Bike Sharing Service Data Explnatory Analysis

September 4, 2019

1 Ford GoBike Bike Sharing Data Explanatory Analysis

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1.2 Investigation Overview

In this invetigation, I'm interested in finding out how the bike sharing service is used, especially if any pattern exists, and whether a user's gender, age and user type determine how he or she uses the service.

1.3 Dataset Overview

The original datasets contain the information about 2,290,554 bike rides with 16 columns. There are 2,161,106 rides left after initial data cleaning. 2 time-relevant variables ('start_time', 'end_time') are converted to datetime data type. The latitude and longitude coordinates of both start and end locations are provided. One numeric variable ('member_birth_year') and two categorical variables ('user_type', 'member_gender') about the users are also available.

```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sb
    import math
    import warnings

%matplotlib inline
```

Import packages and set plot to be embedded inline

• Load the files and merge the datasets into a dataframe

```
In [3]: df_clean = df.copy()
```

• Create a copy for data cleaning

d = radius * c

• Entries with null values in three columns removed

• Convert two time-relevant variables 'start_time' and 'end_time' to datetime data type

```
In [6]: df_clean['member_age'] = 2019 - df_clean['member_birth_year']
       df_clean['member_age_group'] = df_clean['member_age'].apply(lambda x: '18-19' if 18<=x<2
                                                               else '20-29' if 20 \le x \le 30
                                                               else '30-39' if 30 <= x < 40
                                                               else '40-49' if 40 <= x < 50
                                                               else 50-59 if 50 <= x < 60
                                                               else '60 or over')
       df_clean['start_time_year_month'] = df_clean['start_time'].map(lambda x: x.strftime('%Y-
       df_clean['end_time_year_month'] = df_clean['end_time'].map(lambda x: x.strftime('%Y-%m')
       df_clean['duration_min'] = df_clean['duration_sec']/60
       def coordinates_distance(start, end):
           lat1, lon1 = start
           lat2, lon2 = end
           radius = 6371
           dlat = math.radians(lat2 - lat1)
           dlon = math.radians(lon2 - lon1)
           c = 2*math.atan2(math.sqrt(a), math.sqrt(1-a))
```

return d

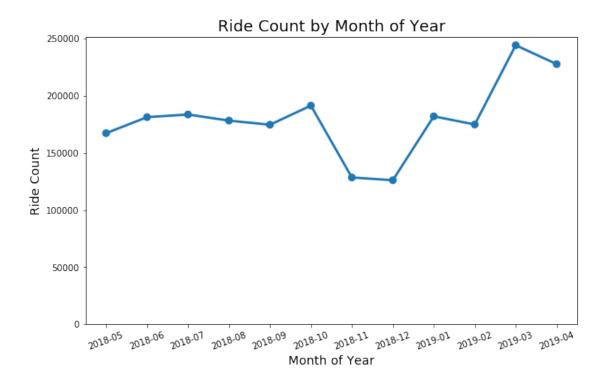
```
df_clean['distance'] = df_clean.apply(lambda x: coordinates_distance((x['start_station_l
df_clean['start_time_weekday'] = df_clean['start_time'].dt.weekday_name
df_clean['end_time_weekday'] = df_clean['end_time'].dt.weekday_name
df_clean['start_time_hour'] = df_clean['start_time'].dt.hour
df_clean['end_time_hour'] = df_clean['end_time'].dt.hour
```

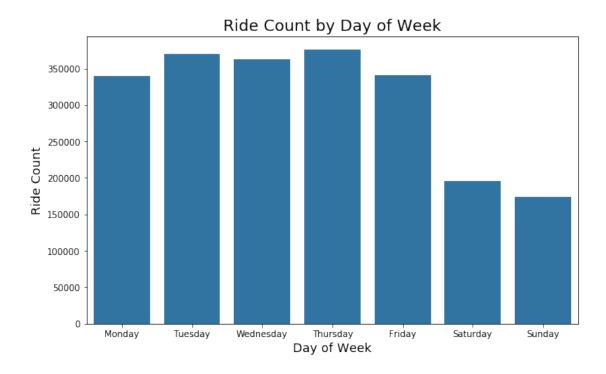
- A new variable 'member_age' (user's age) created
- A new variable 'member_age_group' (users divided into six age groups) created
- Two new variables 'start_time_year_month', 'end_time_year_month' (time variables in 'yyyy-mm' format) created
- A new variable 'duration_min' (duration of ride in minutes) created
- A new variable 'distance' (distance between start and end coordinates in kilometer) created
- Two new variables 'start_time_weekday', 'end_time_weekday' (time variables in day of week format) created
- Two new variables 'start_time_hour', 'end_time_hour' (time variables in hour of day format) created

