Bike Sharing Analysis with Ford GoBike Data

May 4, 2019

1 Bike Sharing Analysis with Ford GoBike Data

Introduction

Over the past decade, bicycle-sharing systems have been growing in number and popularity in cities across the world. Bicycle-sharing systems allow users to rent bicycles for short trips, typically 30 minutes or less. Thanks to the rise in information technologies, it is easy for a user of the system to access a dock within the system to unlock or return bicycles. These technologies also provide a wealth of data that can be used to explore how these bike-sharing systems are used. In this project, I will perform an exploratory analysis on data provided by Ford GoBike, a bike-share system provider.

Primary Wrangling

t's time to collect and explore our data. In this project, we will focus on the record of individual trips taken in from 2017 to November, 2018.

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

```
In [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
```

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

In [3]:
```
makedirs(folder_name_of_csvs)
pd.read_csv('https://s3.amazonaws.com/fordgobike-data/2017-fordgobike-tripdata.csv').to_
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
    response = get(bike_data_url)

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

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

In [4]:
```
# 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)
```

In [5]:
```
df.to_csv('data.csv')
```

In [6]:
```
# Examine DataFrame
df = pd.read_csv('data.csv')
```

In [7]:
```
len(df)
```

Out[7]:
```
2252058
```

In [8]:
```
#Set visualization style
sns.set_style('whitegrid')
sns.set_context("talk")
```

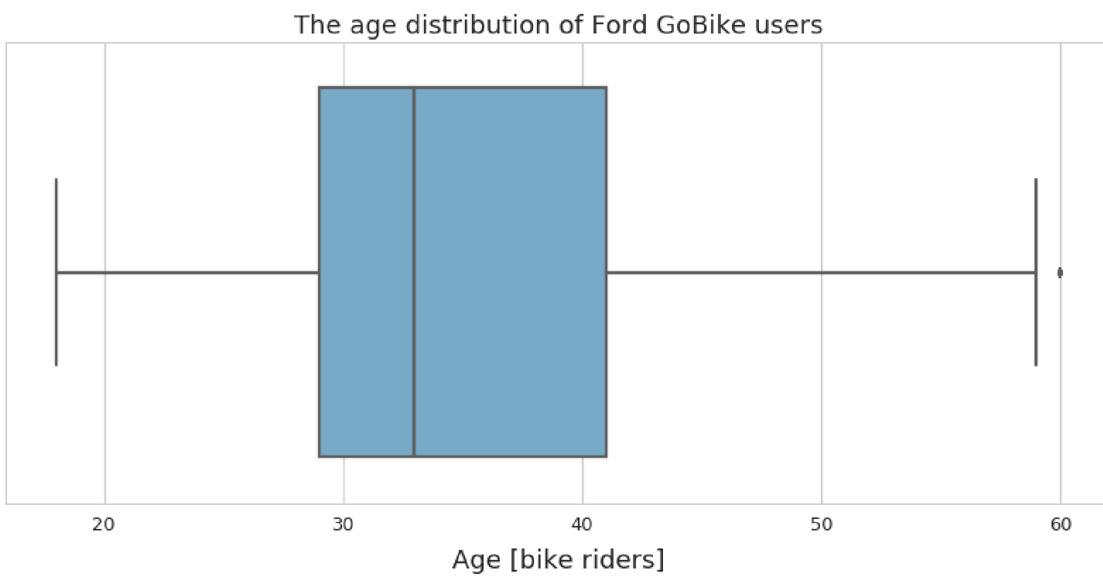
In [9]:
```
#Filter data to include reasonable member age range
df['member_age'] = 2018-df['member_birth_year']
```

In [10]:
```
# Check age distrubition
df['member_age'].describe(percentiles = [.1, .2, .3, .4, .5, .6, .7, .75, .8, .9, .95])
```

Out[10]:
```
count    2.079810e+06
mean     3.553289e+01
std      1.051074e+01
min      1.800000e+01
10%      2.400000e+01
20%      2.700000e+01
30%      2.900000e+01
40%      3.100000e+01
50%      3.300000e+01
```

```
60%       3.600000e+01
70%       3.900000e+01
75%       4.100000e+01
80%       4.400000e+01
90%       5.100000e+01
95%       5.600000e+01
max       1.370000e+02
Name: member_age, dtype: float64
```

```
In [28]: plt.figure(figsize=(14,6))
         sns.boxplot(x='member_age', data=df, palette='Blues', orient='h')
         plt.title("The age distribution of Ford GoBike users", fontsize=18, y=1.0)
         plt.xlabel("Age [bike riders]", fontsize=18, labelpad=10)
         plt.savefig('image01.png');
```



Here is the distrubition of users. Ages from 18 to 56 takes 95% of the users. There were users more than 100 years old. So, we can remove users more than 60 years old.

```
In [12]: df = df[df['member_age']<=60]
```

```
In [13]: df['member_age'].mean()
```

```
Out[13]: 34.783988359178586
```

```
In [17]: df.drop(['Unnamed: 0', 'member_birth_year'], axis=1, inplace=True)
```

Ford GoBike spreaded the service to San Francisco, Oakland and San Jose. However, it's hard to imagine traffic. So regarding this complexity, I decided to focus on San Fancisco area.

In [18]:
```
#Filter data only to include San Francisco rides
max_longitude_sf = -122.3597
min_longitude_sf = -122.5147
max_latitude_sf = 37.8121
min_latitude_sf = 37.7092
```

In [19]:
```
end_station_latitude_mask = (df['end_station_latitude']>=min_latitude_sf) & (df['end_st
start_station_latitude_mask = (df['start_station_latitude']>=min_latitude_sf) & (df['st
```

In [20]:
```
end_station_longitude_mask =(df['end_station_longitude']>=min_longitude_sf) & (df['end_
start_station_longitude_mask = (df['start_station_longitude']>=min_longitude_sf) & (df[
```

In [21]:
```
df = df[end_station_latitude_mask & start_station_latitude_mask & end_station_longitude
```

In [22]:
```
len(df)
```

Out[22]: 1505886

In [23]:
```
# high-level overview of data shape and composition
print(df.shape)
print(df.dtypes)
print(df.head(10))
```

```
(1505886, 17)
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_gender               object
start_station_id           float64
start_station_latitude     float64
start_station_longitude    float64
start_station_name          object
start_time                  object
user_type                   object
member_age                 float64
dtype: object
    Unnamed: 0.1  bike_id bike_share_for_all_trip  duration_sec  \
0            NaN     1035                      No           598
1            NaN     1673                      No           943
2            NaN     3498                      No         18587
3            NaN     3129                      No         18558
17           NaN     2011                      No           258
19           NaN      439                      No          1983
```

```
20          NaN      321                     No           581
22          NaN     3097                    Yes           592
23          NaN     2102                     No           833
25          NaN     3121                     No           277

    end_station_id  end_station_latitude  end_station_longitude  \
0            114.0             37.764478            -122.402570
1            324.0             37.788300            -122.408531
2             15.0             37.795392            -122.394203
3             15.0             37.795392            -122.394203
17           336.0             37.763281            -122.407377
19            11.0             37.797280            -122.398436
20            22.0             37.789756            -122.394643
22            93.0             37.770407            -122.391198
23            85.0             37.770083            -122.429156
25           120.0             37.761420            -122.426435

                                     end_station_name  \
0                           Rhode Island St at 17th St
1                 Union Square (Powell St at Post St)
2   San Francisco Ferry Building (Harry Bridges Pl...
3   San Francisco Ferry Building (Harry Bridges Pl...
17                       Potrero Ave and Mariposa St
19                            Davis St at Jackson St
20                             Howard St at Beale St
22                        4th St at Mission Bay Blvd S
23                           Church St at Duboce Ave
25                              Mission Dolores Park

                    end_time member_gender  start_station_id  \
0   2018-03-01 00:09:45.1870          Male             284.0
1   2018-02-28 23:36:59.9740          Male               6.0
2   2018-02-28 23:30:42.9250        Female              93.0
3   2018-02-28 23:30:12.4500          Male              93.0
17  2018-02-28 23:06:21.4980          Male              88.0
19  2018-02-28 23:02:59.6970          Male             121.0
20  2018-02-28 23:00:09.8260          Male              66.0
22  2018-02-28 22:49:33.8350        Female             284.0
23  2018-02-28 22:47:17.2420        Female             129.0
25  2018-02-28 22:39:46.4050        Female             108.0

    start_station_latitude  start_station_longitude  \
0                37.784872              -122.400876
1                37.804770              -122.403234
2                37.770407              -122.391198
3                37.770407              -122.391198
17               37.770030              -122.411726
19               37.759210              -122.421339
```

```
20              37.778742              -122.392741
22              37.784872              -122.400876
23              37.758862              -122.412544
25              37.764710              -122.419957

