Part_I_exploration_template

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1 Part I - Dataset Exploration for Ford GoBike System Data

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1.2 Introduction

This data set includes information about individual rides made in a bike-sharing system covering the greater San Francisco Bay area. For this analysis I went ahead to gather datasets for the first year quater January - April 2019 from this link: https://s3.amazonaws.com/baywheels-data/index.html

Ford GoBike, like other bike share systems, consists of a fleet of specially designed, sturdy and durable bikes that are locked into a network of docking stations throughout the city. The bikes can be unlocked from one station and returned to any other station in the system, making them ideal for one-way trips. People use bike share to commute to work or school, run errands, get to appointments or social engagements and more. It's a fun, convenient and affordable way to get around

1.3 Preliminary Wrangling

```
In [1]: # import all packages needed for exploration
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sb

        %matplotlib inline
```

```
In [27]: # merge all four csv files into one for the first quater.
         ford_data = pd.concat(
                     map(pd.read_csv, ['January-fordgobike-tripdata.csv', 'Feb-fordgobike-tripda
                                       'April-fordgobike-tripdata.csv']), ignore_index=True,
         ford_data.sample(5)
```

```
Out[27]:        duration_sec               start_time                  end_time  \
         89574          1592  2019-01-20 20:38:21.4610  2019-01-20 21:04:53.8680
         192814         1939  2019-02-28 20:08:56.7470  2019-02-28 20:41:16.5700
         210165          496  2019-02-26 19:26:11.3040  2019-02-26 19:34:27.6320
```

```
261132          736  2019-02-19 20:15:46.5840  2019-02-19 20:28:02.7400
690788          210  2019-04-22 09:00:22.7580  2019-04-22 09:03:53.5620

        start_station_id                                  start_station_name  \
89574                6.0                       The Embarcadero at Sansome St
192814             160.0                           West Oakland BART Station
210165              64.0                                5th St at Brannan St
261132              15.0  San Francisco Ferry Building (Harry Bridges Pl...
690788              44.0  Civic Center/UN Plaza BART Station (Market St ...

        start_station_latitude  start_station_longitude  end_station_id  \
89574                37.804770              -122.403234            17.0
192814               37.805318              -122.294837           274.0
210165               37.776754              -122.399018            60.0
261132               37.795392              -122.394203            66.0
690788               37.781074              -122.411738            58.0

                                      end_station_name  \
89574   Embarcadero BART Station (Beale St at Market St)
192814                           Oregon St at Adeline St
210165                              8th St at Ringold St
261132                            3rd St at Townsend St
690788                              Market St at 10th St

        end_station_latitude  end_station_longitude  bike_id   user_type  \
89574              37.792251            -122.397086     2832    Customer
192814             37.857567            -122.267558     2997  Subscriber
210165             37.774520            -122.409449     5413  Subscriber
261132             37.778742            -122.392741     1672  Subscriber
690788             37.776619            -122.417385     2941  Subscriber

       bike_share_for_all_trip  member_birth_year member_gender
89574                       No                NaN           NaN
192814                      No             1994.0        Female
210165                      No             1987.0          Male
261132                      No             1977.0        Female
690788                      No                NaN           NaN
```

In [3]:
```
ford_data.shape
```

Out[3]:
```
(870904, 16)
```

In [4]:
```
ford_data.describe()
```

Out[4]:
```
         duration_sec  start_station_id  start_station_latitude  \
count  870904.000000     870174.000000           870904.000000
mean      776.665073        139.027635               37.771409
std      1904.675372        113.704274                0.105744
min        61.000000          3.000000                0.000000
```

```
25%      337.000000        44.000000                37.770407
50%      537.000000       102.000000                37.780787
75%      840.000000       238.000000                37.797280
max    86114.000000       420.000000                37.880222

       start_station_longitude  end_station_id  end_station_latitude  \
count            870904.000000   870174.000000         870904.000000
mean               -122.354787      137.507940             37.770832
std                   0.174646      113.653225              0.197522
min                -122.453704        3.000000              0.000000
25%                -122.413004       44.000000             37.770407
50%                -122.398438      100.000000             37.781010
75%                -122.291376      233.000000             37.797320
max                   0.000000      420.000000             37.880222

       end_station_longitude        bike_id  member_birth_year
count          870904.000000  870904.000000      175147.000000
mean             -122.352015    4284.292828        1984.806437
std                 0.568010    1874.995593          10.116689
min              -122.453704      11.000000        1878.000000
25%              -122.411738    2916.000000        1980.000000
50%              -122.398285    4882.000000        1987.000000
75%              -122.291415    5568.000000        1992.000000
max                 0.000000    7108.000000        2001.000000
```

In [5]:
```
ford_data.isnull().sum()
```

Out[5]:
```
duration_sec                    0
start_time                      0
end_time                        0
start_station_id              730
start_station_name            730
start_station_latitude          0
start_station_longitude         0
end_station_id                730
end_station_name              730
end_station_latitude            0
end_station_longitude           0
bike_id                         0
user_type                       0
bike_share_for_all_trip         0
member_birth_year          695757
member_gender              695757
dtype: int64
```

In [28]:
```
#Create a new column to calculate age of Members
ford_data['member_age'] = 2022 - ford_data['member_birth_year']
```

In [39]:
```
#create a copy dataframe for exploration
ford_cleandata = ford_data.copy()
```

In [43]:
```
#drop columns not needed for analysis
ford_cleandata.drop(['start_station_id','end_station_id','start_station_latitude','star
ford_cleandata.sample(10)
```

Out[43]:
```
        duration_sec              start_time                end_time  \
275834          1230 2019-02-17 20:33:08.892 2019-02-17 20:53:39.250
681550           180 2019-04-23 12:55:32.878 2019-04-23 12:58:33.358
159257           326 2019-01-08 09:22:33.134 2019-01-08 09:27:59.996
457618           507 2019-03-21 18:33:01.426 2019-03-21 18:41:28.660
480150           517 2019-03-19 17:07:08.885 2019-03-19 17:15:46.766
286768          1018 2019-02-15 15:52:27.046 2019-02-15 16:09:25.882
594894          1084 2019-03-06 17:10:53.872 2019-03-06 17:28:58.785
173691           711 2019-01-04 16:12:39.862 2019-01-04 16:24:31.520
359053           638 2019-02-04 17:50:49.115 2019-02-04 18:01:27.768
673479           911 2019-04-24 13:51:19.369 2019-04-24 14:06:31.311

                                         start_station_name  \
275834                              Market St at Dolores St
681550                           Washington St at Kearny St
159257                                  Folsom St at 3rd St
457618                                   Mission Playground
480150                                4th St at Harrison St
286768                                   Jackson Playground
594894                             West Oakland BART Station
173691                        The Embarcadero at Steuart St
359053                                  2nd St at Folsom St
673479  Civic Center/UN Plaza BART Station (Market St ...

                                           end_station_name  bike_id  \
275834                                2nd St at Townsend St     5226
681550                                Clay St at Battery St     1168
159257    Mechanics Monument Plaza (Market St at Bush St)     4733
457618                           S Van Ness Ave at Market St     6443
480150                            Mississippi St at 17th St     5936
286768  San Francisco Ferry Building (Harry Bridges Pl...     3223
594894                             West Oakland BART Station     5985
173691                                   Berry St at 4th St     5029
359053  San Francisco Caltrain Station 2  (Townsend St...     3299
673479                                19th St at Florida St     1199

         user_type bike_share_for_all_trip member_gender  member_age
275834  Subscriber                      No          Male        47.0
681550  Subscriber                      No           NaN         NaN
159257  Subscriber                      No           NaN         NaN
457618  Subscriber                      No           NaN         NaN
480150  Subscriber                      No           NaN         NaN
286768  Subscriber                      No          Male        51.0
594894  Subscriber                      No           NaN         NaN
```

```
        173691  Subscriber                         No          NaN         NaN
        359053  Subscriber                         No         Male        30.0
        673479    Customer                         No          NaN         NaN
```