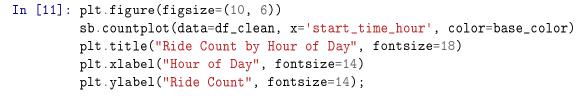
- Maximum value of age is 141, which is very unlikely. Entries with users more than 100 years of age removed
- As deviant travel distance is not of the interest of this analysis, 21 entries with travel distance more than 50 kilometer are removed

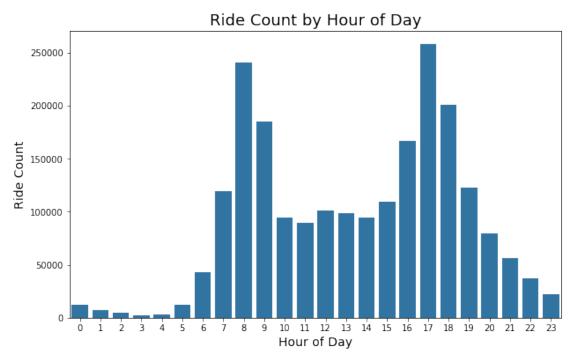
1.4 Distribution of Ride Time

- Monthly ride count ranges between 150,000 and 200,000 from May 2018 to February 2019
- There is a significant drop of count in November and December, 2018, which may be due to the weather
- There is a big jump of ride count in March 2019. The count drops slightly in the following month, but still fairly higher than the counts in 2018
- The demand for the service is significantly higher during the week (Monday to Friday) than weekends
- The peak hours of the service are from 8 to 9 a.m. and 4 to 6 p.m.





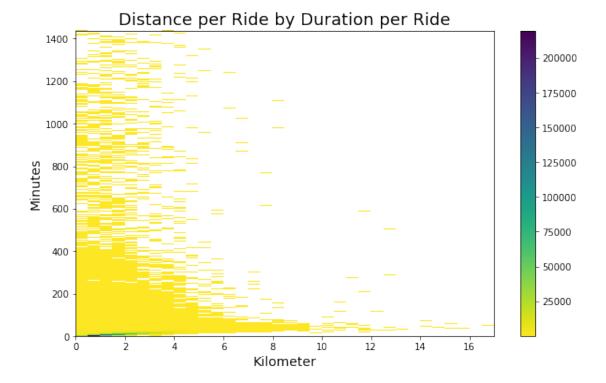




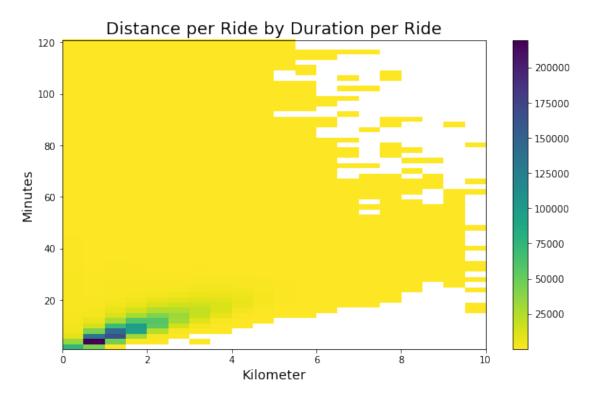
1.5 Distance vs. Duration

- Most rides are within 4 kilometer in distance and 20 minutes in duration. There is a linear correlation between distance and duration per ride within this range
- The most frequent rides are about 0.5 to 1 kilometer in distance and 3 to 5 minutes in duration
- Duration per ride is relatively shorter between November 2018 and February 2019. However, the distance per ride during this period of time is not significantly shorter
- Distance per ride increases steadily over time
- Duration per ride is longer on weekends, but the distance per ride becomes shorter

