friday    Customer    47721
9       Friday  Subscriber    67643
10    Saturday    Customer    90575
11    Saturday  Subscriber    38862
12      Sunday    Customer    79963
13      Sunday  Subscriber    32493
```

[17]:

```
df_5 = df.groupby(['day_of_week', 'usertype'])['tripduration'].mean().to_frame()
df_5.reset_index(inplace=True)
df_5
```

[17]:

```
   day_of_week    usertype  tripduration
0       Monday    Customer   1765.949123
1       Monday  Subscriber    708.334952
2      Tuesday    Customer   1656.959399
3      Tuesday  Subscriber    702.288128
4    Wednesday    Customer   1671.559942
5    Wednesday  Subscriber    698.994823
6     Thursday    Customer   1780.871484
7     Thursday  Subscriber    711.272111
8       Friday    Customer   1796.688502
9       Friday  Subscriber    713.068906
10    Saturday    Customer   1921.553784
11    Saturday  Subscriber    800.801143
12      Sunday    Customer   1904.704163
13      Sunday  Subscriber    784.119626
```

[18]:
```
df_6 = df.groupby(['month', 'usertype'])['tripduration'].mean().to_frame()
df_6.reset_index(inplace=True)
df_6
```

[18]:
```
        month   usertype  tripduration
0        June   Customer   2284.595192
1        June  Subscriber  1465.116384
2        July   Customer   2198.832855
3        July  Subscriber   851.450748
4      August   Customer   1886.985613
5      August  Subscriber   786.317463
6   September   Customer   1742.548061
7   September  Subscriber   756.803417
8     October   Customer   1628.405663
9     October  Subscriber   698.240438
10   November   Customer   1535.432937
11   November  Subscriber   645.155327
12   December   Customer   1521.822912
13   December  Subscriber   654.228910
```

[19]:
```
df_7 = df.groupby(['hour', 'usertype'])['trip_id'].count().to_frame()
df_7.reset_index(inplace=True)
df_7.head()
```

[19]:
```
   hour   usertype  trip_id
0     0   Customer     4591
1     0  Subscriber    2714
2     1   Customer     2903
3     1  Subscriber    1582
4     2   Customer     1954
```

[20]:
```
df_8 = df.groupby(['hour', 'usertype'])['tripduration'].mean().to_frame()
df_8.reset_index(inplace=True)
df_8.head()
```

[20]:
```
   hour   usertype  tripduration
0     0   Customer   1926.543455
1     0  Subscriber   772.408622
2     1   Customer   2013.688254
3     1  Subscriber   696.296460
4     2   Customer   2198.434493
```

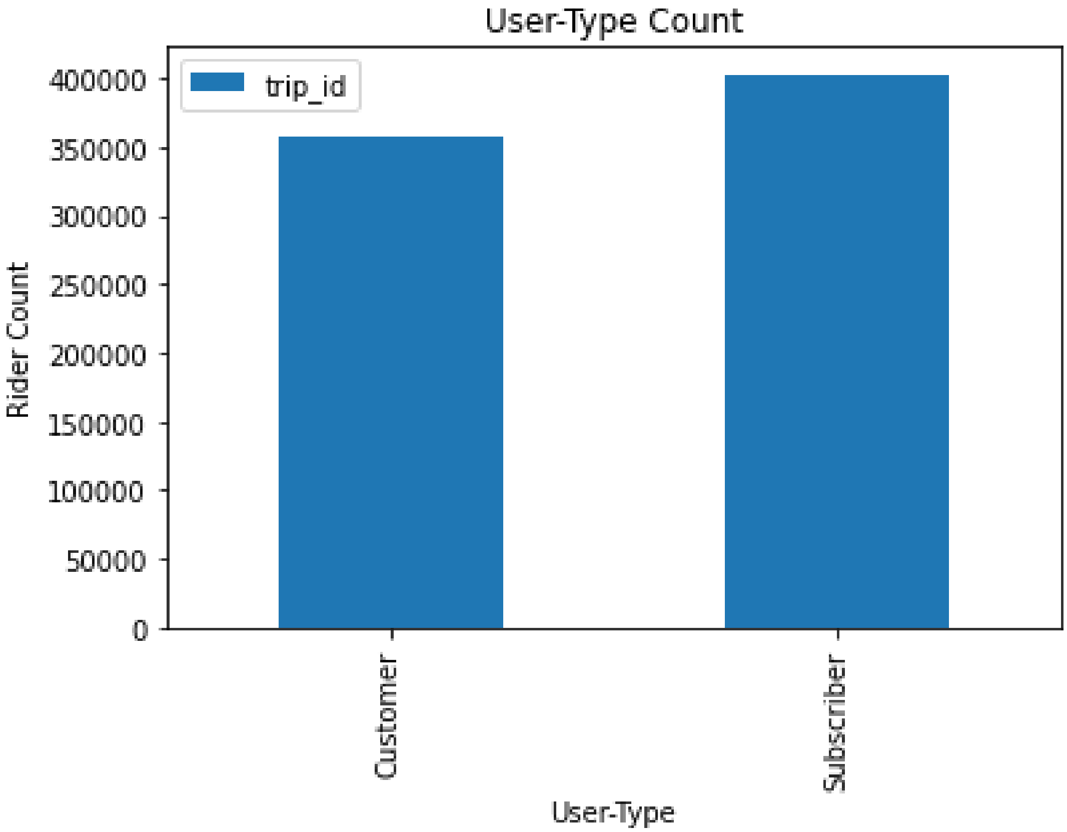
1.6 Share

The Share phase of this project includes making visuals from my analysis that help stakeholders understand my findings