In [7]:
```
#check for missing data
ford_cleandata.isnull().sum()
```

Out[7]:
```
duration_sec                    0
start_time                      0
end_time                        0
start_station_name            730
end_station_name              730
bike_id                         0
user_type                       0
bike_share_for_all_trip         0
member_gender              695757
member_age                 695757
dtype: int64
```

In [40]:
```
#Drop null rows in start_station_name and end_station_name
ford_cleandata.dropna(subset=['start_station_name'], inplace=True)
ford_cleandata.dropna(subset=['end_station_name'], inplace=True)
```

In [41]:
```
#change data types for start time, end time
ford_cleandata['start_time'] = pd.to_datetime(ford_cleandata['start_time'])
ford_cleandata['end_time'] = pd.to_datetime(ford_cleandata['end_time'])
```

In [44]:
```
ford_cleandata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 870174 entries, 0 to 870903
Data columns (total 10 columns):
duration_sec               870174 non-null int64
start_time                 870174 non-null datetime64[ns]
end_time                   870174 non-null datetime64[ns]
start_station_name         870174 non-null object
end_station_name           870174 non-null object
bike_id                    870174 non-null int64
user_type                  870174 non-null object
bike_share_for_all_trip    870174 non-null object
member_gender              174952 non-null object
member_age                 174952 non-null float64
dtypes: datetime64[ns](2), float64(1), int64(2), object(5)
memory usage: 73.0+ MB
```

In [34]:
```
ford_cleandata.shape
```

Out[34]:
```
(870174, 10)
```

1.3.1 What is the structure of your dataset?

After basic cleaning the dataset contains 870174 rows and 10 columns: With Missing values in member_age and member-gender, this is a very high number and can not be dropped. 7 columns had been dropped as i would not be needing them for analysis - start_station_id','end_station_id','start_station_latitude','start_station_longitude', 'end_station_latitude', 'end_station_longitude','member_birth_year

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

1.Trip duration (time) 2.Distribution of User Type 3.Monthly bike ride trend 4.Does Age have correlation with how long a rider rides

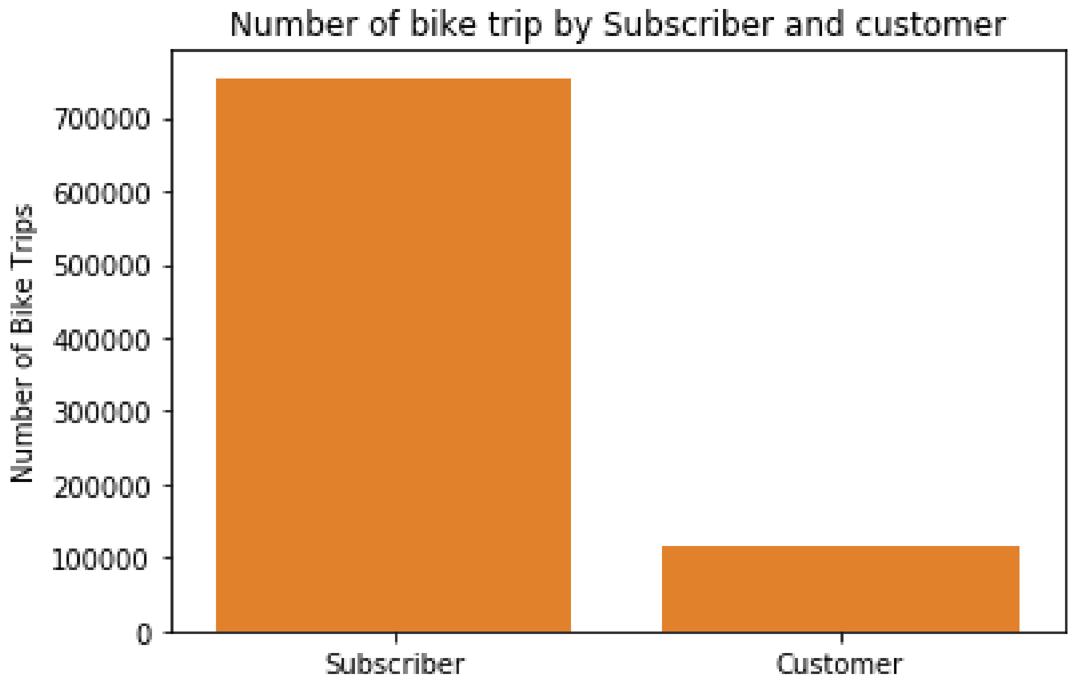
1.3.3 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

The duration_sec column will provide infomation we need to calculate the average trip time. The user-type column willl be used to find the distribution. Also, we can extract exact month from start_time and end time he duration_sec column will define the average trip timefor further analysis. The age of riders has been calculated from the birth year column of riders.

1.4 Univariate Exploration

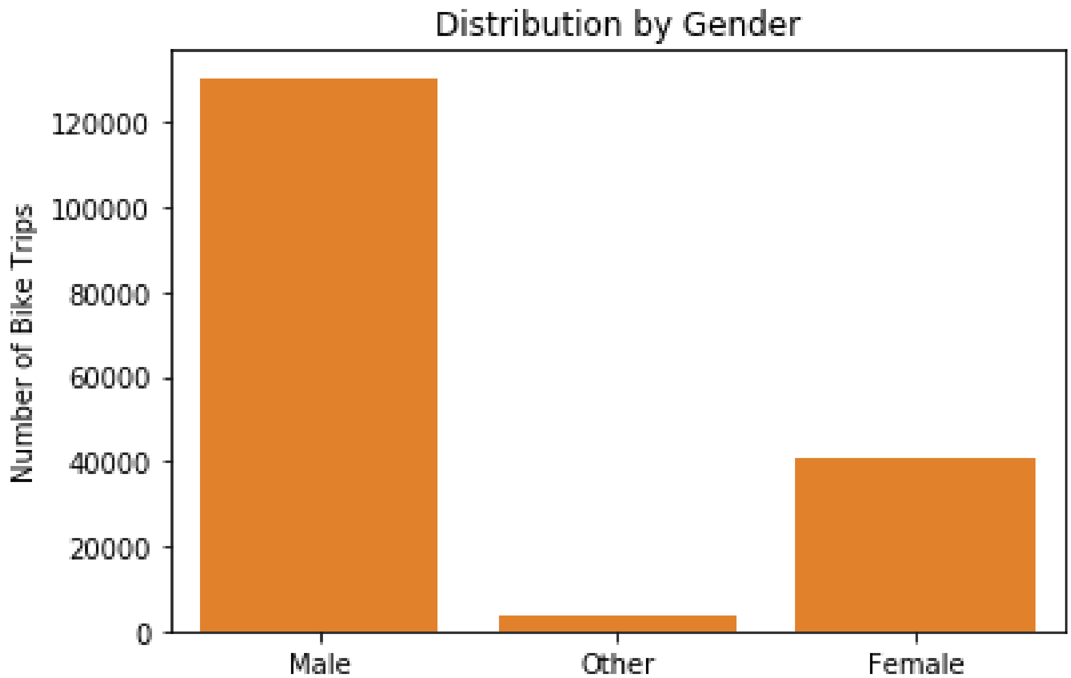
1.4.1 Distribution of User Type

In [9]:
```
#Create a countplot that shows relationship of usertypes

base_color = sb.color_palette()[1]
plot = sb.countplot(data=ford_cleandata, x='user_type',color=base_color)
plt.xlabel('')
plt.ylabel('Number of Bike Trips')
plt.title('Number of bike trip by Subscriber and customer');
#show the plot
plt.show()
```



This shows that the subscribers tend to take more rides than customers of the Ford go bike system

```
In [13]: #Create a countplot that shows relationship of riders by gender

         base_color = sb.color_palette()[1]
         plot = sb.countplot(data=ford_cleandata, x='member_gender',color=base_color)
         plt.xlabel('')
         plt.ylabel('Number of Bike Trips')
         plt.title('Distribution by Gender');
         #show the plot
         plt.show()
```



A large number of riders are male, while a portion are female, a less portion may have reasons for not revealing their gender.

