Exploratory Analysis - Ford Bike System

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from mpl_toolkits.basemap import Basemap
import numpy as np
import statsmodels.api as sm
import seaborn as sns
```

In [2]:
```
#read bike data
df = pd.read_csv('../201904-fordgobike-tripdata.csv')
```

In [3]:
```
#view data
df.head()
```

Out[3]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latituc
0	50305	2019-04-30 22:33:55.1550	2019-05-01 12:32:20.4540	368.0	Myrtle St at Polk St	37.7854:
1	53725	2019-04-30 20:43:41.6320	2019-05-01 11:39:06.9170	246.0	Berkeley Civic Center	37.8690(
2	78072	2019-04-30 10:32:46.4890	2019-05-01 08:13:58.9750	64.0	5th St at Brannan St	37.7767!
3	78969	2019-04-30 10:00:51.5500	2019-05-01 07:57:01.2620	67.0	San Francisco Caltrain Station 2 (Townsend St...	37.7766:
4	1128	2019-04-30 23:59:04.7390	2019-05-01 00:17:53.0910	124.0	19th St at Florida St	37.7604،

In [4]:
```
#data size
df.shape
```

Out[4]:
```
(239111, 16)
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['duration_sec', 'start_time', 'end_time', 'start_station_id',
       'start_station_name', 'start_station_latitude',
       'start_station_longitude', 'end_station_id', 'end_station_name',
       'end_station_latitude', 'end_station_longitude', 'bike_id', 'user_
type',
       'member_birth_year', 'member_gender', 'bike_share_for_all_trip'],
      dtype='object')
```

In [6]:
```
#data types
df.dtypes
```

Out[6]:
```
duration_sec                   int64
start_time                    object
end_time                      object
start_station_id             float64
start_station_name            object
start_station_latitude       float64
start_station_longitude      float64
end_station_id               float64