```
[21]: plt.figure(figsize=(10,5))
      df_1.plot.bar()
      plt.title('User-Type Count')
      plt.ylabel('Rider Count')
      plt.xlabel('User-Type')
```

```
[21]: Text(0.5, 0, 'User-Type')

<Figure size 720x360 with 0 Axes>
```

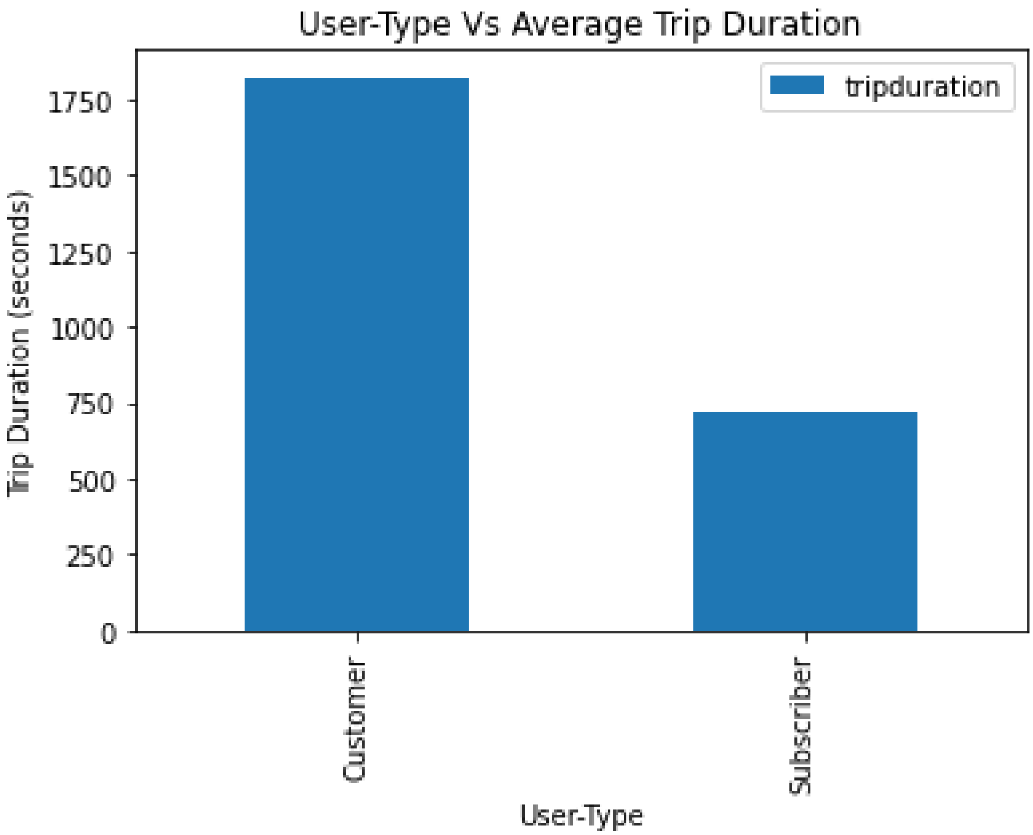


As expected the number of subscriber riders exceed that of the casual riders, I did some aggregation to discover behaviors between the two categories.