                                 start_station_name  \
0   Yerba Buena Center for the Arts (Howard St at ...
1                        The Embarcadero at Sansome St
2                         4th St at Mission Bay Blvd S
3                         4th St at Mission Bay Blvd S
17                                11th St at Bryant St
19                                  Mission Playground
20                               3rd St at Townsend St
22  Yerba Buena Center for the Arts (Howard St at ...
23                              Harrison St at 20th St
25                                16th St Mission BART

                 start_time   user_type  member_age
0   2018-02-28 23:59:47.0970  Subscriber        30.0
1   2018-02-28 23:21:16.4950    Customer        31.0
2   2018-02-28 18:20:55.1900    Customer        32.0
3   2018-02-28 18:20:53.6210    Customer        37.0
17  2018-02-28 23:02:02.5250  Subscriber        29.0
19  2018-02-28 22:29:56.6310  Subscriber        28.0
20  2018-02-28 22:50:27.9530  Subscriber        29.0
22  2018-02-28 22:39:40.9490  Subscriber        28.0
23  2018-02-28 22:33:23.6680  Subscriber        28.0
25  2018-02-28 22:35:08.6470  Subscriber        34.0
```

What is the structure of your dataset?

There are 1505886 rides in the dataset with 16 features like bike_id, user_type, member_age, start_station_name etc. Most variables are numeric in the dataset.

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

I'm most interested in figuring out and understanding the users' behaviors and personal details like;

Average riding duration

Average riding distance

Leisure or to go far away

Age groups of users

Genders

Weekly day distrubition etc. in the dataset.

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

I expect that age group and purpose of usage will make a strong effect in the dataset. I also think that the other investigations will clarify the customers' behaviors as well.

Univariate Exploration

In [24]:
```
#Generate new fields for date from start_time and end_time
df['start_time']=pd.to_datetime(df['start_time'])
df['end_time']=pd.to_datetime(df['end_time'])
```

In [25]:
```
df['start_time_date']=df['start_time'].dt.date
df['end_time_date']=df['end_time'].dt.date
```

In [26]:
```
df['start_time_year_month']=df['start_time'].map(lambda x: x.strftime('%Y-%m'))
df['end_time_year_month']=df['end_time'].map(lambda x: x.strftime('%Y-%m'))
```

In [29]:
```
df['start_time_year_month_renamed'] = df['start_time'].dt.strftime('%y' + '-' + '%m')
```

In [30]:
```
df['start_time_year']=df['start_time'].dt.year.astype(int)
df['end_time_year']=df['end_time'].dt.year.astype(int)
```

In [31]:
```
df['start_time_month']=df['start_time'].dt.month.astype(int)
df['end_time_month']=df['end_time'].dt.month.astype(int)
```

In [32]:
```
df['start_time_hour_minute']=df['start_time'].map(lambda x: x.strftime('%H-%m'))
df['end_time_hour_minute']=df['end_time'].map(lambda x: x.strftime('%H-%m'))
```

In [33]:
```
df['start_time_hour']=df['start_time'].dt.hour
df['end_time_hour']=df['end_time'].dt.hour
```

In [34]:
```
df['start_time_weekday']=df['start_time'].dt.weekday_name
df['end_time_weekday']=df['end_time'].dt.weekday_name
```

In [35]:
```
df['start_time_weekday_abbr']=df['start_time'].dt.weekday.apply(lambda x: calendar.day_
df['end_time_weekday_abbr']=df['end_time'].dt.weekday.apply(lambda x: calendar.day_abbr
```

In [36]:
```
#Generate a new field for member age group from member_age_bin
df['member_age_bins'] = df['member_age'].apply(lambda x: '10 - 20' if 10<x<=20
                                               else '20 - 30' if 20<x<=30
                                               else '30 - 40' if 30<x<=40
                                               else '40 - 50' if 40<x<=50
                                               else '50 - 60' if 50<x<=60
                                               else x)
```

In [37]:
```
#Generate minutes for trip duration from duration_sec
df['duration_min'] = df['duration_sec']/60
```

In [38]:
```
#Generate new fields for distance
def distance(origin, destination):
    """
    Parameters
    ----------
    origin : tuple of float
        (lat, long)
    destination : tuple of float
        (lat, long)
```

```
        Returns
        -------
        distance_in_km : float
        """
        lat1, lon1 = origin
        lat2, lon2 = destination
        radius = 6371  # km

        dlat = math.radians(lat2 - lat1)
        dlon = math.radians(lon2 - lon1)
        a = (math.sin(dlat / 2) * math.sin(dlat / 2) +
             math.cos(math.radians(lat1)) * math.cos(math.radians(lat2)) *
             math.sin(dlon / 2) * math.sin(dlon / 2))
        c = 2 * math.atan2(math.sqrt(a), math.sqrt(1 - a))
        d = radius * c

        return d
```

```
In [39]: df['distance_km_estimates'] = df.apply(lambda x: distance((x['start_station_latitude'],
         df['distance_miles_estimates'] = df['distance_km_estimates']*0.621371
```

2 Question 1. How is Ford GoBike growing?

Average count of rides per bike per day

I decided to select August in order to compare the data findings because it is in summer season.

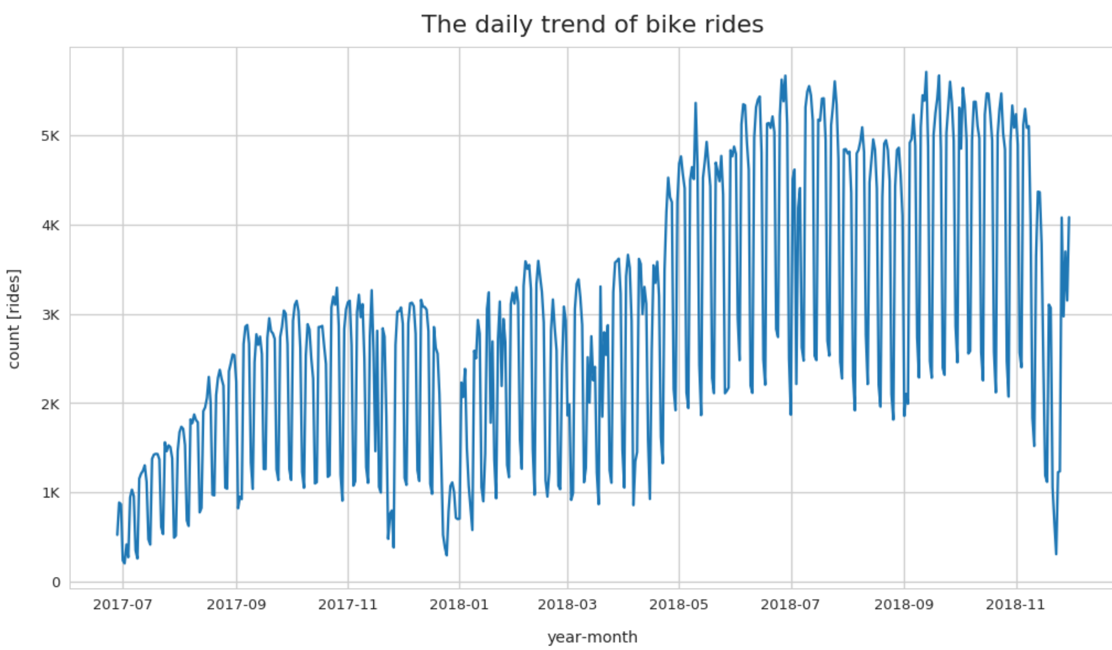
```
In [40]: count_of_rides = df.groupby('start_time_year_month_renamed')['bike_id'].size().reset_in

In [41]: count_of_unique_rides = df.groupby('start_time_year_month_renamed')['bike_id'].nunique(

In [42]: count_of_rides_df = count_of_rides.merge(count_of_unique_rides, on='start_time_year_mon

In [43]: count_of_rides_df['number_of_used'] = count_of_rides_df['bike_id']/count_of_rides_df['u

In [44]: August2017_avg_num_bike_used_per_day = (count_of_rides_df[count_of_rides_df['start_time

In [45]: August2018_avg_num_bike_used_per_day = (count_of_rides_df[count_of_rides_df['start_time

In [46]: print(August2017_avg_num_bike_used_per_day, August2018_avg_num_bike_used_per_day)

1.1737976638461707 2.6237395924856703

In [47]: August2018_avg_num_bike_used_per_day/August2017_avg_num_bike_used_per_day

Out[47]: 2.2352571259074496
```

Compared these two months in different years, the average increased 2.23 times in August 2018, where average count of rides per bike per day reaches to (2.6237).

Count of daily bike rides from July 2017 to November 2018

```
In [48]: def transform_axis_fmt(tick_val, pos):
             if tick_val >= 1000:
                 val = int(tick_val/1000)
                 return '{:d}K'.format(val)
             elif tick_val >= 1000000:
                 val = int(tick_val/1000000)
                 return '{:d}M'.format(val)
             else:
                 return int(tick_val)
```

