```
#import of libraries
import pandas as pd
import glob
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Exploratory Data Analysis on Lyft Bike-Share Data

For this project I am using the Lyft bike sharing trips data collected between Jan 2019 and May 2019 from the Bay Area (California). This data has been taken from Kaggle and is available at; https://www.kaggle.com/jolasa/bay-area-bike-sharing-trips

Let's begin by importing our data into pandas. This notebook assumes you're using Google Colab. Be sure to adust the "path" directory to the folder of CSV files.

```
#path must point to the folder with .CSV files.
path = r'/content/data' # use your path
all_files = glob.glob(path + "/*.csv")

li = []

for filename in all_files:
    df = pd.read_csv(filename, index_col=None, header=0)
    li.append(df)

#big frame with all csv data from Jan to May.
data = pd.concat(li, axis=0, ignore_index=True)
data.head()
```

	month	trip_duration_sec	start_station_id	start_stat:
0	Februrary	52185	21.0	Montgomery St BART Station (Market St a
1	Februrary	42521	23.0	The Embarcadero at S
2	Februrary	61854	86.0	Market St at D
3	Februrary	36490	375.0	Grove St at Mas
4	Februrary	1585	7.0	Frank H Oga

```
data.shape
```

```
(1053067, 10)
```

There are 10 columns with over a million data entries. each collumn reffers to month, trip duration (seconds), start station id, start station name, end station id, endstation name, bike ID, user type, member DOB and member genger. For several attributes such as Education, each datapoint is a representative for description as follows:

Month

1. January
2. February
3. March
4. April
5. May

User Type

1. Customer
2. Subscriber

Member Gender

1. Male
2. Female

Data Cleaning

Before we explore our data, lets clean up any missing values by deleting them. Due to the number of entries, deleting rows with missing attributes should not have a drastic affect on the exploration of the data later.

```
#Count missing values in each column.
data.isna().sum()
```

```
month                    0
trip_duration_sec        0
start_station_id       745
start_station_name     745
end_station_id         745
end_station_name       745
bike_id                  0
user_type                0
member_birth_year    49376
member_gender        49370
dtype: int64
```

```
#drop any rows with missing values
```

```
data = data.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)


#check if we have any missing attributes in any rows.
#True = rows with missing attributes.
#False = everything is populated.
data.isnull().values.any()
```

```
False
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1002956 entries, 0 to 1053066
Data columns (total 10 columns):
 #   Column              Non-Null Count    Dtype  
---  ------              --------------    -----  
 0   month               1002956 non-null  object 
 1   trip_duration_sec   1002956 non-null  int64  
 2   start_station_id    1002956 non-null  float64
 3   start_station_name  1002956 non-null  object 
 4   end_station_id      1002956 non-null  float64
 5   end_station_name    1002956 non-null  object 
 6   bike_id             1002956 non-null  int64  
 7   user_type           1002956 non-null  object 
 8   member_birth_year   1002956 non-null  float64
 9   member_gender       1002956 non-null  object 
dtypes: float64(3), int64(2), object(5)
memory usage: 84.2+ MB
```

When we check what data types we're working with, some of the columns are of the incorrect type. For example, "start_station_id", "end_station_id" and "member_birth_year" are "float64" while they really should be "int64". Let's change this.

```
#Change the following fields to an appropriate data type.
data = data.astype({'start_station_id': np.int64})
data = data.astype({'end_station_id': np.int64})
data = data.astype({'member_birth_year': np.int64})


data.shape
```

```
(1002956, 10)
```

Once the null values have been removed, we shall take a look at the descriptive statistics in the dataset below. As from the above code, the shape of the dataframe has not drastically changes, we still have over a million data entries to explore.

```
#Print all of the object data types and their unique values
for column in data.columns:
    if data[column].dtype == object:
        print(str(column) + ' : ' + str(data[column].unique()))
        print(data[column].value_counts())
```

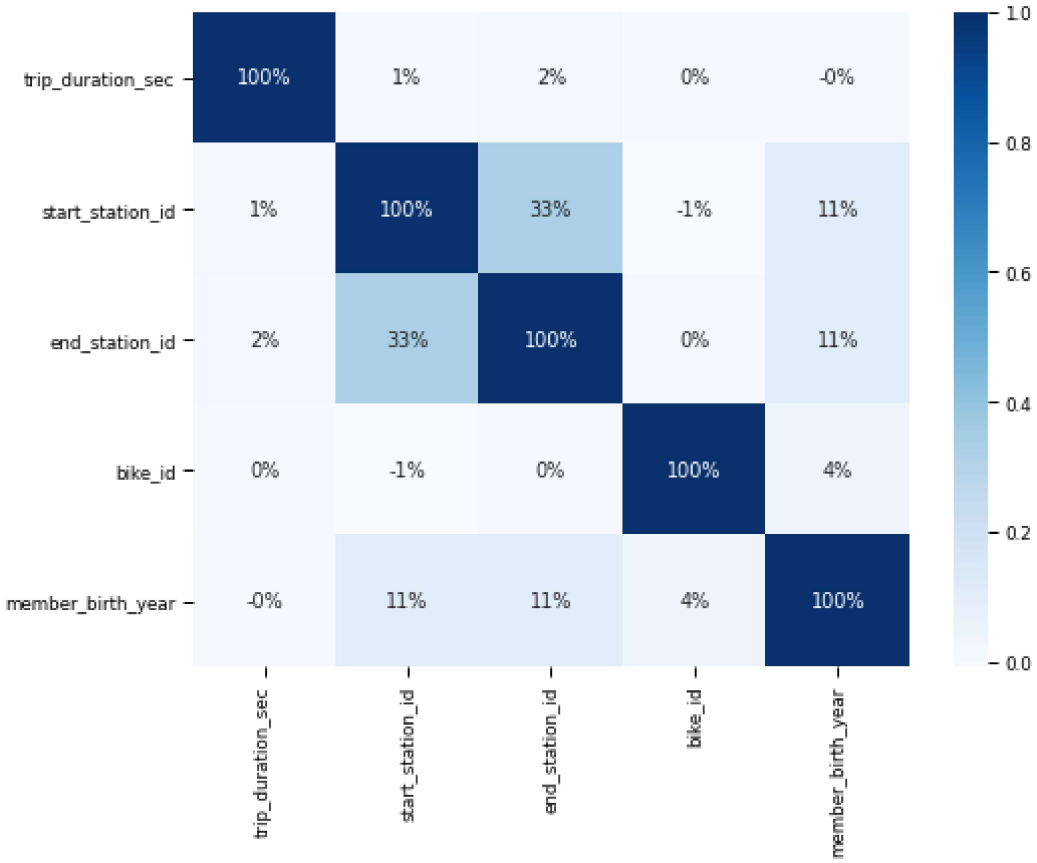
```
   print("_____")