```
[22]: plt.figure(figsize=(10,5))
      df_2.plot.bar()
      plt.title('User-Type Vs Average Trip Duration')
      plt.ylabel('Trip Duration (seconds)')
      plt.xlabel('User-Type')
```

```
[22]: Text(0.5, 0, 'User-Type')
```

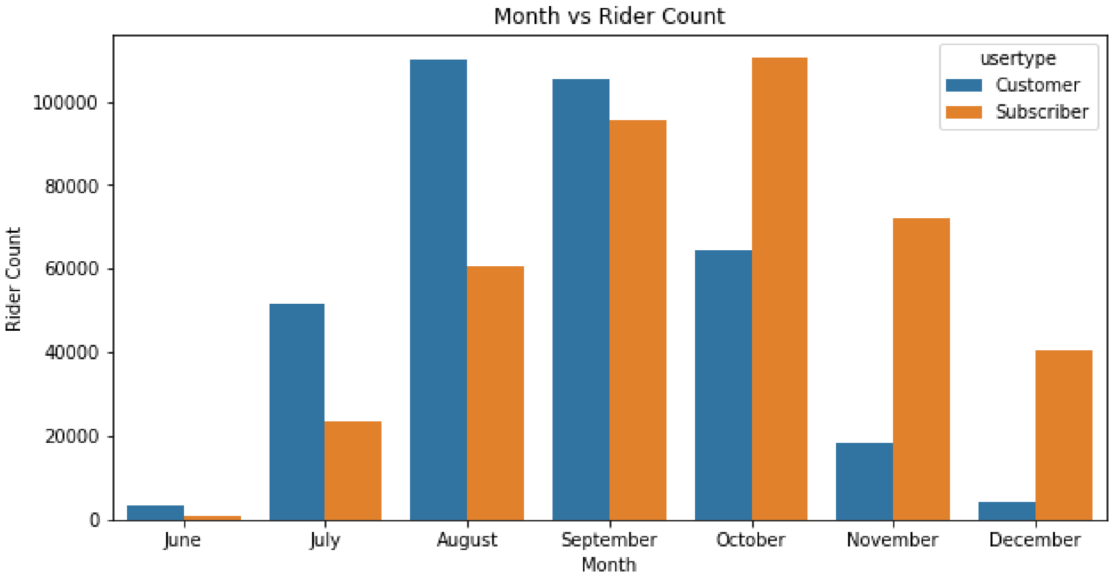
```
<Figure size 720x360 with 0 Axes>
```



Suprising to see that customer(casual) riders spend more time on average riding bikes than subscriber riders.