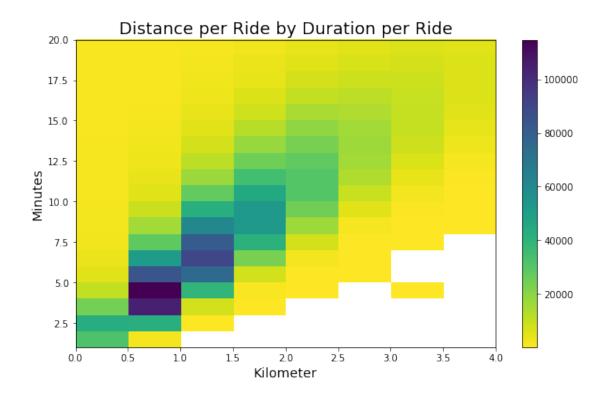
```
In [12]: plt.figure(figsize=(10, 6))
    bins_x = np.arange(0, df_clean['distance'].max()+0.5, 0.5)
    bins_y = np.arange(1, df_clean['duration_min'].max()+2, 2)
    plt.hist2d(data=df_clean, x='distance', y='duration_min', bins=[bins_x, bins_y], cmap='plt.colorbar()
    plt.title('Distance per Ride by Duration per Ride', fontsize=18)
    plt.xlabel('Kilometer', fontsize=14)
    plt.ylabel('Minutes', fontsize=14);
```

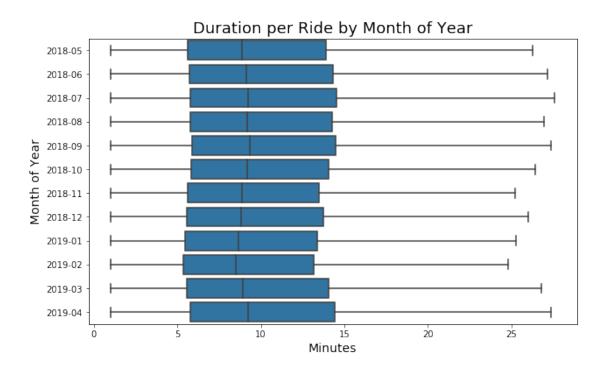


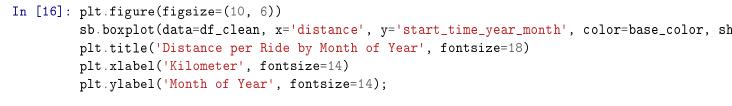
```
bins_x = np.arange(0, df_min_dis['distance'].max()+0.5, 0.5)
bins_y = np.arange(1, df_min_dis['duration_min'].max()+2, 2)
plt.hist2d(data=df_min_dis, x='distance', y='duration_min', bins=[bins_x, bins_y], cmap plt.colorbar()
plt.title('Distance per Ride by Duration per Ride', fontsize=18)
plt.xlabel('Kilometer', fontsize=14)
plt.ylabel('Minutes', fontsize=14);
```

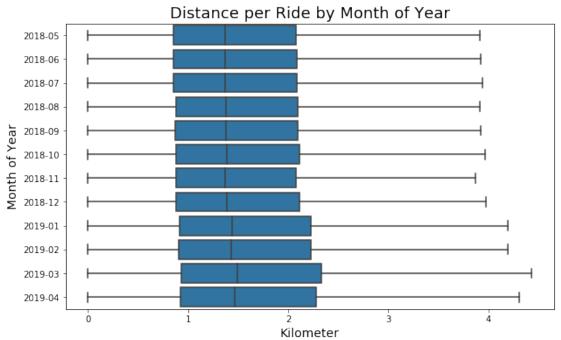


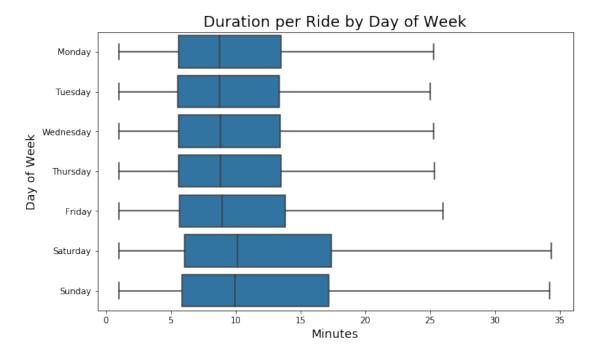
```
In [14]: df_min_dis_2 = df_clean[(df_clean['distance'] <= 4) & (df_clean['duration_min'] <= 20)]
    plt.figure(figsize=(10, 6))
    bins_x = np.arange(0, df_min_dis_2['distance'].max()+0.5, 0.5)
    bins_y = np.arange(1, df_min_dis_2['duration_min'].max()+1, 1)
    plt.hist2d(data=df_min_dis_2, x='distance', y='duration_min', bins=[bins_x, bins_y], cm
    plt.colorbar()
    plt.title('Distance per Ride by Duration per Ride', fontsize=18)
    plt.xlabel('Kilometer', fontsize=14)
    plt.ylabel('Minutes', fontsize=14);</pre>
```