1.4.2 Age distribution

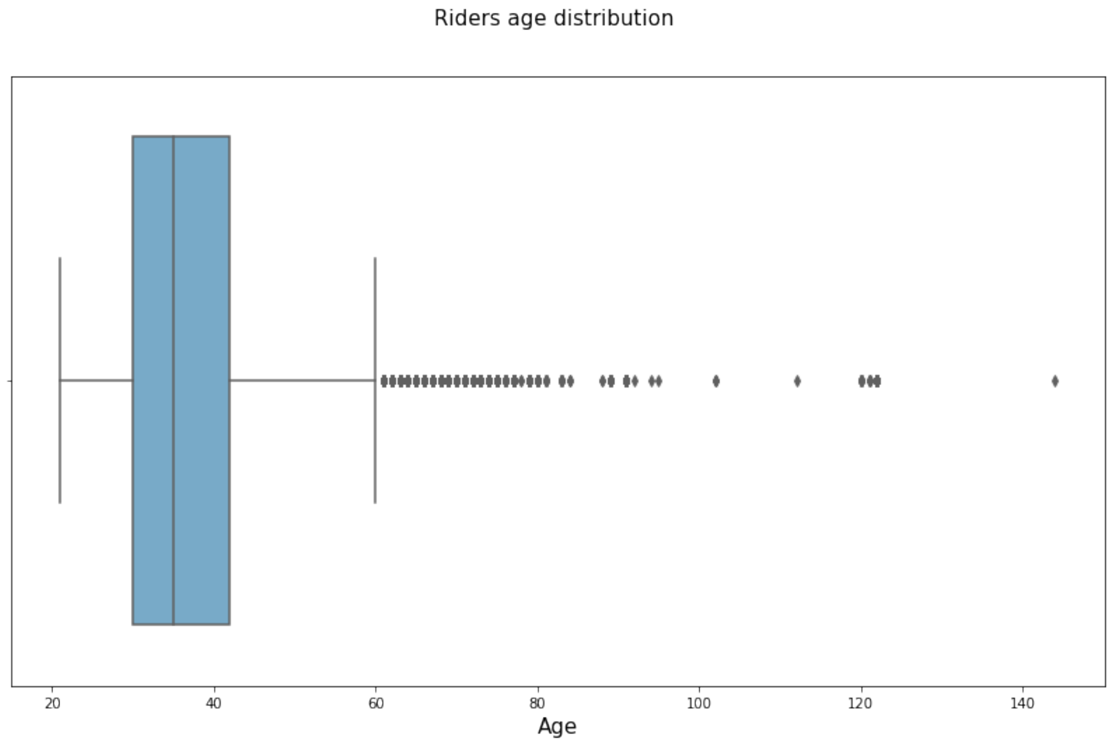
In [14]:
```
#the unique counts of age of riders
ford_cleandata.member_age.value_counts()
```

Out[14]:
```
34.0    10214
29.0     9323
33.0     8967
32.0     8640
31.0     8484
30.0     8245
35.0     8010
36.0     7953
28.0     7654
27.0     7420
37.0     7023
38.0     6557
39.0     5953
42.0     5011
40.0     4987
26.0     4637
41.0     4344
43.0     3756
```

```
25.0      3476
24.0      3208
44.0      2830
45.0      2706
48.0      2633
23.0      2504
47.0      2503
46.0      2435
49.0      2080
54.0      1927
51.0      1924
50.0      1909
         ...
68.0       301
70.0       189
71.0       180
72.0       178
69.0       158
75.0       135
67.0       134
77.0       105
73.0        99
91.0        89
122.0       53
74.0        51
21.0        34
79.0        30
80.0        21
89.0        20
76.0        19
120.0       11
83.0        11
81.0         9
121.0        6
84.0         3
102.0        3
88.0         2
78.0         2
92.0         1
112.0        1
94.0         1
95.0         1
144.0        1
Name: member_age, Length: 75, dtype: int64
```

In [15]:
```
#a graph to show age distribution
plt.figure(figsize=(14,8))
sb.boxplot(x='member_age', data=ford_cleandata, palette='Blues')
```

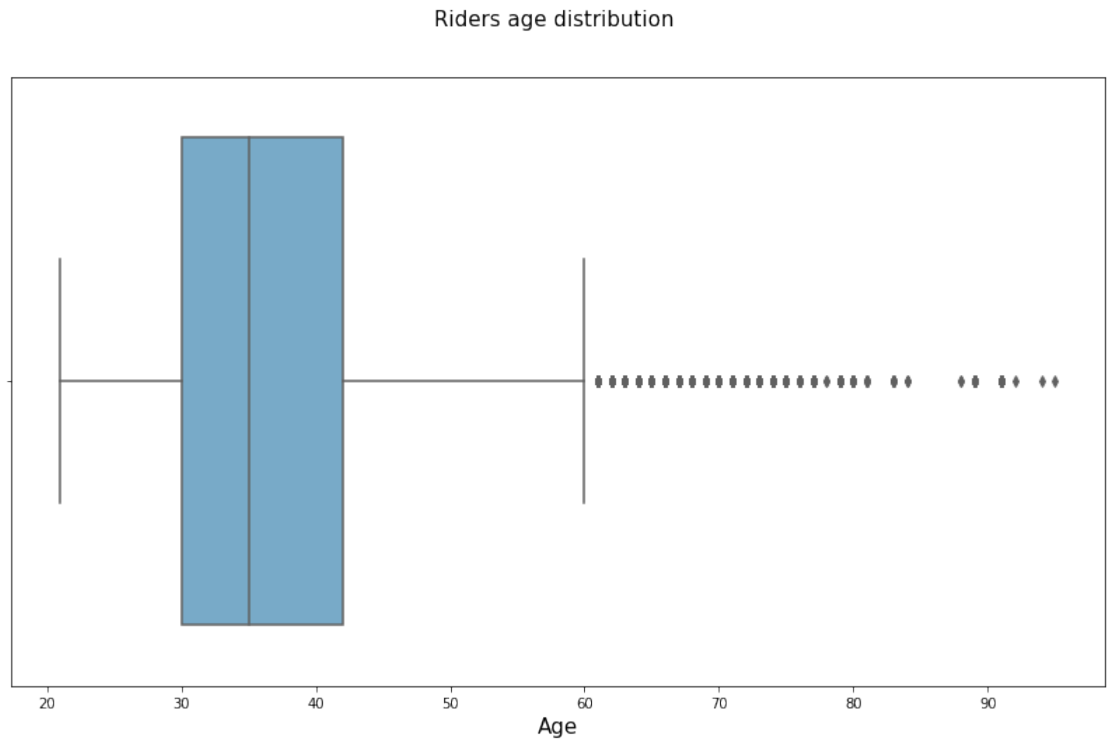
```
plt.title("Riders age distribution ", fontsize=15, y=1.07)
plt.xlabel("Age", fontsize=15);
```