```
[23]: plt.figure(figsize=(10,5))
      sns.barplot(x='month', y='trip_id', data=df_3, hue='usertype')
      plt.title('Month vs Rider Count')
      plt.ylabel('Rider Count')
      plt.xlabel('Month')
```

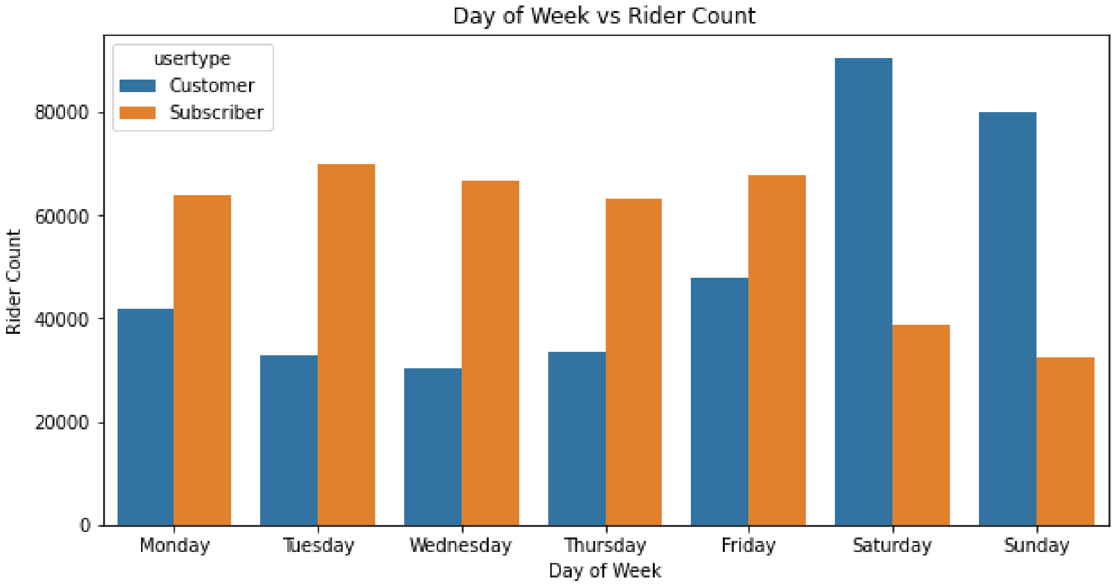
```
[23]: Text(0.5, 0, 'Month')
```



In the months of June, July, August and September Casual riders were more than Subscribers, but from October to December the Subsctibers were almost double the amount of Casual in every month.

[24]:
```
plt.figure(figsize=(10,5))
sns.barplot(x='day_of_week', y='trip_id', data=df_4, hue='usertype')
plt.title('Day of Week vs Rider Count')
plt.ylabel('Rider Count')
plt.xlabel('Day of Week')
```

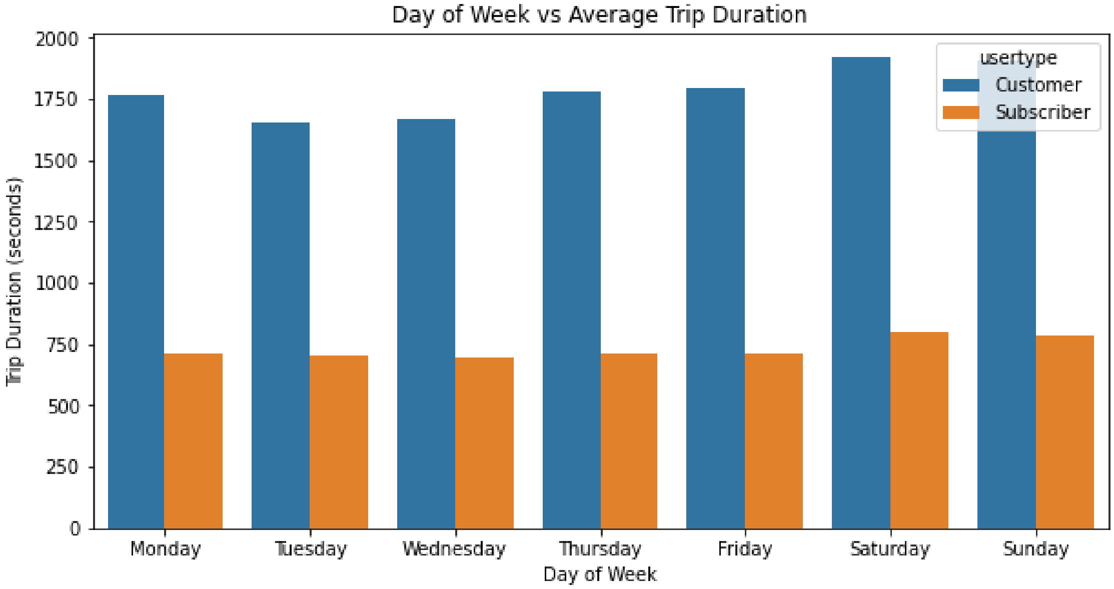
[24]:
```
Text(0.5, 0, 'Day of Week')
```



On the week days Subscriber riders spend more time on bikes than Casual riders, while in the weekend Casual riders double Subscribers numbers.