end_station_name              object
end_station_latitude         float64
end_station_longitude        float64
bike_id                        int64
user_type                     object
member_birth_year            float64
member_gender                 object
bike_share_for_all_trip       object
dtype: object
```

Exploratory Data Analysis

Where are the bike stations located?

In [7]:
```
#view start station groups
df.groupby(['start_station_id']).count().head()
```

Out[7]:

	duration_sec	start_time	end_time	start_station_name	start_station_latitude	start_s
start_station_id						
3.0	3422	3422	3422	3422	3422	
4.0	830	830	830	830	830	
5.0	3390	3390	3390	3390	3390	
6.0	2941	2941	2941	2941	2941	
7.0	1045	1045	1045	1045	1045	

In [8]:
```
#find lat / long extremities given a dataframe
def geoBound(df,lat_name,lon_name):
    lonmax = df[lon_name].max()
    lonmin = df[lon_name].min()
    latmax = df[lat_name].max()
    latmin = df[lat_name].min()
    return lonmax,lonmin,latmax,latmin
```

In [9]:
```
#look for anomalies
df.sort_values(by=['start_station_latitude'])[['start_station_latitude','st
```

Out[9]:

	start_station_latitude	start_station_longitude
40680	0.000000	0.000000
185448	37.315158	-121.897833
34563	37.315158	-121.897833
37213	37.315158	-121.897833
107025	37.315158	-121.897833

In [10]:
```
#drop anomalous value
df = df.drop([40680])
```

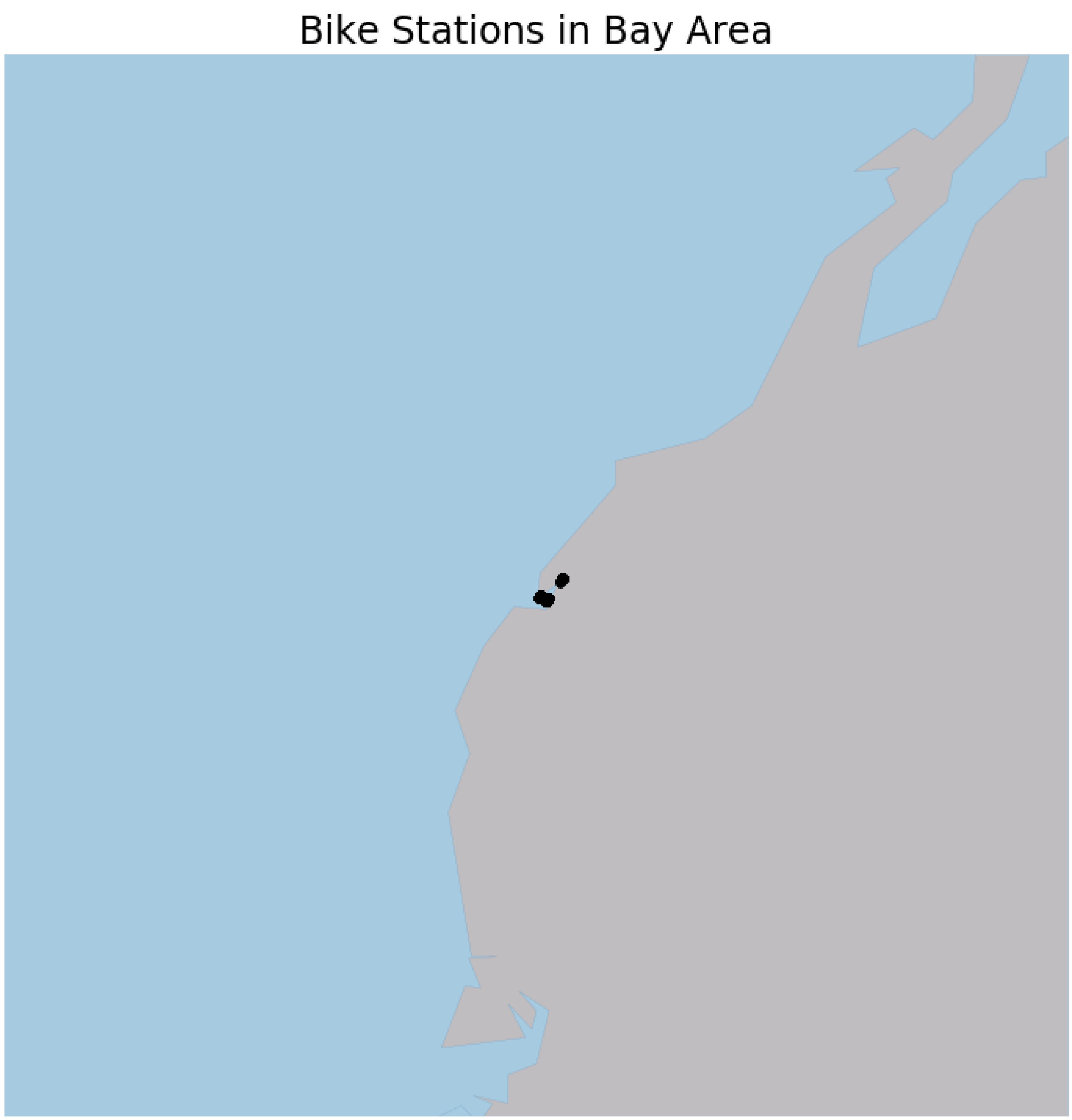
In [11]:
```
bounds = geoBound (df,'start_station_latitude','start_station_longitude')
bounds
```

Out[11]:
```
(-121.8741186, -122.4537044763565, 37.88022244590679, 37.315157929983116)
```

In [12]:
```
# map of station - view of san francisco area
my_dpi=96
plt.figure(figsize=(1300/my_dpi, 900/my_dpi), dpi=my_dpi)