```
In [49]: df.groupby('start_time_date').agg({'bike_id':'count'}).plot(style='-', legend=False, fi
         plt.title('The daily trend of bike rides', fontsize=22, y=1.015)
         plt.xlabel('year-month', labelpad=16)
         plt.ylabel('count [rides]', labelpad=16)
         ax = plt.gca()
         ax.yaxis.set_major_formatter(tick.FuncFormatter(transform_axis_fmt))
         plt.savefig('image02.png');
```



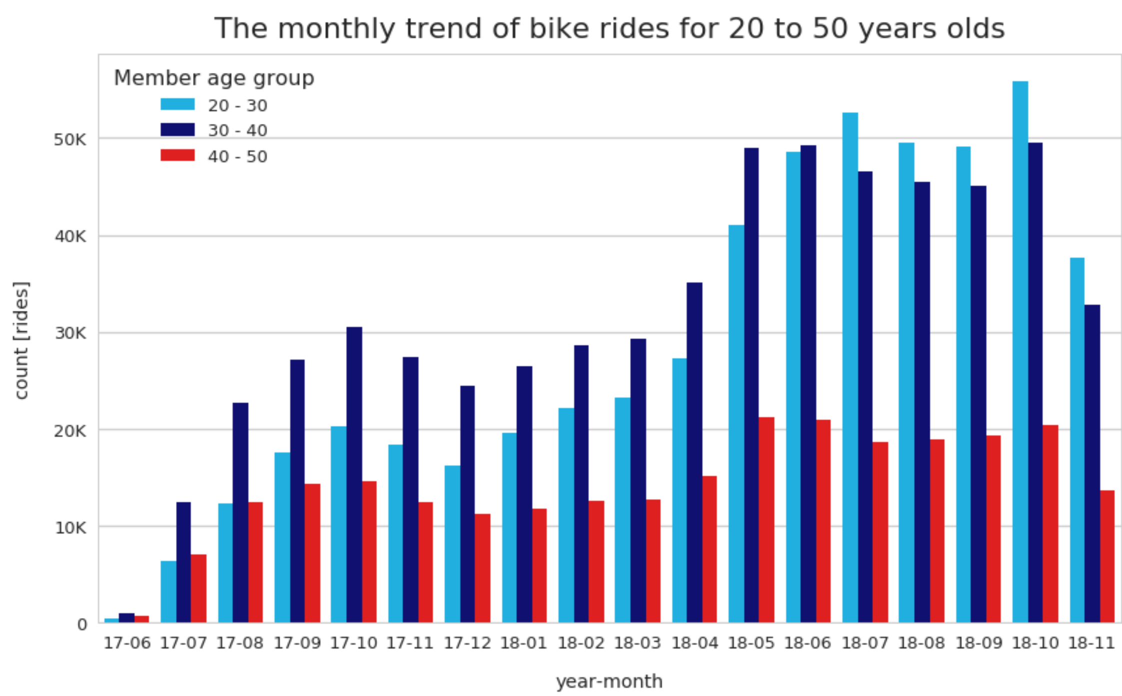
Compared to begining of July 2017, where daily rides were less than 1K, it increased to more than 5000 after less than year (June 2018) There is huge decrease around January 2018 and November 2018 because it's too cold. (Winter session time starts).

```
In [ ]: plt.figure(figsize=(14,8))
        sns.countplot(x='start_time_year_month_renamed', palette="Greens", data=df.sort_values(b
        plt.title('The monthly trend of bike rides', fontsize=22, y=1.015)
        plt.xlabel('year-month', labelpad=16)
        plt.ylabel('count [rides]', labelpad=16)
```

```
ax = plt.gca()
ax.yaxis.set_major_formatter(tick.FuncFormatter(transform_axis_fmt))
plt.savefig('image03.png')
```

Compared to begining of July 2017, where daily rides were less than 1K, it increased to more than 5000 after less than year (June 2018) There is huge decrease around January 2018 and November 2018 because it's too cold. (Winter session time starts).

```
In [53]: plt.figure(figsize=(14,8))
         my_palette = {'20 - 30': 'deepskyblue', '30 - 40': 'navy', '40 - 50': 'red'}
         ax = sns.countplot(x='start_time_year_month_renamed', hue='member_age_bins', palette=my
         plt.title('The monthly trend of bike rides for 20 to 50 years olds', fontsize=22, y=1.0
         plt.xlabel('year-month', labelpad=16)
         plt.ylabel('count [rides]', labelpad=16)
         leg = ax.legend()
         leg.set_title('Member age group',prop={'size':16})
         ax = plt.gca()
         ax.yaxis.set_major_formatter(tick.FuncFormatter(transform_axis_fmt))
         plt.savefig('image04.png');
```



20-30 years old users are rapidly growing compared to other user groups. When the service first started 30-40 years old users were dominant, however 20-30 years old users became leader in a year.

3 Question 2. How does rides trend change per age, gender, weekday, and hour of a day?

Total rides

```
In [54]: df['bike_id'].sum()
```

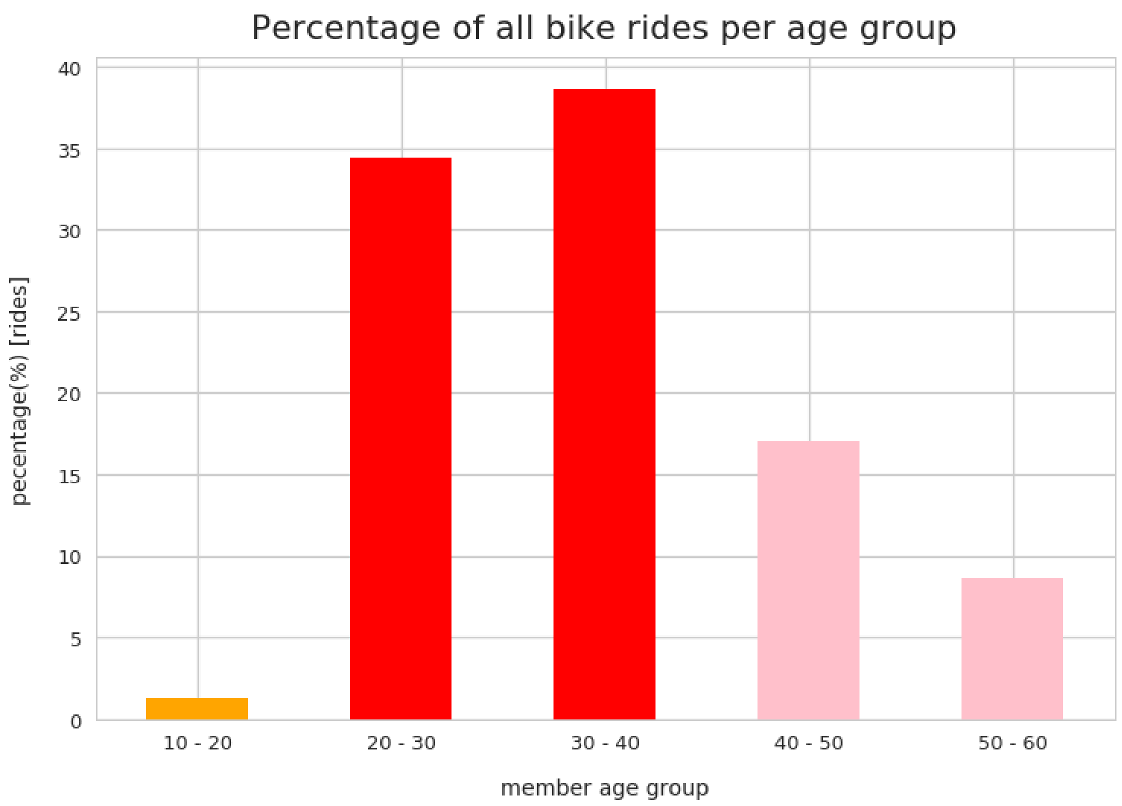
```
Out[54]: 3314668961
```

There were 3.31 billion rides.
Distrubition of bike rides vs user age group

```
In [55]: trip_by_age_df = df.groupby('member_age_bins').agg({'bike_id':'count'})
```

```
In [56]: trip_by_age_df['perc'] = (trip_by_age_df['bike_id']/trip_by_age_df['bike_id'].sum())*10
```

```
In [61]: new_color = ['orange', 'red', 'red', 'pink', 'pink']
         trip_by_age_df['perc'].plot(kind='bar', color=new_color, figsize=(12,8))
         plt.title('Percentage of all bike rides per age group', fontsize=22, y=1.015)
         plt.xlabel('member age group', labelpad=16)
         plt.ylabel('pecentage(%) [rides]', labelpad=16)
         plt.xticks(rotation=360)
         plt.savefig('image05.png');
```



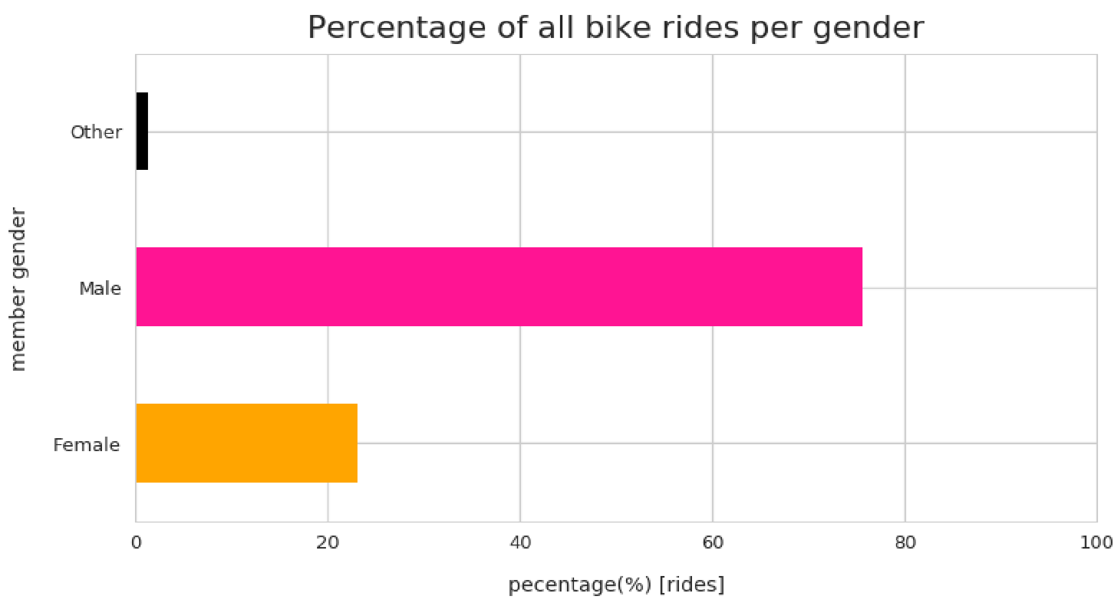
20 to 40 years old people took the more than %70 of bike rides. Among those, 30 to 40 years old people's rides account almost %40 of all bike rides.

Bike rides per gender