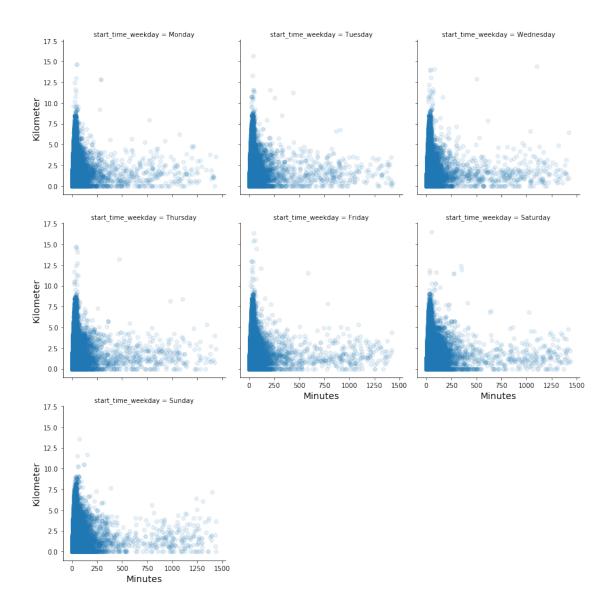






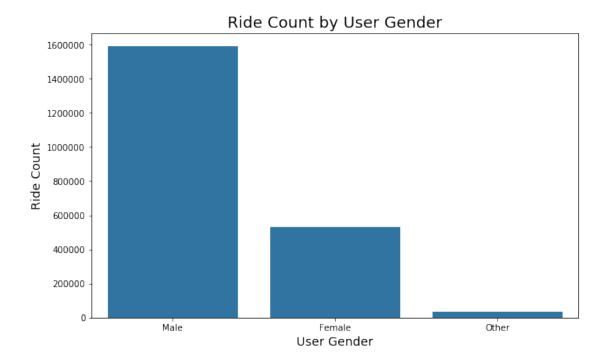


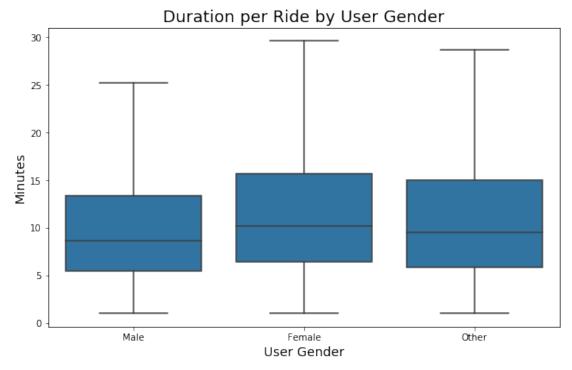




1.6 Gender

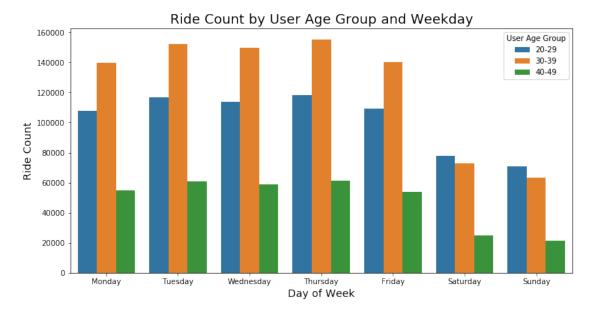
- Rides by male users are more than twice as much than female users
- Female users generally spend more time per ride than male users