Outliers are shown so we will drop rows with abnormal age, from 100 and above

```
In [35]: #Drop rows with abnormal age, 100 and above
         ford_cleandata =ford_cleandata[ford_cleandata['member_age'] <= 100]
```

```
In [36]: #recheck with a graph to show age distribution
         plt.figure(figsize=(14,8))
         sb.boxplot(x='member_age', data=ford_cleandata, palette='Blues')
         plt.title("Riders age distribution ", fontsize=15, y=1.07)
         plt.xlabel("Age", fontsize=15);
```




```
In [38]: ford_cleandata.sample(10)

Out[38]:         duration_sec              start_time                end_time  \
         243746           340 2019-02-21 17:53:10.277 2019-02-21 17:58:51.047
         302167           751 2019-02-12 18:13:22.191 2019-02-12 18:25:53.281
         262844          1035 2019-02-19 17:50:57.700 2019-02-19 18:08:13.495
         359828           587 2019-02-04 16:51:49.227 2019-02-04 17:01:36.511
         374105           783 2019-02-01 08:34:39.943 2019-02-01 08:47:43.895
         196312           535 2019-02-28 16:13:34.907 2019-02-28 16:22:30.448
         309388           557 2019-02-11 22:43:10.139 2019-02-11 22:52:27.281
         227920           493 2019-02-23 17:36:45.529 2019-02-23 17:44:58.742
         268548           750 2019-02-19 08:14:14.301 2019-02-19 08:26:44.606
         311213           179 2019-02-11 18:13:27.178 2019-02-11 18:16:26.643

                                           start_station_name  \
         243746                           Downtown Berkeley BART
         302167  Salesforce Transit Center (Natoma St at 2nd St)
         262844                          Beale St at Harrison St
         359828                              Folsom St at 3rd St
         374105                            Howard St at Beale St
         196312                              Howard St at 2nd St
         309388                              Jones St at Post St
         227920                            MLK Jr Way at 14th St
         268548   San Francisco Caltrain (Townsend St at 4th St)
```

```
311213                          West Oakland BART Station

                                    end_station_name  bike_id   user_type  \
243746                     Bancroft Way at College Ave     5785  Subscriber
302167                             Berry St at King St     5014  Subscriber
262844                         23rd St at Tennessee St     5016  Subscriber
359828                           3rd St at Townsend St     5150  Subscriber
374105                            8th St at Ringold St      987  Subscriber
196312  San Francisco Caltrain (Townsend St at 4th St)     1832  Subscriber
309388                    16th St Mission BART Station 2     2497  Subscriber
227920                           MLK Jr Way at 14th St     5620  Subscriber
268548                           Howard St at Beale St     2714  Subscriber
311213                             Union St at 10th St      275  Subscriber

       bike_share_for_all_trip member_gender  member_age
243746                      No          Male        35.0
302167                      No          Male        31.0
262844                      No        Female        42.0
359828                      No          Male        29.0
374105                      No          Male        35.0
196312                      No          Male        41.0
309388                      No          Male        35.0
227920                      No          Male        54.0
268548                      No          Male        46.0
311213                      No          Male        36.0
```

Most of the riders are ranged from ages 30 - 45 years old which makes sense for long distance races

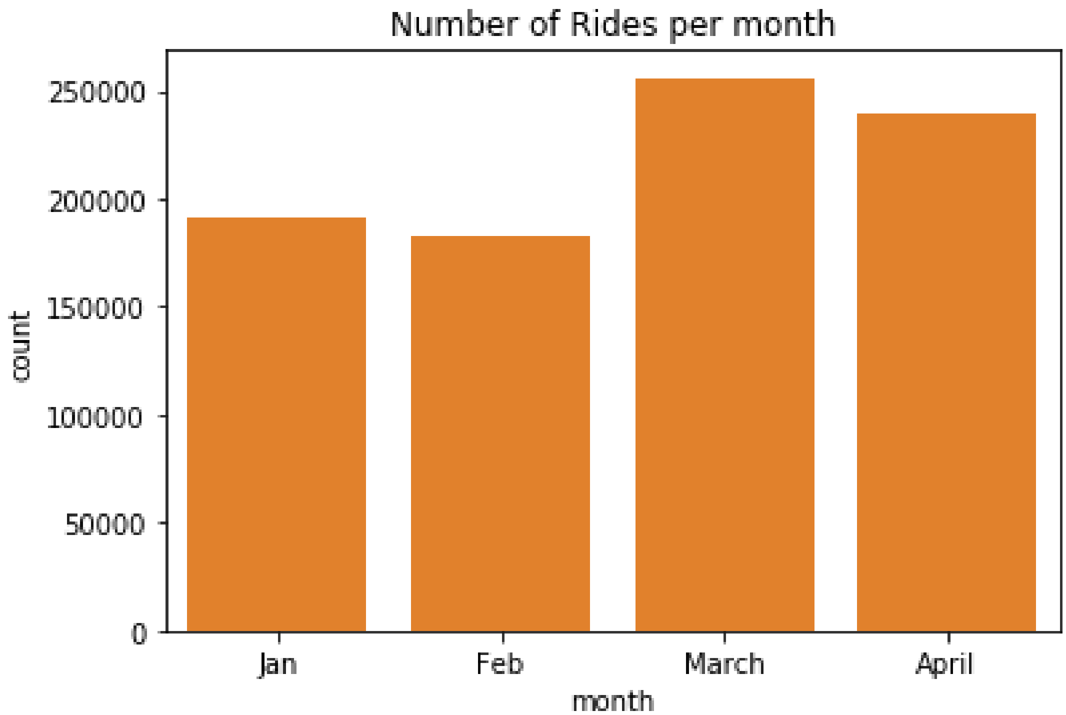
1.4.3 Monthly bike ride trend

```
In [45]: ford_cleandata['month'] = ford_cleandata.start_time.dt.month
```

```
In [46]: ford_cleandata['month'].value_counts()
```

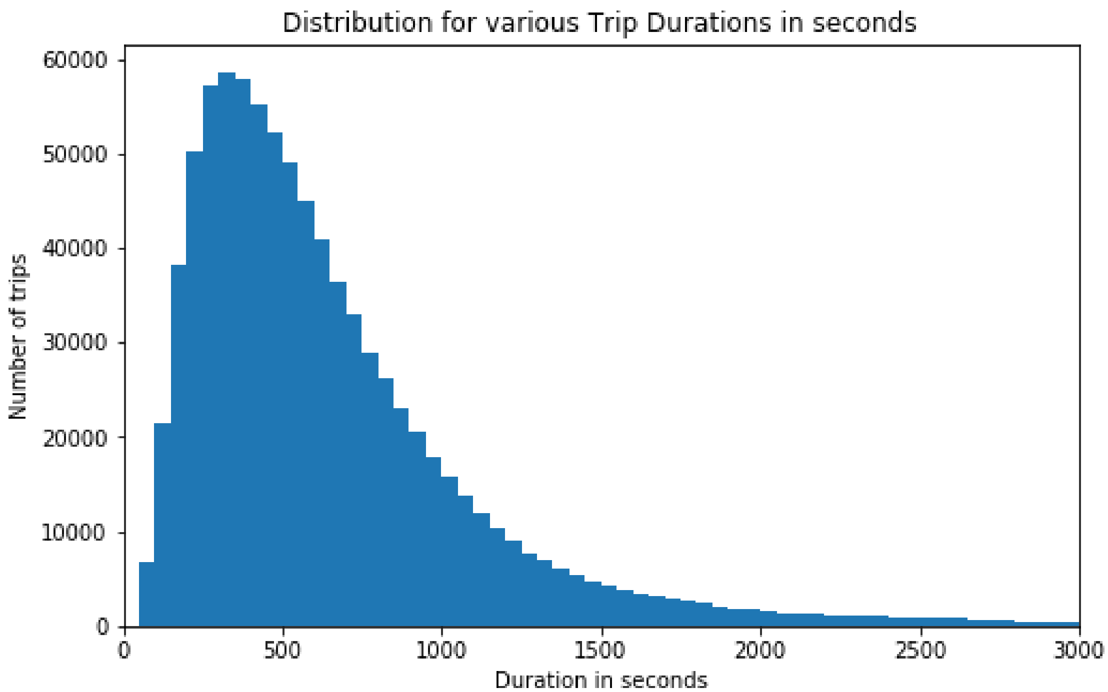
```
Out[46]: 3    256078
         4    239047
         1    191834
         2    183215
         Name: month, dtype: int64
```

```
In [47]: sb.countplot(data=ford_cleandata, x='month', color=sb.color_palette()[1])
         plt.title('Number of Rides per month');
         plt.xticks([0, 1, 2, 3], ['Jan', 'Feb', 'March', 'April']);
```