```
In [62]: trip_by_gender_df = df.groupby('member_gender').agg({'bike_id':'count'})
```

```
In [63]: trip_by_gender_df['perc'] = (trip_by_gender_df['bike_id']/trip_by_gender_df['bike_id'].
```

```
In [65]: new_color = ['orange', 'deeppink', 'black']
         trip_by_gender_df['perc'].plot(kind='barh', color=new_color, figsize=(12,6))
         plt.title('Percentage of all bike rides per gender', fontsize=22, y=1.015)
         plt.ylabel('member gender', labelpad=16)
         plt.xlabel('pecentage(%) [rides]', labelpad=16)
         plt.xticks(rotation=360)
         plt.xlim(0,100)
         plt.savefig('image06.png');
```



Male took around %76 of all bike rides, and female took around %22 of them.

Bike rides per weekday

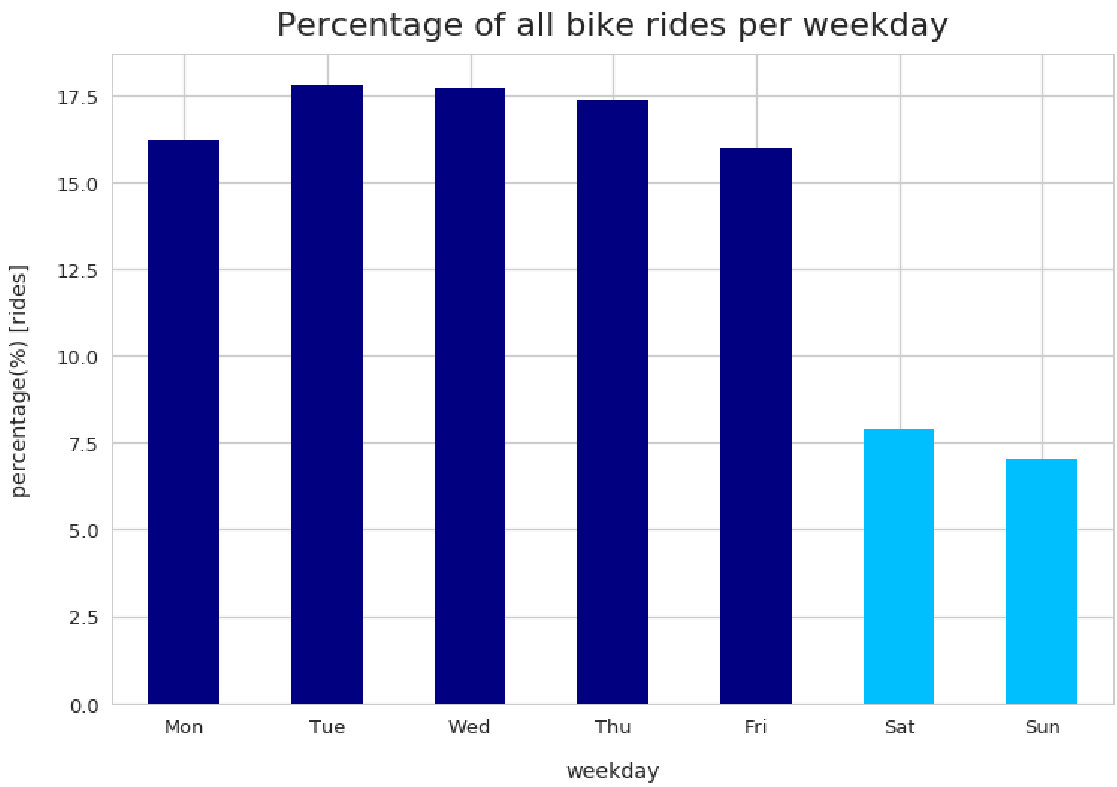
```
In [66]: trip_by_weekday_df = df.groupby('start_time_weekday_abbr').agg({'bike_id':'count'})
```

```
In [67]: trip_by_weekday_df['perc'] = (trip_by_weekday_df['bike_id']/trip_by_weekday_df['bike_id
```

```
In [68]: weekday_index = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']
```

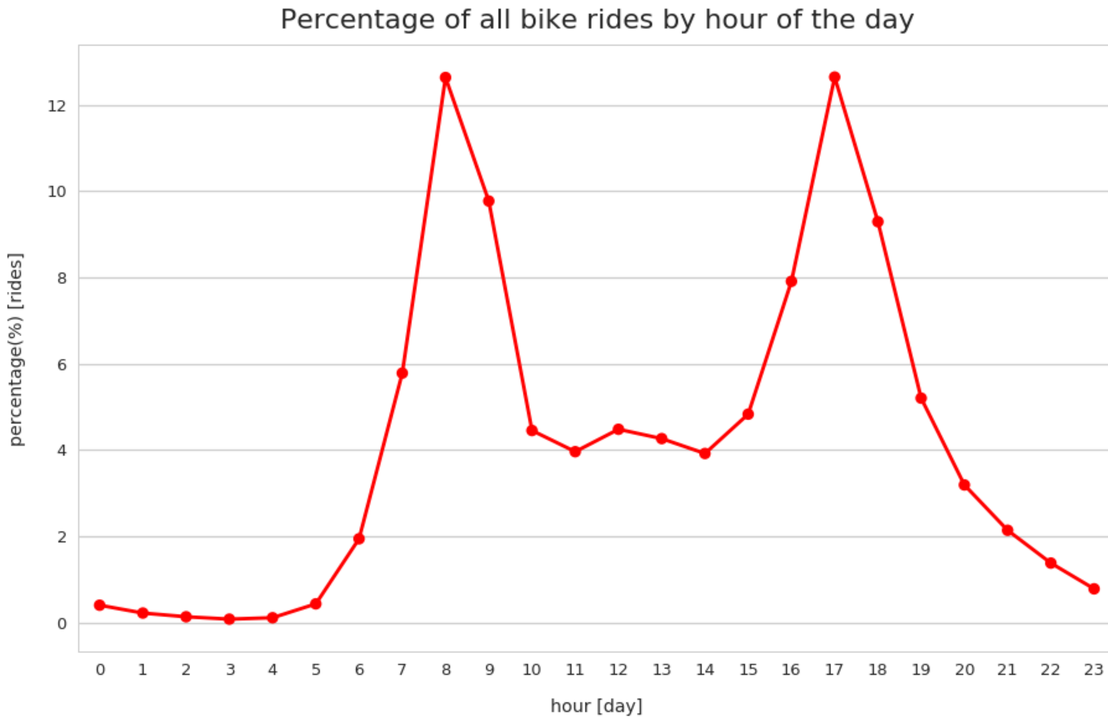
```
In [69]: new_color = ['navy', 'navy', 'navy', 'navy', 'navy', 'deepskyblue', 'deepskyblue']
         trip_by_weekday_df.reindex(weekday_index)['perc'].plot(kind='bar', color=new_color, fig
         plt.title('Percentage of all bike rides per weekday', fontsize=22, y=1.015)
```

```
plt.xlabel('weekday', labelpad=16)
plt.ylabel('percentage(%) [rides]', labelpad=16)
plt.xticks(rotation=360)
plt.savefig('image07.png');
```



People use this service on weekdays more than weekends.
Peak hours of the day

```
In [70]: trip_by_hour_df = df.groupby('start_time_hour').agg({'bike_id':'count'}).reset_index()

In [71]: trip_by_hour_df['bike_id'] = (trip_by_hour_df['bike_id']/trip_by_hour_df['bike_id'].sum