# Make the background map
#m=Basemap(llcrnrlon=bounds[1], llcrnrlat=bounds[3],urcrnrlon=bounds[0],urc
m=Basemap(llcrnrlon=-135, llcrnrlat=50,urcrnrlon=-110,urcrnrlat=25)
m.drawmapboundary(fill_color='#A6CAE0', linewidth=0)
m.fillcontinents(color='#ffa07a', alpha=0.3)
m.drawcoastlines(linewidth=0.1, color="steelblue")
m.drawstates(color='white')

# Add a point per position
m.scatter(df['start_station_longitude'], df['start_station_latitude'], s=10
plt.title('Bike Stations in Bay Area',fontsize=18)
plt.show()
```



Bikes stations in this data set are in northern california

In [13]:
```
# zoom in view of start stations
my_dpi=96
plt.figure(figsize=(1300/my_dpi, 900/my_dpi), dpi=my_dpi)

# Make the background map
m=Basemap(llcrnrlon=bounds[1], llcrnrlat=bounds[3],urcrnrlon=bounds[0],urcr
m.drawmapboundary(fill_color='#A6CAE0', linewidth=0)
m.fillcontinents(color='#ffa07a', alpha=0.3)
m.drawcoastlines(linewidth=0.1, color="steelblue")
m.drawstates(color='white')

# Add a point per position
m.scatter(df['start_station_longitude'], df['start_station_latitude'], s=10
plt.title('Bike Stations (Zoomed In)',fontsize=18)
plt.show()
```

Bike Stations (Zoomed In)

Zoomed in view of bike stations

How many bikes are there?

In [14]:
```
#find number of unique bike ids
df['bike_id'].nunique()
```

Out[14]:
```
4520
```

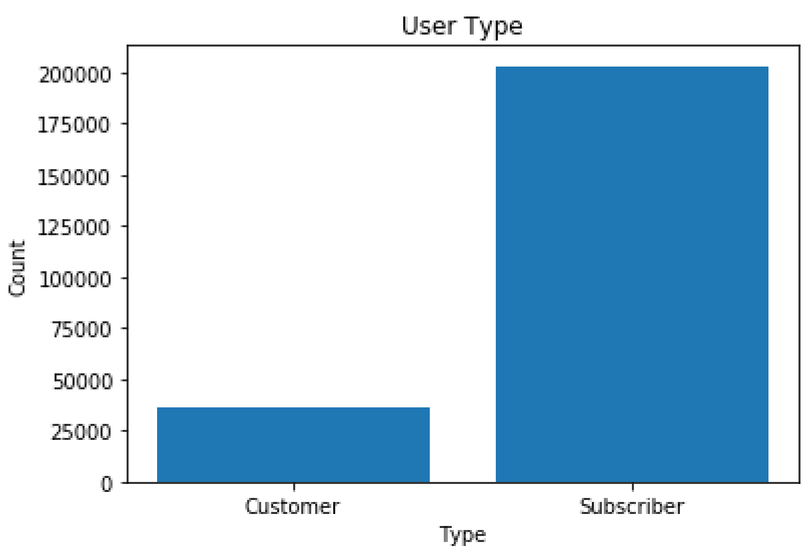
There are 4520 unique bikes in this dataset

Which types of customers are using the bikes?

In [15]:
```
#group data by user type to find number of customers vs subscribers
df.groupby('user_type')[['user_type']].size()
```

Out[15]:
```
user_type
Customer       35914
Subscriber    203196
dtype: int64
```

In [16]:
```
#barplot of user types (ie no of customers vs subscribers for all observati
users = df.groupby('user_type')[['user_type']].size().values
index = ('Customer','Subscriber')
y_pos = np.arange(len(index))
plt.bar(y_pos, users)
plt.xticks(y_pos, index)
plt.title('User Type')
plt.xlabel('Type')
plt.ylabel('Count')
plt.show()
```



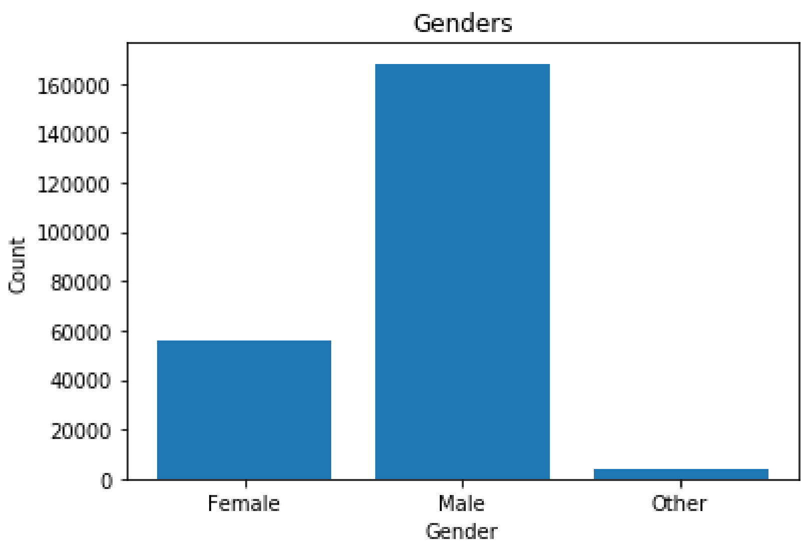
35914 trips were taken by customers, 203196 trips were taken by subscribers

Do men or women ride the bikes more?

In [17]:
```
#group observations by gender
df.groupby('member_gender')[['member_gender']].size()
```

Out[17]:
```
member_gender
Female     55498
Male      168139
Other       4274
dtype: int64
```

In [18]:
```
#barplot of observations by gender
genders = df.groupby('member_gender')[['member_gender']].size().values
index = ('Female','Male','Other')
y_pos = np.arange(len(index))
plt.bar(y_pos, genders)
plt.xticks(y_pos, index)
plt.title('Genders')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