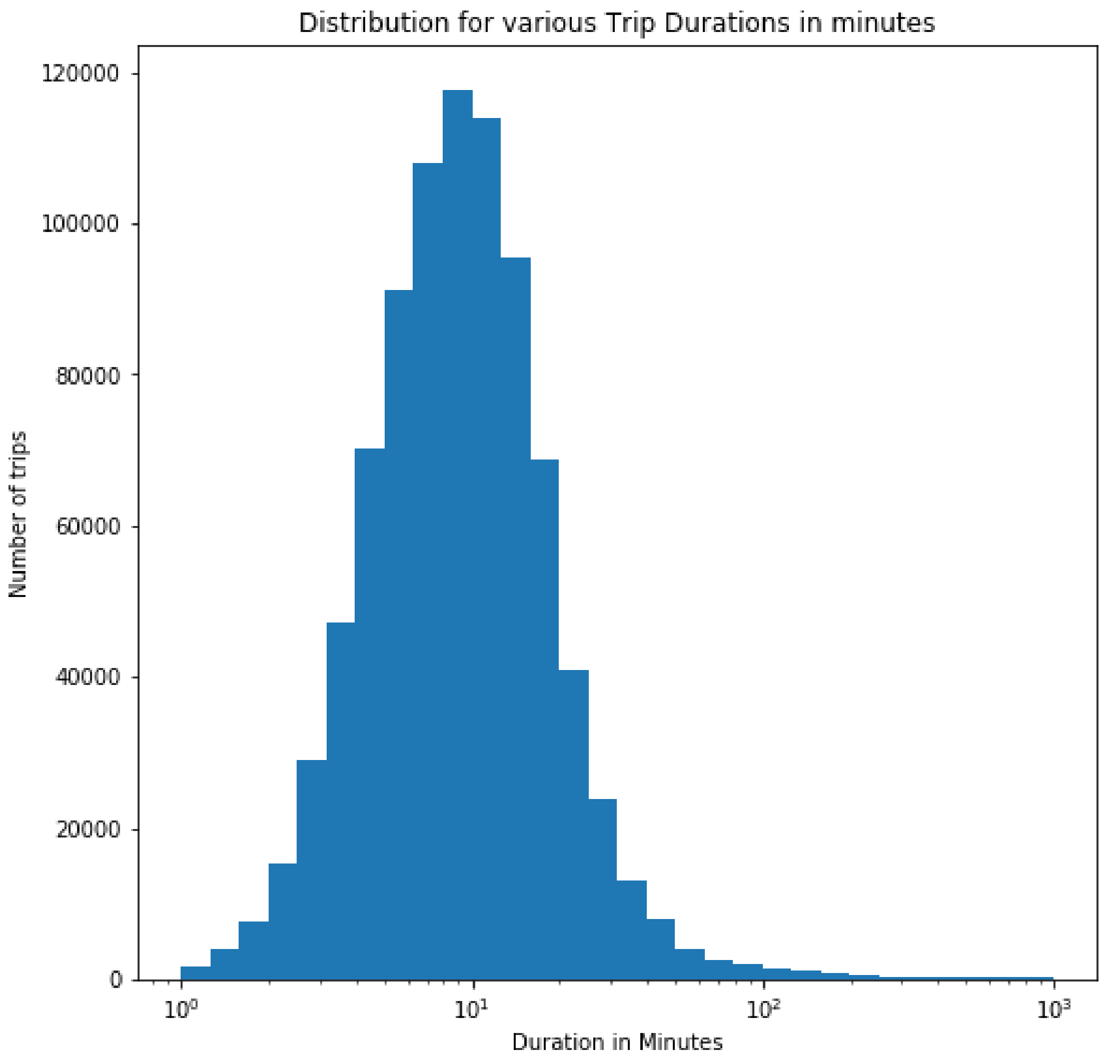


1.4.4 Trip duration (time)

```
In [48]: # Plot a histogram representing time spent on each race in seconds
         binsize = 50
         bins = np.arange(50, ford_cleandata['duration_sec'].max()+binsize, binsize)

         plt.figure(figsize=[8, 5])
         plt.hist(data = ford_cleandata, x = 'duration_sec', bins=bins)
         plt.title('Distribution for various Trip Durations in seconds')
         plt.xlabel('Duration in seconds')
         plt.ylabel('Number of trips')
         plt.xlim([0, 3000]);
```



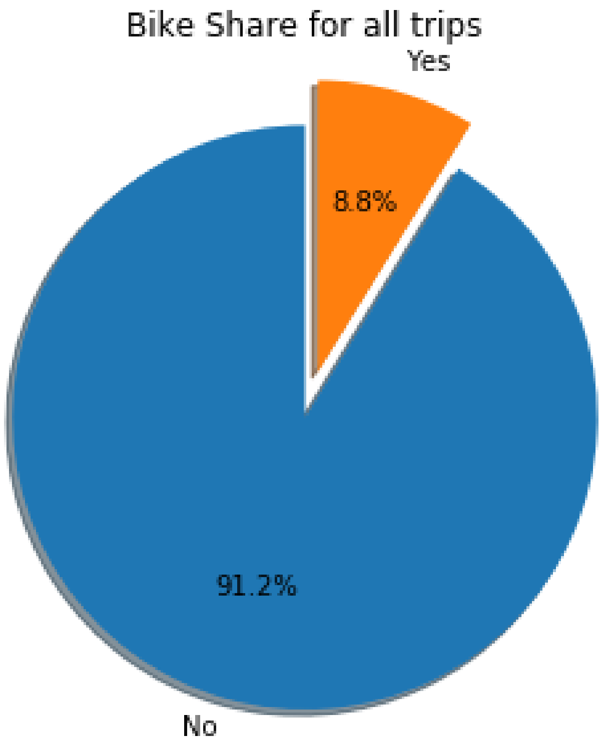

```
In [49]: #to get the average duration of a races in minutes, we will convert the seconds column
         ford_cleandata['race_mins'] = ford_cleandata['duration_sec'] / 60

         plt.figure(figsize=[8,8])
         bins =10**np.arange(0 , 3+0.1 , 0.1)
         ticks =  [ 0.1 , 0.3 , 1 , 3, 10, 30, 100, 300]
         labels = ['{}'.format(v) for v in ticks]
         plt.hist(ford_cleandata['race_mins'],bins=bins)
         plt.xticks(ticks,labels)
         plt.xscale('log')
         plt.title('Distribution for various Trip Durations in minutes')
         plt.xlabel('Duration in Minutes')
         plt.ylabel('Number of trips')
         plt.show()
```



1.4.5 Bike Share for all rides

```
In [33]: # By plotting a pie graph, we call tell the distribution of bikes.

         labels = list(ford_cleandata.bike_share_for_all_trip.unique())
         sizes = ford_cleandata.bike_share_for_all_trip.value_counts()
         explode = (0.16, 0)

         fig1, ax1 = plt.subplots()
         ax1.pie(sizes, labels=labels, autopct='%1.1f%%',
                 shadow=True, startangle=90 , explode = explode )

         ax1.axis('equal')
         plt.tight_layout()
```

```
plt.title('Bike Share for all trips')
plt.show()
```



A very low proportion of bike riders shared bikes compared to those who weren't.

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

Age: most of riders age falls between 30 and 45 years old.

Gender: A large number of riders are male, while a portion are female, a less portion may have reasons for not revealing their gender. it needs more investigationg because a lot of riders did not indicate their gender, and this would be difficult to determine.