```
[25]: plt.figure(figsize=(10,5))
      sns.barplot(x='day_of_week', y='tripduration', data=df_5, hue='usertype')
      plt.title('Day of Week vs Average Trip Duration')
      plt.ylabel('Trip Duration (seconds)')
      plt.xlabel('Day of Week')
```

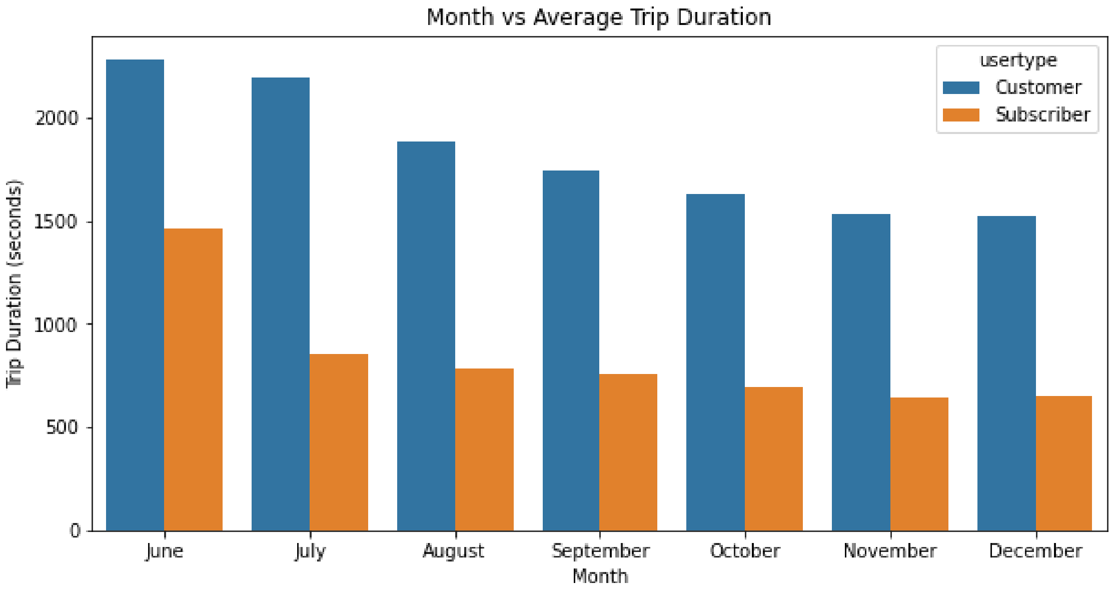
```
[25]: Text(0.5, 0, 'Day of Week')
```



Casual riders spend more time on bikes every day of the week than Subscribers, even though there are more Subscriber riders in the week day than Casual riders.