55498 trips were taken by females, 168139 trips were taken by males, and 4274 trips were taken by other

In general which linear variables affect trip duration?

In [19]:
```
#create an intercept for a linear regresssion
df['intercept'] = 1
```

In [20]:
```
#drop missing value for linear regression
df2 = df.copy()
df2 = df2.dropna()
#linear regression with linear variables
X = df2[['start_station_latitude','start_station_longitude','end_station_id
Y = df2[['duration_sec']]
model = sm.OLS(Y,X.astype(float)).fit()
```

In [21]:
```
#low r squared, so only .5% of variation in y can be explained by the model
model.summary()
```

Out[21]:

OLS Regression Results

Dep. Variable:	duration_sec	**R-squared:**	0.005
Model:	OLS	**Adj. R-squared:**	0.005
Method:	Least Squares	**F-statistic:**	154.5
Date:	Tue, 14 May 2019	**Prob (F-statistic):**	1.15e-228
Time:	00:07:46	**Log-Likelihood:**	-2.0334e+06
No. Observations:	227847	**AIC:**	4.067e+06
Df Residuals:	227839	**BIC:**	4.067e+06
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
start_station_latitude	-932.1639	248.038	-3.758	0.000	-1418.312	-446.016
start_station_longitude	-1448.7727	88.448	-16.380	0.000	-1622.128	-1275.417
end_station_id	1.0361	0.038	27.425	0.000	0.962	1.110
end_station_latitude	273.5565	249.349	1.097	0.273	-215.162	762.275
end_station_longitude	83.2994	76.996	1.082	0.279	-67.611	234.210
bike_id	-0.0024	0.002	-1.375	0.169	-0.006	0.001
member_birth_year	-0.6712	0.386	-1.738	0.082	-1.428	0.086
intercept	-1.402e+05	5064.583	-27.688	0.000	-1.5e+05	-1.3e+05