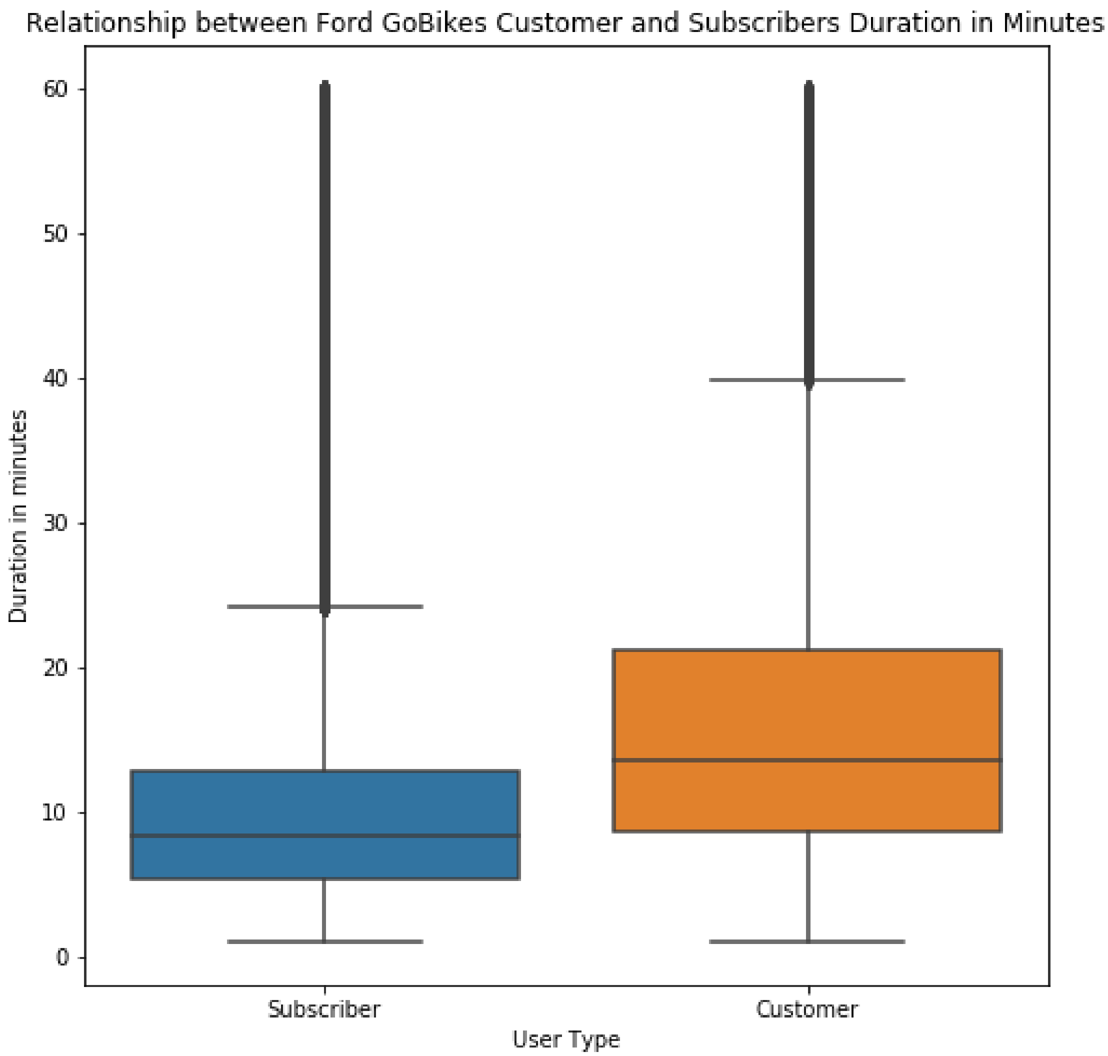
Subscribe: the number of trips in subscribers is more than the number in customers this may be because of pricing and population.

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

The new column age had a lot of outliers, that has been dealth with by dropping rows with high numbers. New column to calculate the month in which a race was done.

1.5 Bivariate Exploration

In [50]:
```
#A boxplot will show the relationship between usertypes and duration of bike trips
plt.figure(figsize = [8, 8])
base_color = sb.color_palette()[3]
sb.boxplot(data = ford_cleandata.query('race_mins <= 60'), x = 'user_type', y = 'race_m
plt.title('Relationship between Ford GoBikes Customer and Subscribers Duration in Minut
plt.xlabel('User Type')
plt.ylabel('Duration in minutes')
plt.show()
```