In [73]: plt.figure(figsize=(15,9))
         sns.pointplot(x='start_time_hour', y='bike_id', scale=.7, color='red', data=trip_by_hou
         plt.title('Percentage of all bike rides by hour of the day', fontsize=22, y=1.015)
         plt.xlabel('hour [day]', labelpad=16)
         plt.ylabel('percentage(%) [rides]', labelpad=16)
         plt.savefig('image08.png');
```



8am and 5pm are the peak hours for this service. Also, people use this service when they are in lunch time as well.

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

I checked each variables one by one. (Average rides, daily and monthly trend of riders, age groups, genders, weekdays or weekends comparision, peak hours, user types with distances etc.) All these variables are important in order to understand the dataset and communicating the datafindings at the end of this project. We can talk about some of the variables. For example; There were 3.31 billion rides. 20-30 years old users are rapidly growing compared to other user groups. When the service first started 30-40 years old users were dominant, however 20-30 years old users became leader in a year. 20 to 40 years old people took the more than %70 of bike rides. Among those, 30 to 40 years old people's rides account almost %40 of all bike rides. Male took around %76 of all bike rides, and female took around %24 of them. People use this service on weekdays more than weekends. 8am and 5pm are the peak hours for this service. Also, people use this service when they are in lunch time as well.

5 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?

I tidy up the data which contains member ages more than 60 years old. Ages from 18 to 56 takes 95% of the users. There were users more than 100 years old. Regarding this situation and results of age distrubition, we can remove users more than 60 years old. I generated new fields such as duration, time, age groups etc. in order to calculate them easily and understand the dataframe. Ford GoBike spreaded the service to San Francisco, Oakland and San Jose. However, it's hard to imagine traffic. So regarding this complexity, I decided to focus on San Fancisco area by limiting with latitude and longitude.

6 Bivariate Exploration

7 Question 3. Are there any difference between subscribers' and customers' behaviors?

Percentage of bike rides of subscribers vs customers

```
In [74]: count_of_rides_per_user_type = df.groupby('user_type').size().reset_index(name='count')
```

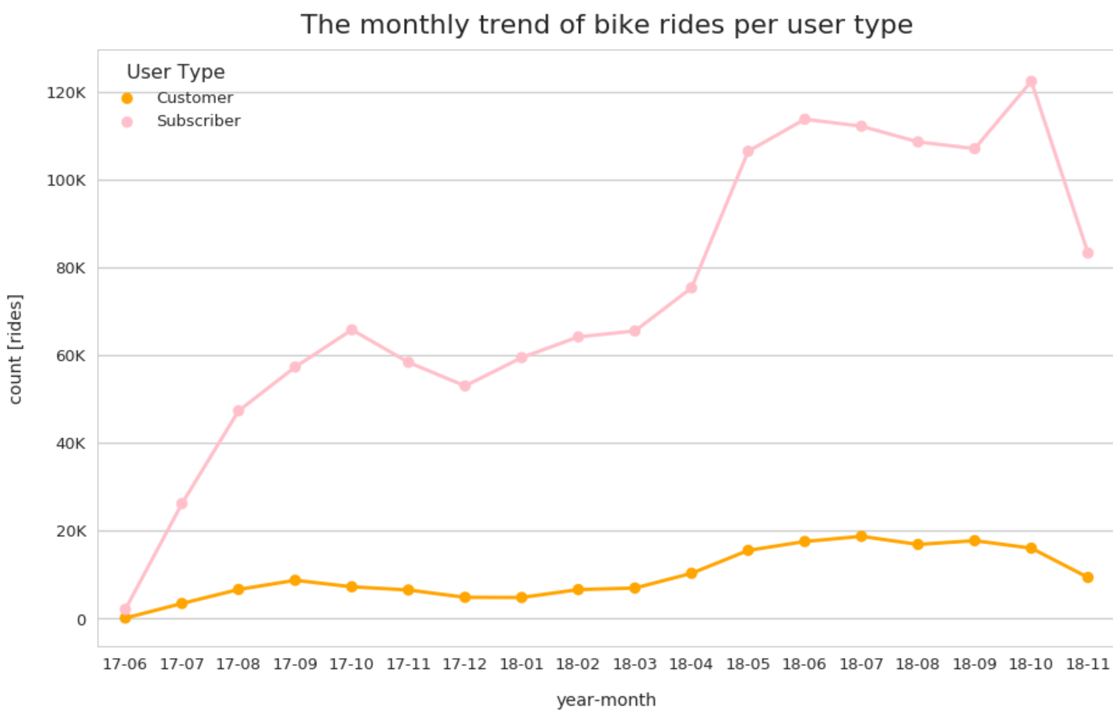
```
In [75]: count_of_rides_per_user_type['count']/len(df)*100
```

```
Out[75]: 0    11.842464
         1    88.157536
         Name: count, dtype: float64
```

Percentage of subscribers is almost %88.15. Percentage of customers is almost %11.85.
User trends of bike rides of subscribers vs customers

```
In [76]: user_type_count_per_year_df = df.groupby(["start_time_year_month_renamed", "user_type"]
```

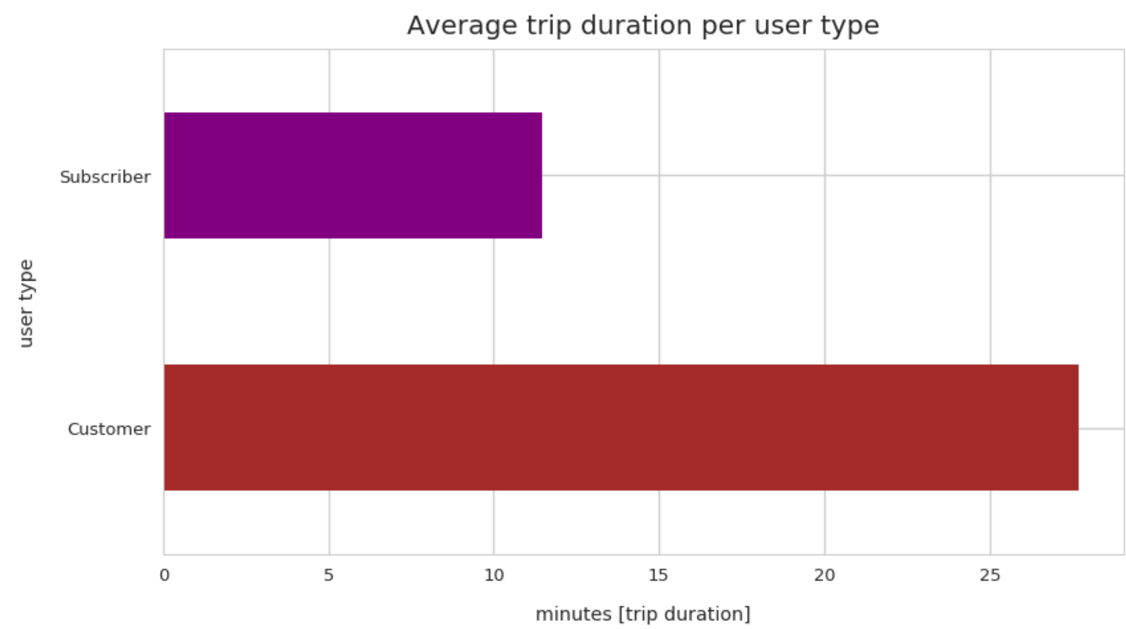
```
In [80]: plt.figure(figsize=(15,9))
         my_palette = {'Subscriber':'pink', 'Customer':'orange'}
         ax = sns.pointplot(x='start_time_year_month_renamed', y=0, hue='user_type', palette=my_
         plt.title('The monthly trend of bike rides per user type', fontsize=22, y=1.015)
         plt.xlabel('year-month', labelpad=16)
         plt.ylabel('count [rides]', labelpad=16)
         leg = ax.legend()
         leg.set_title('User Type',prop={'size':16})
         ax = plt.gca()
         ax.yaxis.set_major_formatter(tick.FuncFormatter(transform_axis_fmt))
         plt.savefig('image09.png');
```



Customers' rides seems increasing slightly. There is a decrease on November 2018 for subscribers but it seems like it is related with winter season.

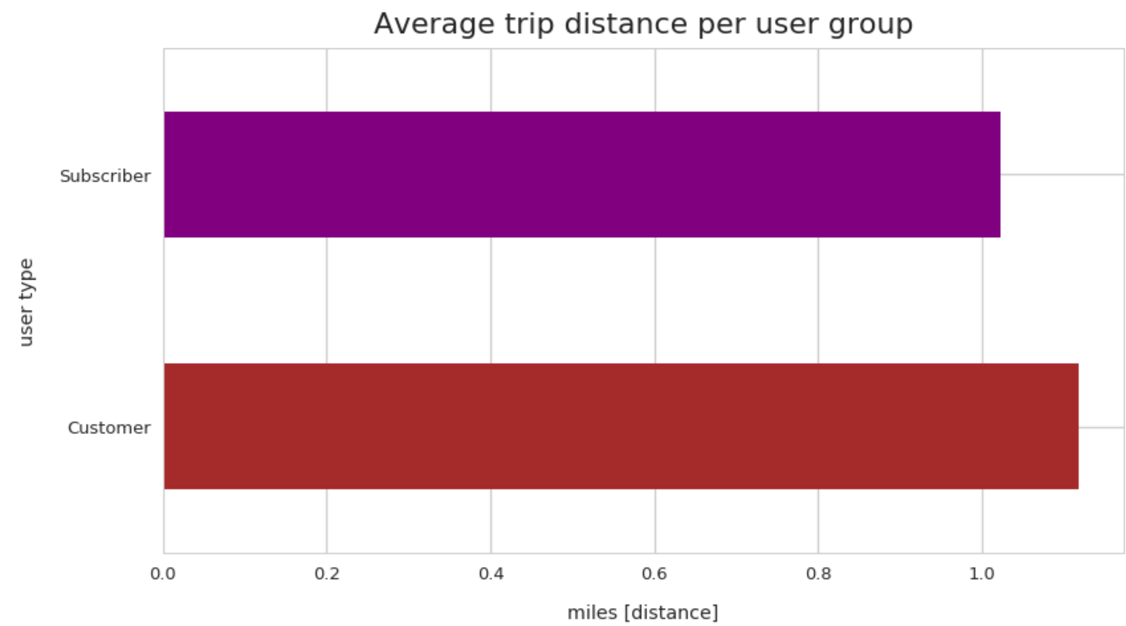
```
In [81]: new_color=['brown', 'purple']
         ax = df.groupby('user_type')['duration_min'].mean().plot(kind='barh', color=new_color,
         ax.set_title('Average trip duration per user type', fontsize=20, y=1.015)
         ax.set_ylabel('user type', labelpad=16)
         ax.set_xlabel('minutes [trip duration]', labelpad=16)
```