Omnibus:	565968.311	**Durbin-Watson:**	1.940
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	8292575938.093
Skew:	27.175	**Prob(JB):**	0.00
Kurtosis:	936.025	**Cond. No.**	6.15e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.15e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

Really weak r squared. 0.5% of the variation in trip duration can be explained by the model

In [22]:
```
df2 = df2.drop('intercept',axis=1)
```

In [23]:
```
corr = df2.corr()
corr
```

Out[23]:

	duration_sec	start_station_id	start_station_latitude	start_station_longitude	e
duration_sec	1.000000	0.010489	0.013379	-0.034430	
start_station_id	0.010489	1.000000	-0.208497	0.431878	
start_station_latitude	0.013379	-0.208497	1.000000	-0.705841	
start_station_longitude	-0.034430	0.431878	-0.705841	1.000000	
end_station_id	0.031919	0.326992	-0.198060	0.451673	
end_station_latitude	0.002797	-0.061853	0.289935	-0.203495	
end_station_longitude	-0.002595	0.052152	-0.077462	0.103982	
bike_id	0.001795	0.016041	0.004169	-0.038727	
member_birth_year	-0.004507	0.110345	-0.074800	0.117910	

In [24]:
```
# Correlation Matrix Heatmap
f, ax = plt.subplots(figsize=(10, 6))
hm = sns.heatmap(round(corr,2), annot=True, ax=ax, cmap="coolwarm",fmt='.2f
f.subplots_adjust(top=0.93)
t= f.suptitle('Bike Rides Correlation Heatmap', fontsize=14)
```

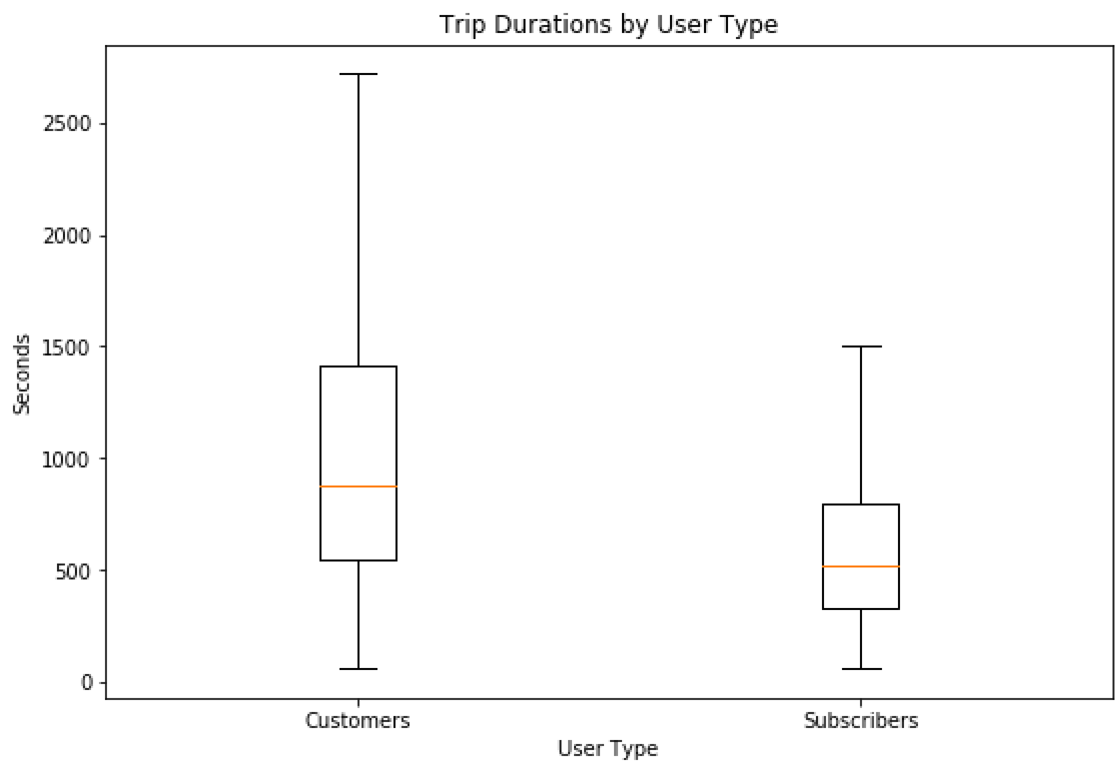
Duration is not strongly correlated with any variable

How does user type affect trip duration?