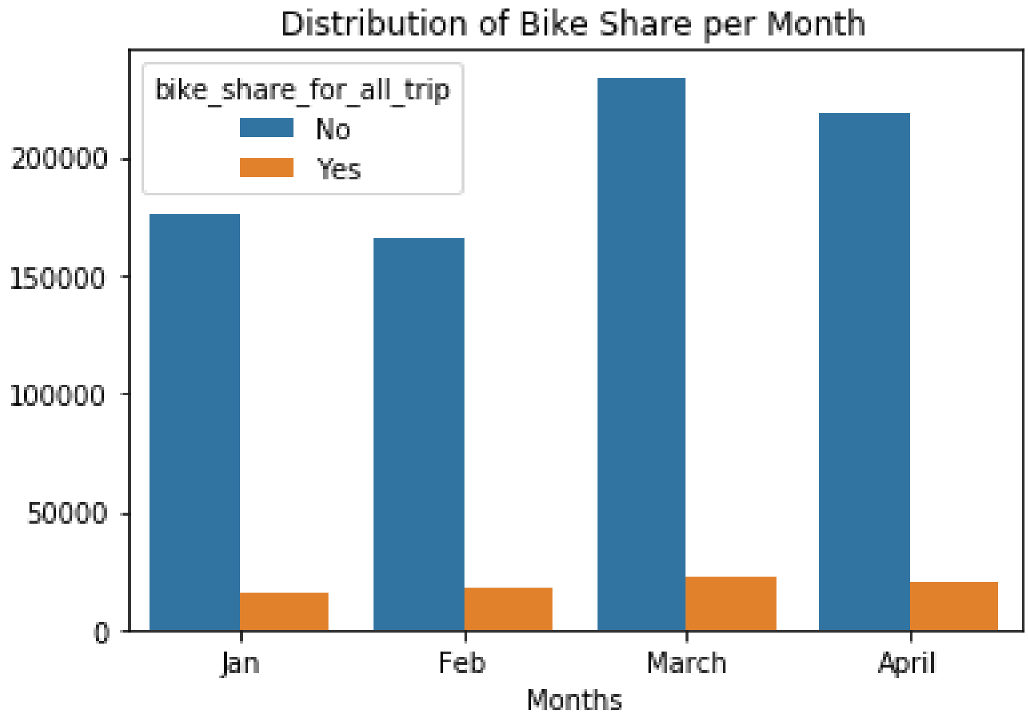


Customers had longer bike trips than subscribers

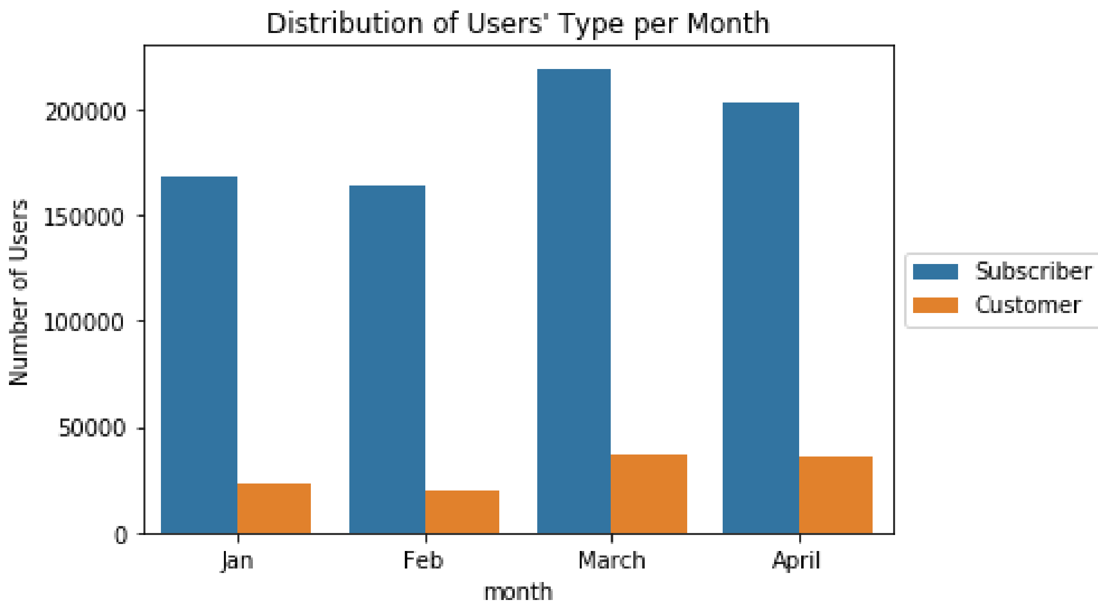
In [35]:
```
#use a countplot to show the relationship between the distribution of bike share and th
sb.countplot(data=ford_cleandata, x='month', hue='bike_share_for_all_trip')
plt.xticks([0, 1, 2, 3], ['Jan', 'Feb', 'March', 'April']);
```

```
plt.xlabel('Months')
plt.ylabel('')
plt.title("Distribution of Bike Share per Month")
```

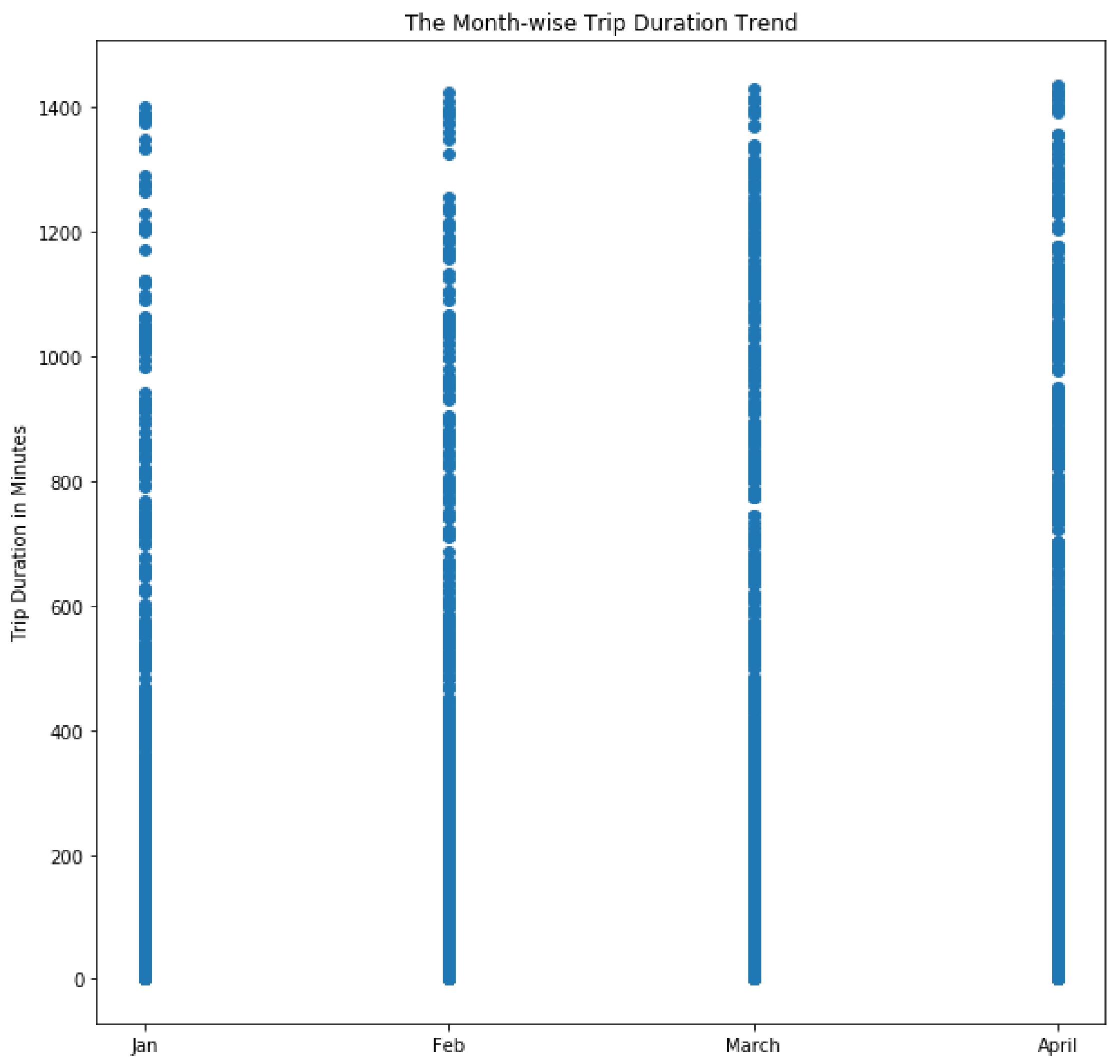
Out[35]: Text(0.5,1,'Distribution of Bike Share per Month')



In [39]:
```
#a countplot to show the relationship between user types and the month of each trip
g = sb.countplot(data=ford_cleandata, x='month', hue='user_type')
g.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.xticks([0, 1, 2, 3], ['Jan', 'Feb', 'March', 'April']);
#plt.xlabel('Months')
plt.ylabel('Number of Users')
plt.title("Distribution of Users' Type per Month");
```



In [40]:
```
# Makes the figure enlarged for better visualization
plt.figure(figsize = [10,10])
plt.scatter(data = ford_cleandata , x = 'month' , y = 'race_mins')
plt.xticks([1, 2, 3, 4 ], ['Jan', 'Feb', 'March', 'April']);
plt.title('The Month-wise Trip Duration Trend')
plt.xlabel(' ')
plt.ylabel('Trip Duration in Minutes');
```



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

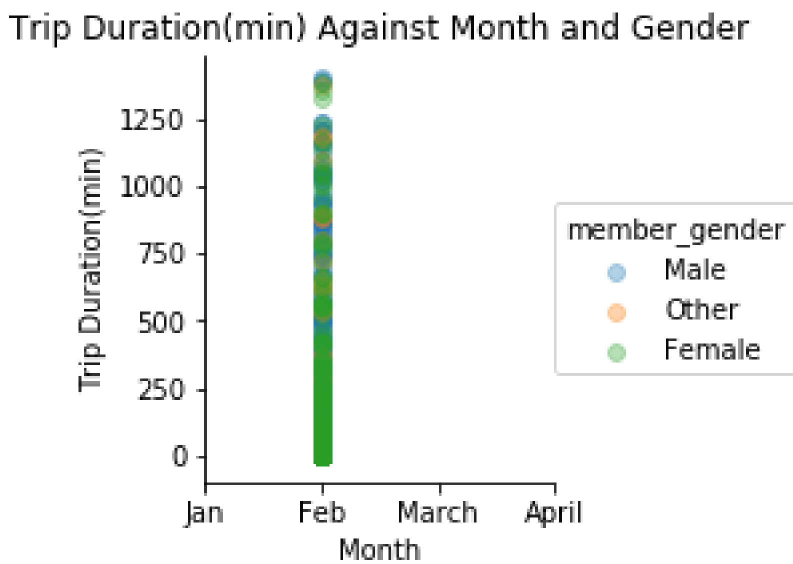
Younger riders between the age 20 and 45 tend to take more rides than older people. A high percentage of riders are customers compared to subscribers. Female users average bike trip duration is slightly more than male users. Subscribed users numbers are way more greater than customers despite of the gender.