```
Out[81]: Text(0.5,0,'minutes [trip duration]')
```



Subscribers' average trip duration is around 11 minutes.
Customers' average trip duration is around 28 minutes.
Average trip distance of subscribers vs customers

```
In [82]: ax = df.groupby('user_type')['distance_miles_estimates'].mean().plot(kind='barh', color
         ax.set_title('Average trip distance per user group', fontsize=22, y=1.015)
         ax.set_ylabel('user type', labelpad=16)
         ax.set_xlabel('miles [distance]', labelpad=16)

Out[82]: Text(0.5,0,'miles [distance]')
```

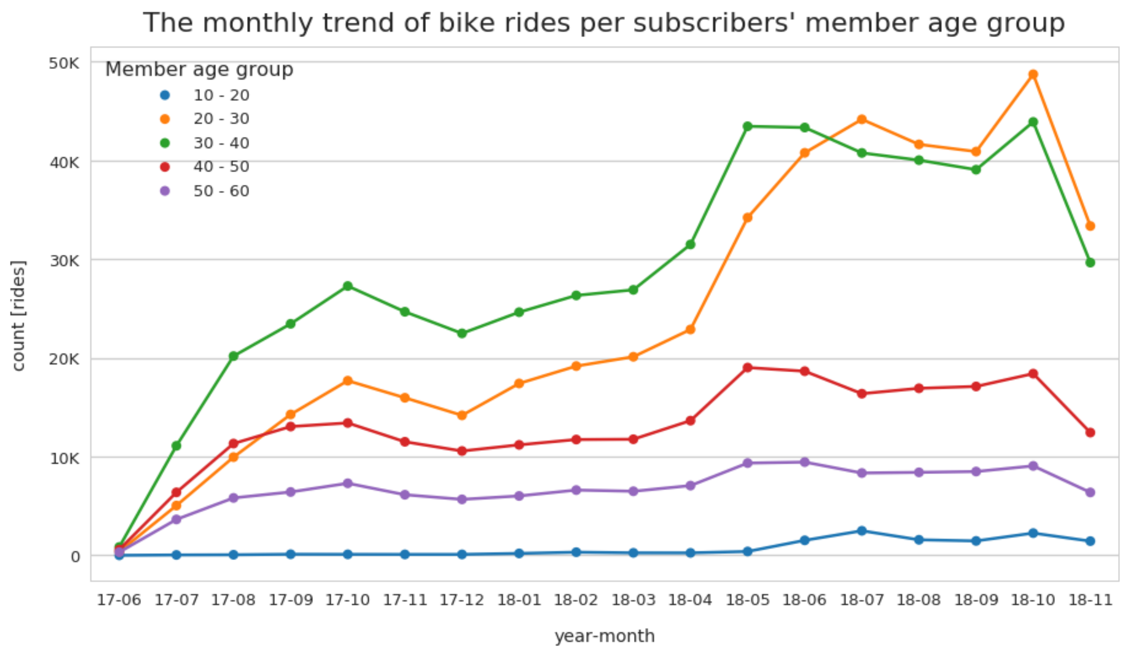


Subscribers and customers trip distance were about the same, which is slightly more than one mile.

The trend of subscribers' bike rides per age group

```
In [83]: subscriber_age_df = df[df['user_type']=='Subscriber'].groupby(['start_time_year_month_r
```

```
In [84]: plt.figure(figsize=(15,8))
         ax = sns.pointplot(x='start_time_year_month_renamed', y='bike_id', hue='member_age_bins
         plt.title("The monthly trend of bike rides per subscribers' member age group", fontsize
         plt.xlabel('year-month', labelpad=16)
         plt.ylabel('count [rides]', labelpad=16)
         leg = ax.legend()
         leg.set_title('Member age group',prop={'size':16})
         ax = plt.gca()
         ax.yaxis.set_major_formatter(tick.FuncFormatter(transform_axis_fmt))
         plt.savefig('image12.png');
```



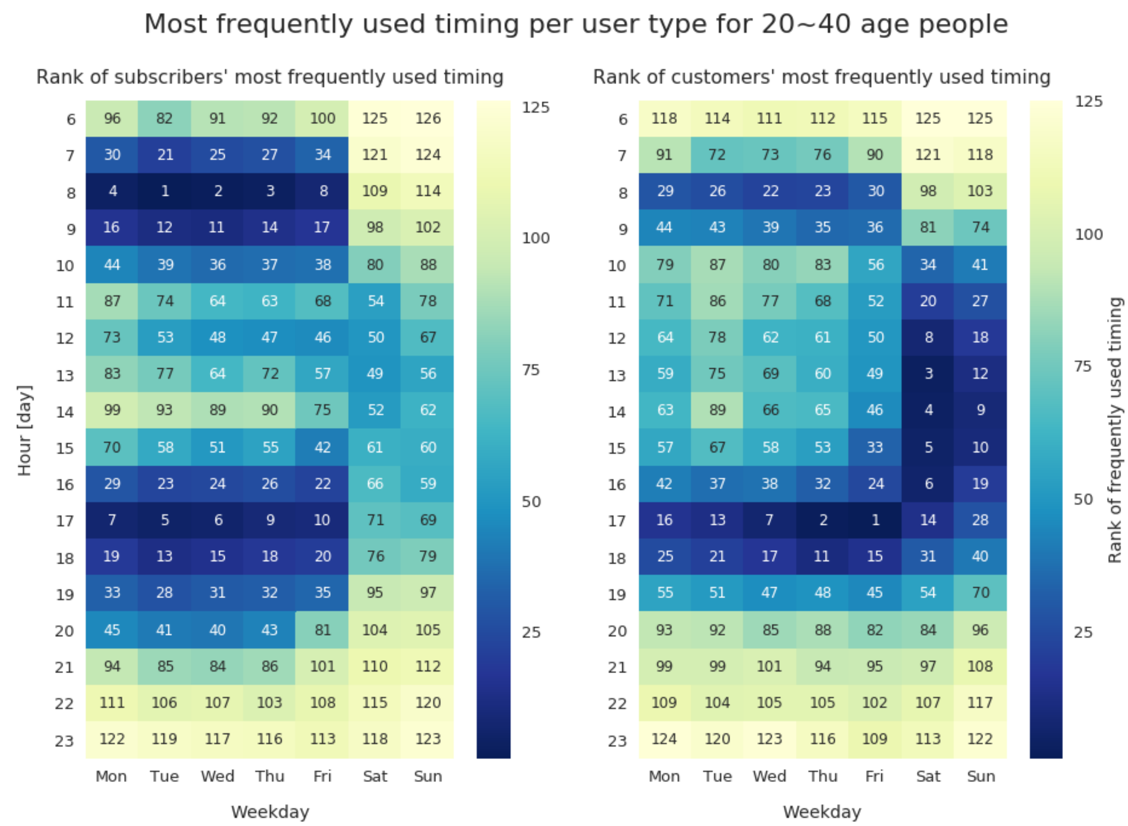
Main purpose bike rides for subscribers and customers (20~40 years age group)

```
In [85]: subscriber_hour_df = df[(df['member_age']>=20) & (df['member_age']<40)
                                  &(df['start_time_hour']>5)&(df['user_type']=='Subscriber'
                                 ].groupby(['start_time_weekday_abbr', 'start_time_hour']).
```

```
In [86]: subscriber_hour_df['start_time_weekday_abbr'] = pd.Categorical(subscriber_hour_df['star
```

```
In [87]: subscriber_hour_df['count_perc'] = subscriber_hour_df['count'].apply(lambda x: (x/subsc
```

```
In [88]: subscriber_hour_df['rank'] = subscriber_hour_df['count_perc'].rank(ascending=False).ast

In [89]: subscriber_hour_df_pivoted = subscriber_hour_df.pivot_table(index='start_time_hour', co

In [90]: customer_hour_df = df[(df['member_age']>=20) & (df['member_age']<40)
                                &(df['start_time_hour']>5)&(df['user_type']=='Customer')
                               ].groupby(['start_time_weekday_abbr', 'start_time_hour']).