In [25]:
```
#ride durations for customers, subscribers separately
customers = df[df['user_type']=='Customer'][['duration_sec']].values
subscribers = df[df['user_type']=='Subscriber'][['duration_sec']].values
data_to_plot = [customers, subscribers]
```

In [26]:
```
#create box plots to compare trip durations between customers and subscribe
fig = plt.figure(1, figsize=(9, 6))
ax = fig.add_subplot(111)
bp = ax.boxplot(data_to_plot,showfliers=False)
ax.set_xticklabels(['Customers', 'Subscribers'])
plt.title('Trip Durations by User Type')
plt.xlabel('User Type')
plt.ylabel('Seconds')
```

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



In [27]:
```
#trip duration quartiles for customers
df[df['user_type']=='Customer'][['duration_sec']].describe()
```

Out[27]:

	duration_sec
count	35914.000000
mean	1527.475943
std	3870.654407
min	61.000000
25%	546.000000
50%	879.000000
75%	1415.000000
max	85496.000000

In [28]:
```
#trip duration quartiles for subscribers
df[df['user_type']=='Subscriber'][['duration_sec']].describe()
```

Out[28]:

	duration_sec
count	203196.000000
mean	674.568235
std	1379.449580
min	61.000000
25%	330.000000
50%	521.000000
75%	800.000000
max	86114.000000

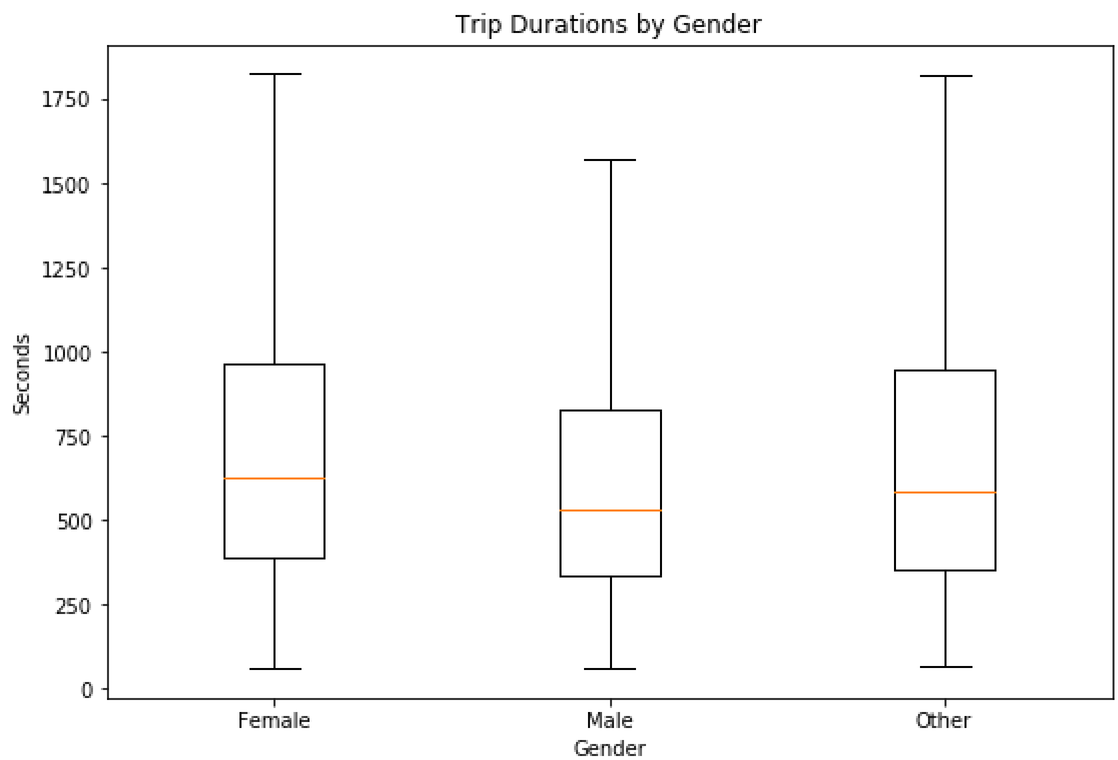
Customers have median trip duration of 879 seconds, subscribers have median duration of 521 seconds. THere is more variation in customer trip duration