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

Trip duration in female users and customer users is longer despite of their low count in the dataset A lot of missing data for gender and age, so we cannot base any conclusion on those two observations

1.6 Multivariate Exploration

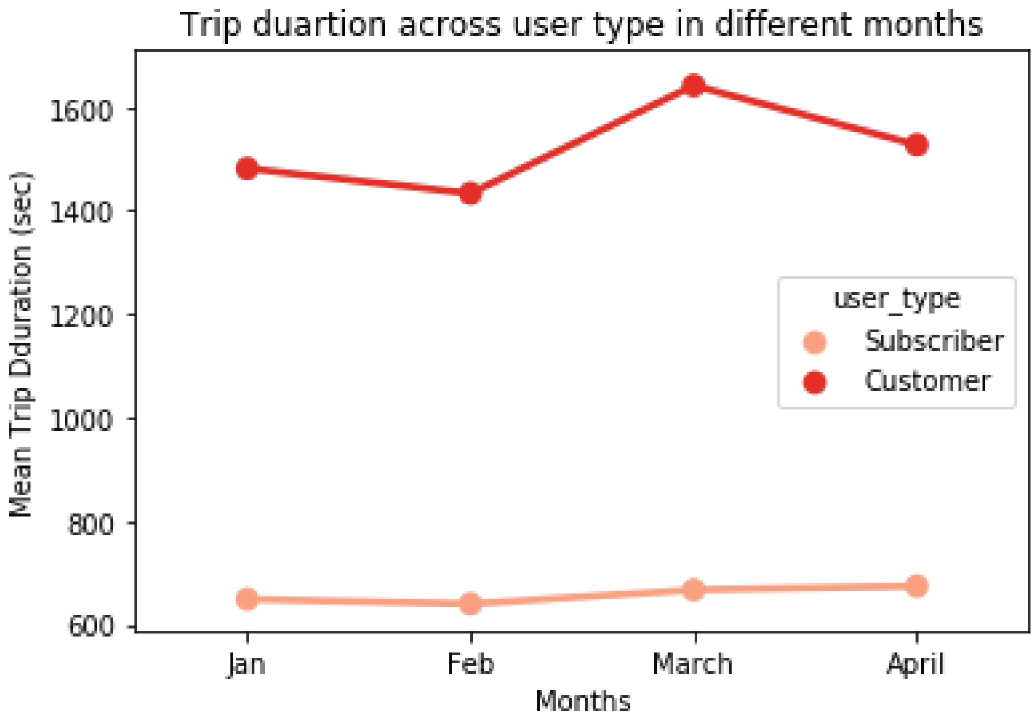
In [51]:
```
# Find out if Gender affects a trip duration during thr first quater of the year using
graph = sb.FacetGrid(data = ford_cleandata, hue = 'member_gender')
graph.map(plt.scatter, 'month','race_mins', alpha = 1/3).add_legend()
plt.xticks([1, 2, 3, 4 ], ['Jan', 'Feb', 'March', 'April'])
plt.title('Trip Duration(min) Against Month and Gender')
plt.xlabel('Month')
plt.ylabel('Trip Duration(min)');
```



Only Feburay bike riders gave gender details so no valid conclusion can be drawn from this

1.6.1 Does duration of trip affects the user types and the month

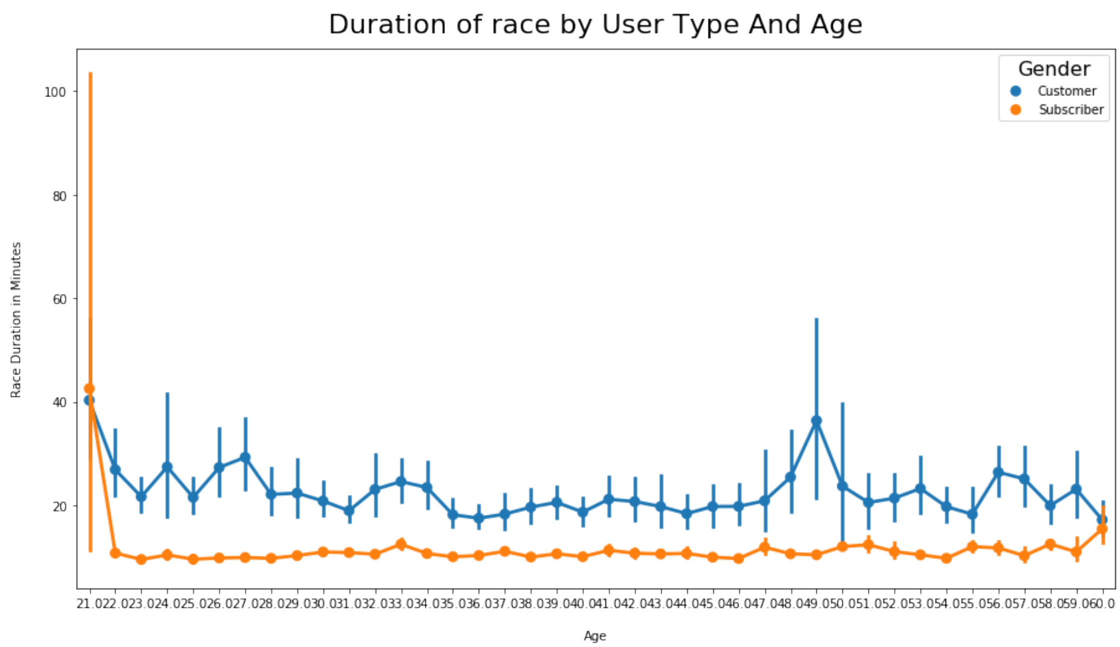
In [42]:
```
#finding how duration affects the user types and the month
sb.pointplot(data = ford_cleandata, x = 'month', y = 'duration_sec', hue = 'user_type',
plt.title('Trip duartion across user type in different months')
plt.xticks([0, 1, 2, 3], ['Jan', 'Feb', 'March', 'April']);
plt.ylabel('Mean Trip Dduration (sec)')
plt.xlabel('Months')
plt.show();
```



The Customers had longer trips and this is spread across the four months

1.6.2 Does age affect how long a biker rode, and whats the relationship with user type also

```
In [52]: plt.figure(figsize=(15,8))
         ax = sb.pointplot(x='member_age', y='race_mins', hue='user_type',data=ford_cleandata.qu
         plt.title('Duration of race by User Type And Age', fontsize=22, y=1.015)
         plt.xlabel('Age', labelpad=16)
         plt.ylabel('Race Duration in Minutes', labelpad=16)
         leg = ax.legend()
         leg.set_title('Gender',prop={'size':16})
         ax = plt.gca();
```



1.7 Conclusions

The dataset is for the first 4 months in the year 2019, January, Febuary,March and April. A large number of riders are male, while a portion are female, a less portion may have reasons for not revealing their gender. Outliers are shown so we will drop rows with abnormal age, from 100 and above. Most of the riders are ranged from ages 30 - 45 years old which makes sense for long distance races. A lot of the bikes rides are covered in short minutes, the average trips takes around 500 - 550 seconds. The age disparity and the duration of trips shows that younger people takes shorter trips compared to older people. A very low proportion of bike riders shared bikes compared to those who weren't. The category user type shows that a over 80% of riders are subscribers as compared to nearly 20% of customers, this may be linked to the prices of hikes and funding system needed to take on a trip.This has a great effect on the number of trips taken and the duration of it. Subscribers takes longer and more trips than customers.

1.8 Recommendation:

Ford go bike should make conscious effort to make more users subscribers. Marketing strategy should be put in place to get new subscribers or convert customers to subscribers.

```
In [53]: ford_cleandata.to_csv('ford_cleandata1.csv')
```

```
In [ ]:
```