In [91]: customer_hour_df['start_time_weekday_abbr'] = pd.Categorical(customer_hour_df['start_ti

In [92]: customer_hour_df['count_perc'] = customer_hour_df['count'].apply(lambda x: (x/customer_

In [93]: customer_hour_df['rank'] = customer_hour_df['count_perc'].rank(ascending=False).astype(

In [94]: customer_hour_df_pivoted = customer_hour_df.pivot_table(index='start_time_hour', column

In [95]: plt.figure(figsize=(15,10))
         plt.subplot(121)
         plt.suptitle('Most frequently used timing per user type for 20~40 age people', fontsize
         sns.heatmap(subscriber_hour_df_pivoted, fmt='d', annot=True, cmap='YlGnBu_r', annot_kws
         plt.title("Rank of subscribers' most frequently used timing", y=1.015)
         plt.xlabel('Weekday', labelpad=16)
         plt.ylabel('Hour [day]', labelpad=16)
         plt.yticks(rotation=360)
         plt.subplot(122)
         sns.heatmap(customer_hour_df_pivoted, fmt='d', annot=True, cmap='YlGnBu_r', annot_kws={
         plt.title("Rank of customers' most frequently used timing", y=1.015)
         plt.xlabel('Weekday', labelpad=16)
         plt.ylabel(' ')
         plt.yticks(rotation=360)
         plt.savefig('image13.png');
```



Subscribers are most frequently used this service around 7~9am and 4~6pm. Customers are used this service at weekend around 10am~5pm and weekday 5pm~6pm. Customers use this service during weekend for leisure and weekdays after work.

8 Question 4. How is the trend of electric bike rides and which age group favors E-Bike more?

Ford GoBike annouced the launch of electric bikes as April 24th, 2018. It can be implied that the new electric bikes were added in a week after April 24th.

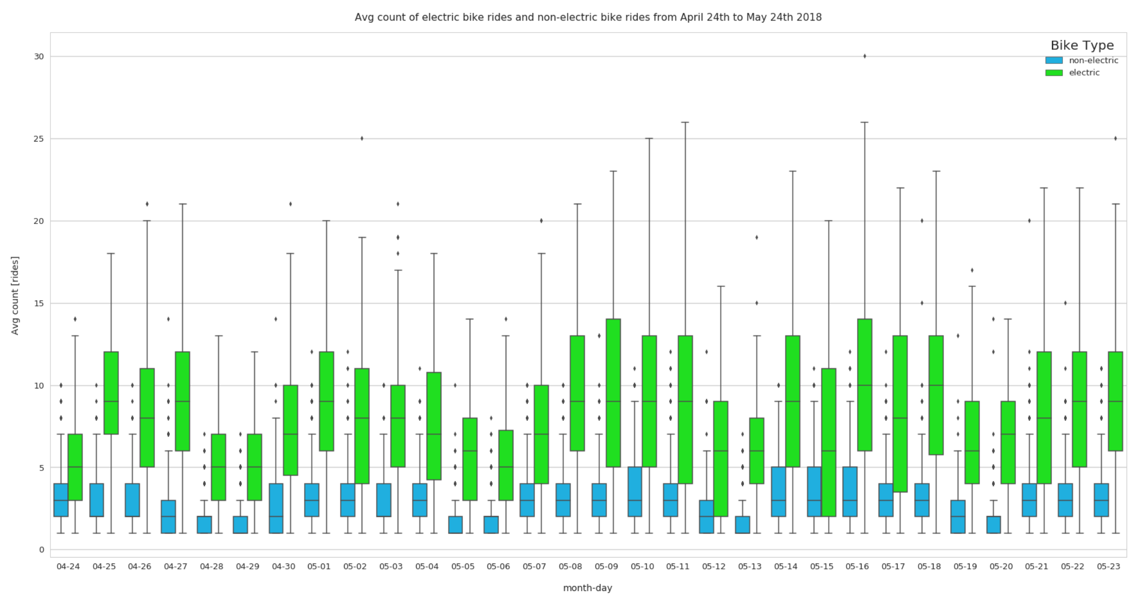
Predict electric bike

```
In [96]: non_electric_bike_id = df[df['start_time'] < pd.Timestamp(2018,4,24)]['bike_id'].unique

In [97]: electric_bike_id = []
         for bike_id in df[(df['start_time'] > pd.Timestamp(2018, 4, 24)) & (df['start_time'] <
             if bike_id not in non_electric_bike_id and bike_id not in electric_bike_id:
                 electric_bike_id.append(bike_id)

In [98]: len(electric_bike_id)

Out[98]: 313
```

```
In [99]: df['electric_bike_id'] = df['bike_id'].isin(electric_bike_id)
```

Verification of electric bikes with box plot for the first month

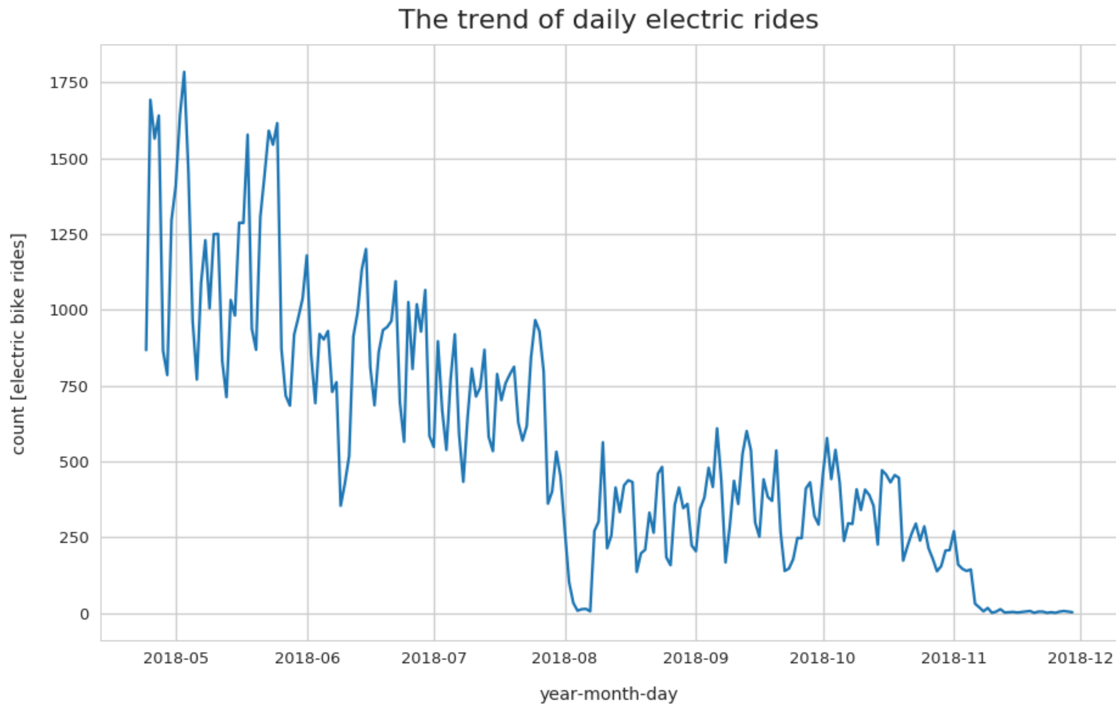
```
In [100]: electric_bike_verification_df = df[(df['start_time']>pd.Timestamp(2018, 4, 24))&(df['s

In [101]: electric_bike_verification_df = electric_bike_verification_df.rename(columns={0:'count

In [102]: electric_bike_verification_df['bike_type']=electric_bike_verification_df['bike_id'].ap

In [103]: electric_bike_verification_df['start_time_date'] = electric_bike_verification_df['star

In [104]: plt.figure(figsize=(30,15))
          my_palette = {"electric":"lime", 'non-electric':'deepskyblue'}
          ax = sns.boxplot(x='start_time_date', y='count', hue='bike_type', linewidth=1.5, palet
          plt.title('Avg count of electric bike rides and non-electric bike rides from April 24t
          plt.xlabel('month-day', labelpad=20)
          plt.ylabel('Avg count [rides]', labelpad=20)
          leg = ax.legend()
          leg.set_title('Bike Type',prop={'size':20})
          plt.savefig('image16.png');
```



There is huge difference between electric bike and normal bike rides. After the news of new launch of electric bike service, there may be high demands on riding electric bikes.

Count of daily electric bike rides from April 24th 2018 to November 30th 2018

```
In [105]: electric_df = df[df['electric_bike_id']==1].reset_index()
          electric_df.groupby('start_time_date').agg({'bike_id':'count'}).plot(style='-', legend
          plt.title('The trend of daily electric rides', fontsize=22, y=1.015)
          plt.xlabel('year-month-day', labelpad=16)
          plt.ylabel('count [electric bike rides]', labelpad=16)
          plt.savefig('image16.png');
```



There is a huge spike at the end of April. After that, it seems the usage trend for electric bikes are decreasing

9 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?

Percentage of subscribers is almost %88.15. Percentage of customers is almost %11.85. Customers' rides seems increasing slightly. There is a decrease on November 2018 for subscribers but it seems like it is related with winter season. Subscribers' average trip duration is around 11 minutes. Customers' average trip duration is around 28 minutes. Subscribers and customers trip distance were about the same, which is slightly more than one mile. I selected the most popular group 20-40 years old people in order to compare hiring days, time of the day, peak times etc. Subscribers are most frequently used this service around 7~9am and 4~6pm. Customers are used this service at weekend around 10am~5pm and weekday 5pm~6pm. Customers use this service during weekend for leisure and weekdays after work. On the other hand, i checked the electrical bike program. Ford GoBike annouced the launch of electric bikes as April 24th, 2018. 91.9% of rides are non-electric bike rides. Electric bike rides accounts for 8.1% of the total rides in the first month. It was inreased suddenly at the beginning of the program launch. There is a huge spike at the end of April. After that, it seems the usage trend for electric bikes are decreasing.

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

I observed that at the beginning of electrical bike hiring program launch there was a high demand about this program. But after a while, it was decreased suddenly. Customers and subscribers may be more comfortable to drive a normal or ramdom bike rather than a electrical and advanced technological bikes.

11 Multivariate Exploration

I want to explore in this part of the analysis is how the three variables (Age group, weekdays, timeframe of subscribers) in relationship with hiring. Because, subscribers are more common and hiring partners of this program.