How does gender affect trip duration?

In [29]:
```
#trip durations for females, males, and other separately
female = df[df['member_gender']=='Female'][['duration_sec']].values
male = df[df['member_gender']=='Male'][['duration_sec']].values
other = df[df['member_gender']=='Other'][['duration_sec']].values
data_to_plot = [female, male, other]
```

In [30]:
```
#create box plots to compare trip durations by gender
fig = plt.figure(1, figsize=(9, 6))
ax = fig.add_subplot(111)
bp = ax.boxplot(data_to_plot,showfliers=False)
ax.set_xticklabels(['Female', 'Male','Other'])
plt.title('Trip Durations by Gender')
plt.xlabel('Gender')
plt.ylabel('Seconds')
```

Out[30]: Text(0, 0.5, 'Seconds')



In [31]:
```
#trip duration quartiles for females
df[df['member_gender']=='Female'][['duration_sec']].describe()
```

Out[31]:

	duration_sec
count	55498.000000
mean	875.889059
std	2071.526549
min	61.000000
25%	389.000000
50%	623.000000
75%	963.000000
max	86114.000000

In [32]:
```
#trip duration quartile for males
df[df['member_gender']=='Male'][['duration_sec']].describe()
```

Out[32]:

	duration_sec
count	168139.000000
mean	730.428901
std	1653.096590
min	61.000000
25%	334.000000
50%	532.000000
75%	830.000000
max	84782.000000

In [33]:
```
#trip duration quartile for other
df[df['member_gender']=='Other'][['duration_sec']].describe()
```

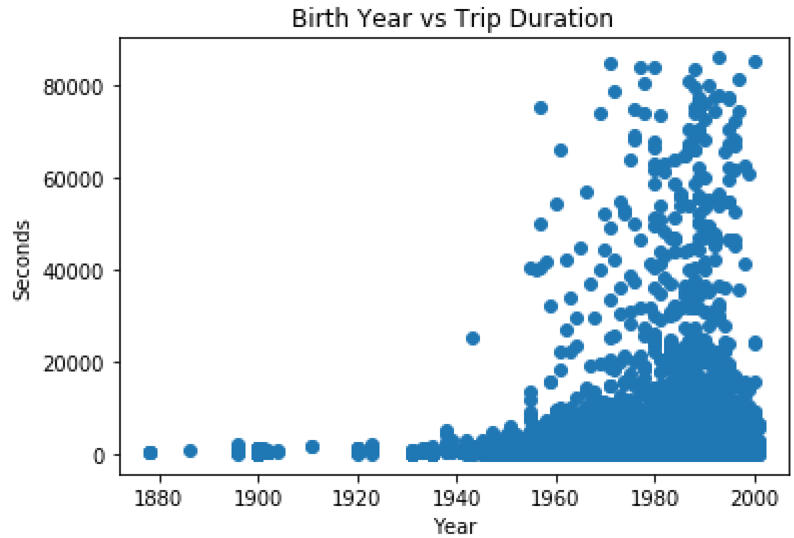
Out[33]:

	duration_sec
count	4274.000000
mean	1054.262518
std	3683.014847
min	66.000000
25%	355.000000
50%	586.000000
75%	946.000000
max	84241.000000

Females have median trip duration of 623 seconds, males have median duration of 532 seconds, and other have median duration of 586 seconds. The three distributions are fairly similar

What is the relationship between age (birth year) and trip duration?