```
[26]: plt.figure(figsize=(10,5))
      sns.barplot(x='month', y='tripduration', data=df_6, hue='usertype')
      plt.title('Month vs Average Trip Duration')
      plt.ylabel('Trip Duration (seconds)')
      plt.xlabel('Month')
```

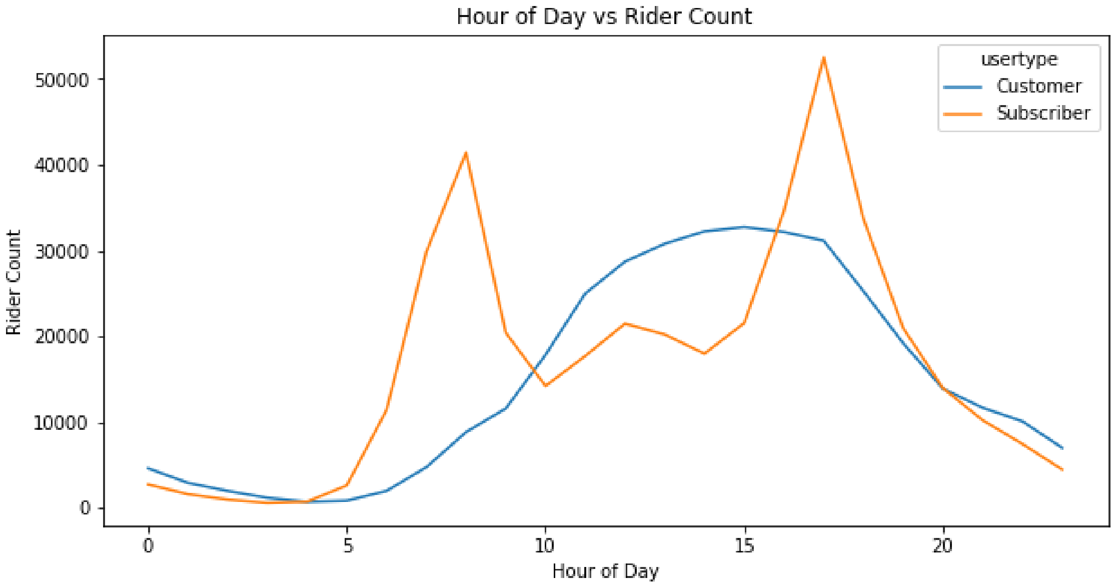
```
[26]: Text(0.5, 0, 'Month')
```



On average Casual riders spend more time on bikes than Subscriber riders in every month, in many instances they even spend double the times of Subscribers.

[27]:
```
plt.figure(figsize=(10,5))
sns.lineplot(x='hour', y='trip_id', data=df_7, hue='usertype')
plt.title('Hour of Day vs Rider Count')
plt.ylabel('Rider Count')
plt.xlabel('Hour of Day')
```

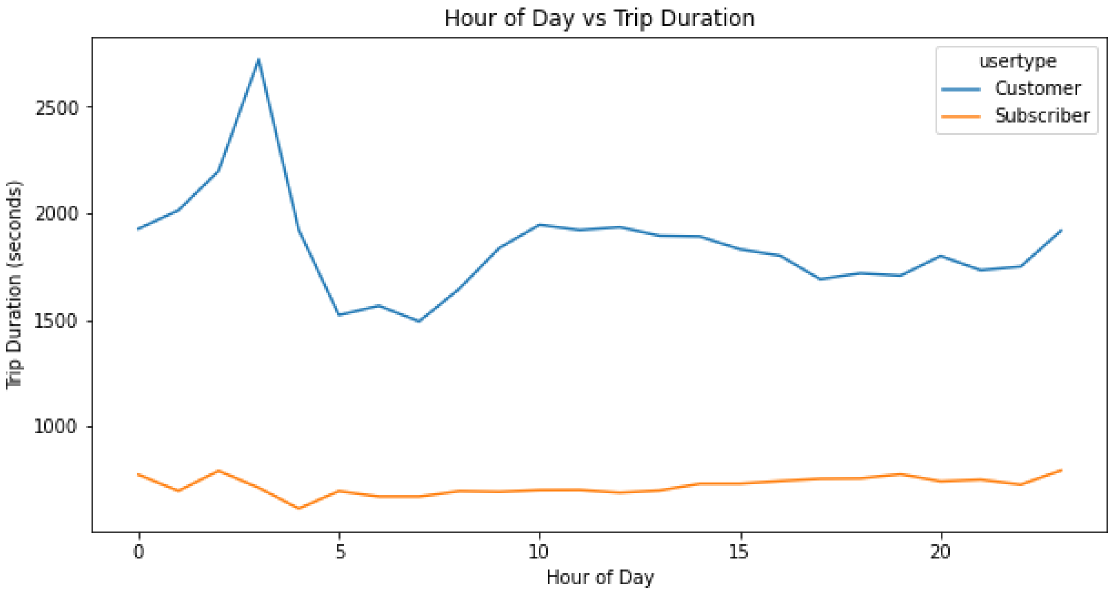
[27]:
```
Text(0.5, 0, 'Hour of Day')
```



From the hours between 08:00 - 20:00 there's a rise in the number of Casual riders, while for the Subscribers most use comes between 06:00 - 09:00, 11:00 - 14:00 and then again between 16:00 - 19:00.

```
[28]: plt.figure(figsize=(10,5))
      sns.lineplot(x='hour', y='tripduration', data=df_8, hue='usertype')
      plt.title('Hour of Day vs Trip Duration')
      plt.ylabel('Trip Duration (seconds)')
      plt.xlabel('Hour of Day')
```

```
[28]: Text(0.5, 0, 'Hour of Day')
```



There is a clear difference between the ride duration of Casual and Subscriber riders, Subscriber riders spend around 700 seconds on average during trips, while Casual riders spend 2,000 seconds on average during trips.

1.7 Act

The objective of this portion of the project is to make decisions based on the findings from our analysis. My stakeholder has asked for 3 data driven suggestions that can see Customer riders become subscribers.

1. The marketing team can aid in developing advertisements meant to captivate Casual riders to obtain subscriptions. From the data I would think a summer and weekend themed advert would be the best angle to explore.

2. Discounts and Free trials should be explored as an option to reduce the number of Casual riders.
3. Create competitions using social media as a means which will create awareness to potential subscribers.

[29]:

```
%%capture
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('Cyclist Bike-Share.ipynb')
```