```
In [106]: subscriber_hour_df2 = df[(df['member_age']>=20) & (df['member_age']<30)
                                   &(df['start_time_hour']>5)&(df['user_type']=='Subscriber
                                  ].groupby(['start_time_weekday_abbr', 'start_time_hour'])
```

```
In [107]: subscriber_hour_df3 = df[(df['member_age']>=30) & (df['member_age']<40)
                                   &(df['start_time_hour']>5)&(df['user_type']=='Subscriber
                                  ].groupby(['start_time_weekday_abbr', 'start_time_hour'])
```

```
In [108]: subscriber_hour_df4 = df[(df['member_age']>=40) & (df['member_age']<50)
                                   &(df['start_time_hour']>5)&(df['user_type']=='Subscriber
                                  ].groupby(['start_time_weekday_abbr', 'start_time_hour'])
```

```
In [109]: subscriber_hour_df2['start_time_weekday_abbr'] = pd.Categorical(subscriber_hour_df2['s
```

```
In [110]: subscriber_hour_df3['start_time_weekday_abbr'] = pd.Categorical(subscriber_hour_df3['s
```

```
In [111]: subscriber_hour_df4['start_time_weekday_abbr'] = pd.Categorical(subscriber_hour_df4['s
```

```
In [112]: subscriber_hour_df2['count_perc'] = subscriber_hour_df2['count'].apply(lambda x: (x/su
```

```
In [113]: subscriber_hour_df3['count_perc'] = subscriber_hour_df3['count'].apply(lambda x: (x/su
```

```
In [114]: subscriber_hour_df4['count_perc'] = subscriber_hour_df4['count'].apply(lambda x: (x/su
```

```
In [115]: subscriber_hour_df2['rank'] = subscriber_hour_df2['count_perc'].rank(ascending=False).
```

```
In [116]: subscriber_hour_df3['rank'] = subscriber_hour_df3['count_perc'].rank(ascending=False).
```

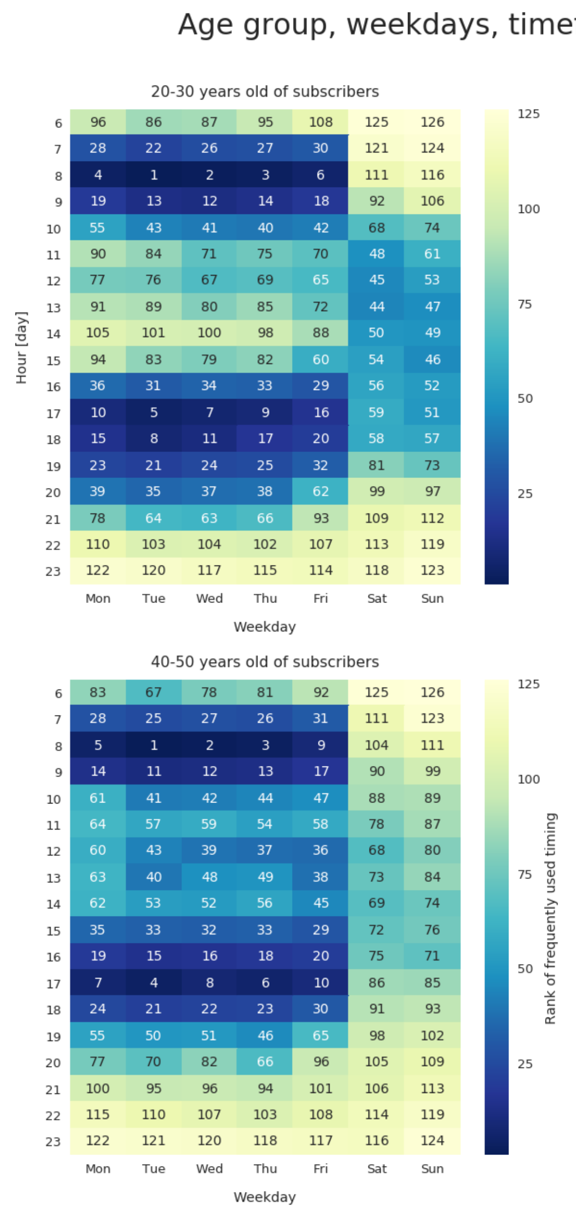
```
In [120]: subscriber_hour_df4['rank'] = subscriber_hour_df4['count_perc'].rank(ascending=False).
```

```
In [121]: subscriber_hour_df_pivoted2 = subscriber_hour_df2.pivot_table(index='start_time_hour',
```

```
In [122]: subscriber_hour_df_pivoted3 = subscriber_hour_df3.pivot_table(index='start_time_hour',
```

```
In [123]: subscriber_hour_df_pivoted4 = subscriber_hour_df4.pivot_table(index='start_time_hour',
```

```
In [124]: plt.figure(figsize=(20,20))
          plt.subplot(221)
          plt.suptitle('Age group, weekdays, timeframe effects on hiring a bike', fontsize=30, y
          sns.heatmap(subscriber_hour_df_pivoted2, fmt='d', annot=True, cmap='YlGnBu_r', annot_k
          plt.title("20-30 years old of subscribers", y=1.015)
          plt.xlabel('Weekday', labelpad=16)
          plt.ylabel('Hour [day]', labelpad=16)
          plt.yticks(rotation=360)
          plt.subplot(222)
          sns.heatmap(subscriber_hour_df_pivoted3, fmt='d', annot=True, cmap='YlGnBu_r', annot_k
          plt.title("30-40 years old of subscribers", y=1.015)
          plt.xlabel('Weekday', labelpad=16)
          plt.ylabel(' ')
          plt.yticks(rotation=360)
          plt.subplot(223)
          sns.heatmap(subscriber_hour_df_pivoted4, fmt='d', annot=True, cmap='YlGnBu_r', annot_k
          plt.title("40-50 years old of subscribers", y=1.015)
          plt.xlabel('Weekday', labelpad=16)
          plt.ylabel(' ')
          plt.yticks(rotation=360)
          plt.savefig('image18.png');
```



12 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?

I extended my investigation of bike hiring with 3 different variables such as age group, timeframe, weekday. The multivariate exploration here showed me that people who are older than the others have more time to drive a bike rather than a young people. 20-30 years old people are active when the time is commute like they drive a bike when they go to their offices or come back to their homes. These figures shows us when we become older, we can see that they drive these bikes everytime in a day like in the lunch time or in the morning or in the afternoon. It may be related with their retirement or older people have much more flexiable working hours rather than youngers.

13 Were there any interesting or surprising interactions between features?

I was interested and also surprised because i did not expect to see these kind of figures for 40-50 years old group. I was expecting to see much less hiring quantities in a day but these figures show that they are active and they are flexiable rather than youngers.

14 Conclusion

There were 3.31 billion rides. 20-30 years old users are rapidly growing compared to other user groups. When the service first started 30-40 years old users were dominant, however 20-30 years old users became leader in a year. 20 to 40 years old people took the more than %70 of bike rides. Among those, 30 to 40 years old people's rides account almost %40 of all bike rides. Male took around %76 of all bike rides, and female took around %24 of them. People use this service on weekdays more than weekends. 8am and 5pm are the peak hours for this service. Also, people use this service when they are in lunch time as well. Percentage of subscribers is almost %88.15. Percentage of customers is almost %11.85. Customers' rides seems increasing slightly but subscibers' rides reached 6 times more than customers' on October 2018. There is a decrease on November 2018 for subscribers but it seems like it is related with winter season. Subscribers' average trip duration is around 11 minutes. Customers' average trip duration is around 28 minutes. Subscribers and customers trip distance were about the same, which is slightly more than one mile. 90% of bike rides take place on weekday. The peak bike rides time for all members is around commute time.

Finally, it seems that 40 to 50 years old age group use the service the most. After Ford GoBike did a pilot launch of e-bike on April 24th 2018, there have been quite a lot of electric bike rides as well, which reached to 10% of daily rides at the end of July 2018. However, daily electric bike rides is on downward trend.

```
In [ ]:
```