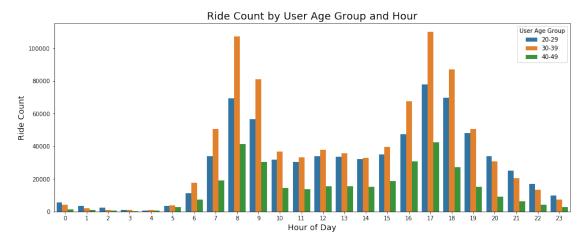


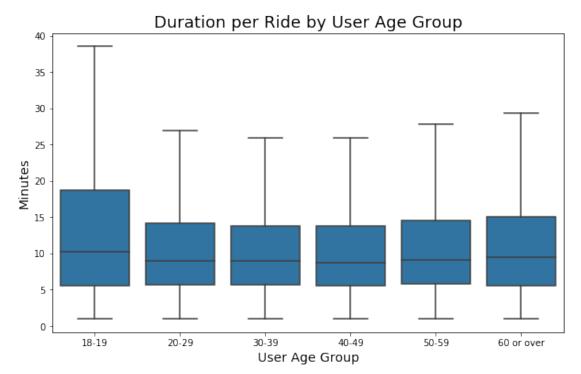
1.7 Age

- '20-29', '30-39' and '40-49' are the top3 user groups, with the '30-39' group being the largest. These three groups account for almost 89% of the rides
- While the '30-39' group is the largest during the week, the '20-29' group uses the service more than other groups on weekends
- While the '30-39' group is the largest during the day (6 a.m. to 7 p.m.), the '20-29' group uses the service more than other groups from 8 p.m. to 2 a.m.
- Compared to other groups, duration per ride for the '18-19' group is more sparsely distributed



```
plt.xlabel('Hour of Day', fontsize=14)
plt.ylabel('Ride Count', fontsize=14);
```

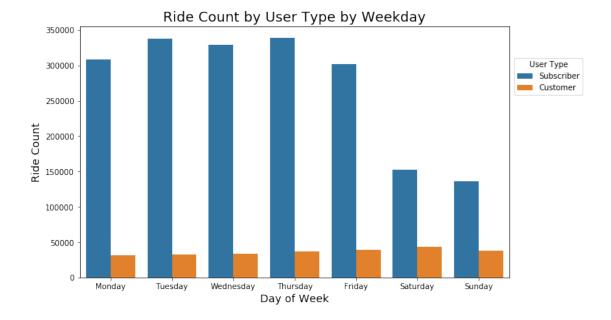




1.8 User Type

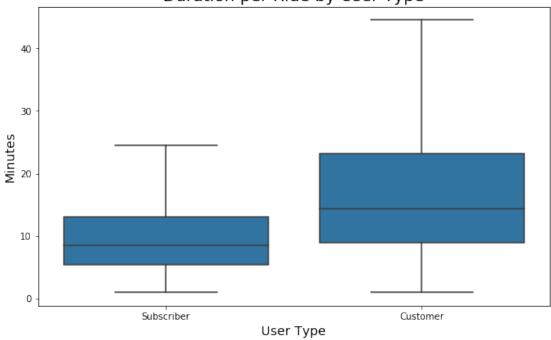
- The majority of the rides in the data is by the subscriber group, and the frequency is much higher than the customer group
- The customer group is younger than the subscriber group. Specifically, the proportion of the '20-29' age group is slightly higher for the customer group
- The proportion of female users in the customer group is slightly higher than the subscriber group
- The subscriber group uses the service more during the week while the customer group more on Saturdays
- Both overall duration per ride and overall distance per ride for the customer group are longer than that of the subscriber group
 - A further investigation shows that while the overall duration per ride for the customer group is longer than the subscriber, it is only true for Friday and Sunday
 - Similar pattern also found in distance: while the overall distance per ride for the customer group is longer than the subscriber group, it is only true for Friday and Sunday

```
In [25]: user_type = ['Subscriber', 'Customer']
    plt.figure(figsize=(10, 6))
    ax = sb.countplot(data=df_clean, x='start_time_weekday', hue='user_type', order=weekday
    ax.legend(loc='right', bbox_to_anchor=(1.18, 0.8), title='User Type')
    plt.title('Ride Count by User Type by Weekday', fontsize=18)
    plt.xlabel('Day of Week', fontsize=14)
    plt.ylabel('Ride Count', fontsize=14);
```



```
plt.title('Duration per Ride by User Type', fontsize=18)
plt.xlabel('User Type', fontsize=14)
plt.ylabel('Minutes', fontsize=14);
```

Duration per Ride by User Type



Distance per Ride by User Type