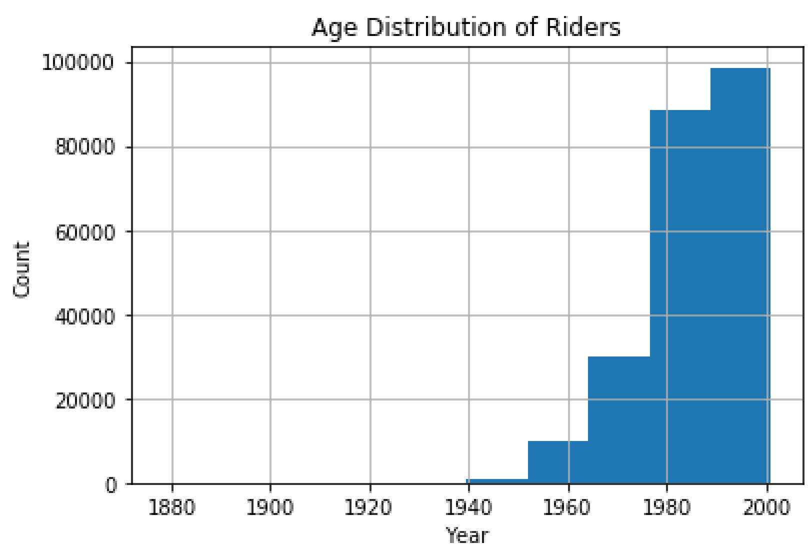
In [34]:
```
#scatter birth year vs trip duration
plt.scatter(df['member_birth_year'],df['duration_sec'])
plt.title('Birth Year vs Trip Duration')
plt.xlabel('Year')
plt.ylabel('Seconds');
```



No clear linear trend, but older people dont take long trips. More variation in younger riders.

What is the age distribution of riders?

In [35]:
```
df['member_birth_year'].hist()
plt.xlabel('Year')
plt.ylabel('Count')
plt.title('Age Distribution of Riders');
```



Summary of Main Findings

The goal of this analysis was to have a high level understanding and overview of the Ford Go Bike

System. In order to have the most current view of the company, the April 2019 dataset was pulled from this site [https://s3.amazonaws.com/fordgobike-data/index.html (https://s3.amazonaws.com/fordgobike-data/index.html)](https://s3.amazonaws.com/fordgobike-data/index.html) .

After scanning the data, I was interested in exploring the following two topics:

1. Where are the bikes located and how many are there?
2. Who is using the bikes and how often?

During the data cleaning process, I reviewed data types, dropped anomalous values, and dropped NaN line items when necessary. I then used maps, bar charts, and box plots from the matplotlib library to visualize my data.

My analysis yeiled the following findings:

- Bike stations are in Northern California (San Jose area).
- There are 4520 unique bikes.
- More trips are taken by subscribers than by customers. (203196 by subscribers, 35914 by customers)
- More trips are taken by men than by women and other. (55498 by females, 168139 males, and 4274 by other)
- One-time customers take longer trips than regular subscribers. (Customers median trip is 879 sec, subscribers median trip is 521 sec)
- Females trips are longer than male or other trips. Female median is 623 sec, male median is 532 sec, and other median is 586)
- No continuous variable is strongly correlated with trip duration.
- Older people dont take long trips, there is more variation in younger generation.
- There are more young riders than older riders.

Note that the numbered bullets are included in the explanatory analysis. The duplicated numbering indicates that multiple findings are on the same slide.

```
In [ ]:
```