month : ['Februrary' 'March' 'May' 'January' 'April']
March        244355
April        227848
January      182122
Februrary    174952
May          173679
Name: month, dtype: int64
_____
start_station_name : ['Montgomery St BART Station (Market St at 2nd St)'
 'Market St at Dolores St' 'Grove St at Masonic Ave' 'Frank H Ogawa Plaza'
 '4th St at Mission Bay Blvd S' 'Palm St at Willow St'
 'Washington St at Kearny St' 'Post St at Kearny St' 'Jones St at Post St'
 'Civic Center/UN Plaza BART Station (Market St at McAllister St)'
 'Valencia St at 21st St' 'Bancroft Way at College Ave'
 'Howard St at Mary St' '22nd St at Dolores St' 'Laguna St at Hayes St'
 '5th St at Folsom' 'Telegraph Ave at 23rd St' 'Page St at Scott St'
 'Lake Merritt BART Station' 'West St at 40th St'
 'The Embarcadero at Sansome St' 'Folsom St at 9th St'
 'University Ave at Oxford St' 'MLK Jr Way at University Ave'
 'The Embarcadero at Bryant St' '17th St at Valencia St'
 'Valencia St at 16th St' 'Valencia St at 22nd St' 'Franklin Square'
 'San Pablo Ave at MLK Jr Way' '19th St at Mission St'
 'Market St at 10th St' 'Folsom St at 13th St'
 'San Francisco Ferry Building (Harry Bridges Plaza)' '4th St at 16th St'
 'Beale St at Harrison St' 'Broadway at Battery St'
 'Cesar Chavez St at Dolores St' 'San Fernando St at 4th St'
 'Grove St at Divisadero' 'Sanchez St at 17th St'
 'Harmon St at Adeline St' 'Mission Playground' 'Davis St at Jackson St'
 'Haste St at Telegraph Ave' 'Howard St at 8th St' 'Folsom St at 3rd St'
 'Father Alfred E Boeddeker Park' 'Hubbell St at 16th St'
 'San Francisco Public Library (Grove St at Hyde St)'
 'Bancroft Way at Telegraph Ave' '19th Street BART Station'
 '18th St at Noe St' 'Hyde St at Post St' '24th St at Market St'
 'Vine St at Shattuck Ave'
 'San Francisco Caltrain (Townsend St at 4th St)'
 'Valencia St at Clinton Park' 'Union Square (Powell St at Post St)'
 'Broderick St at Oak St'
 'San Francisco Caltrain Station 2  (Townsend St at 4th St)'
 'North Berkeley BART Station' 'Downtown Berkeley BART'
 'Channing Way at Shattuck Ave' 'Fell St at Stanyan St'
 'San Salvador St at 9th St' 'Marston Campbell Park'
 'Oregon St at Adeline St' '11th St at Natoma St' 'Harrison St at 20th St'
 'Haste St at College Ave' '24th St at Bartlett St'
 'Sanchez St at 15th St' 'Telegraph Ave at 19th St'
 'Powell St BART Station (Market St at 5th St)' 'Jersey St at Castro St'
 'Pierce St at Haight St' 'MacArthur BART Station'
 'El Embarcadero at Grand Ave' '23rd St at San Bruno Ave'
 'Golden Gate Ave at Hyde St' 'S Van Ness Ave at Market St'
 'Jackson Playground' 'San Fernando St at 7th St'
 'West St at University Ave' 'Myrtle St at Polk St'
 'Woolsey St at Sacramento St' 'Townsend St at 7th St'
 'Harrison St at 17th St' 'West Oakland BART Station'
 'Cyril Magnin St at Ellis St' 'Fulton St at Bancroft Way'
 '14th St at Mission St' 'San Pedro Square' 'Market St at Franklin St'
 'Folsom St at 19th St' 'College Ave at Taft Ave'
 'Rhode Island St at 17th St' 'Shattuck Ave at Hearst Ave'
 'The Embarcadero at Vallejo St' 'The Embarcadero at Steuart St'
 'Webster St at Grove St' 'Raymond Kimbell Playground'
 'Victoria Manalo Draves Park' '20th St at Bryant St'
```

Data Visualisation

Let's start exploring our data, it may be best to see what collumns may correlate to what. Though this may not make much sense, since some the data isnt numerical, and some of the values repeat (such as bike_id). But lets do it anyway and see what shows.

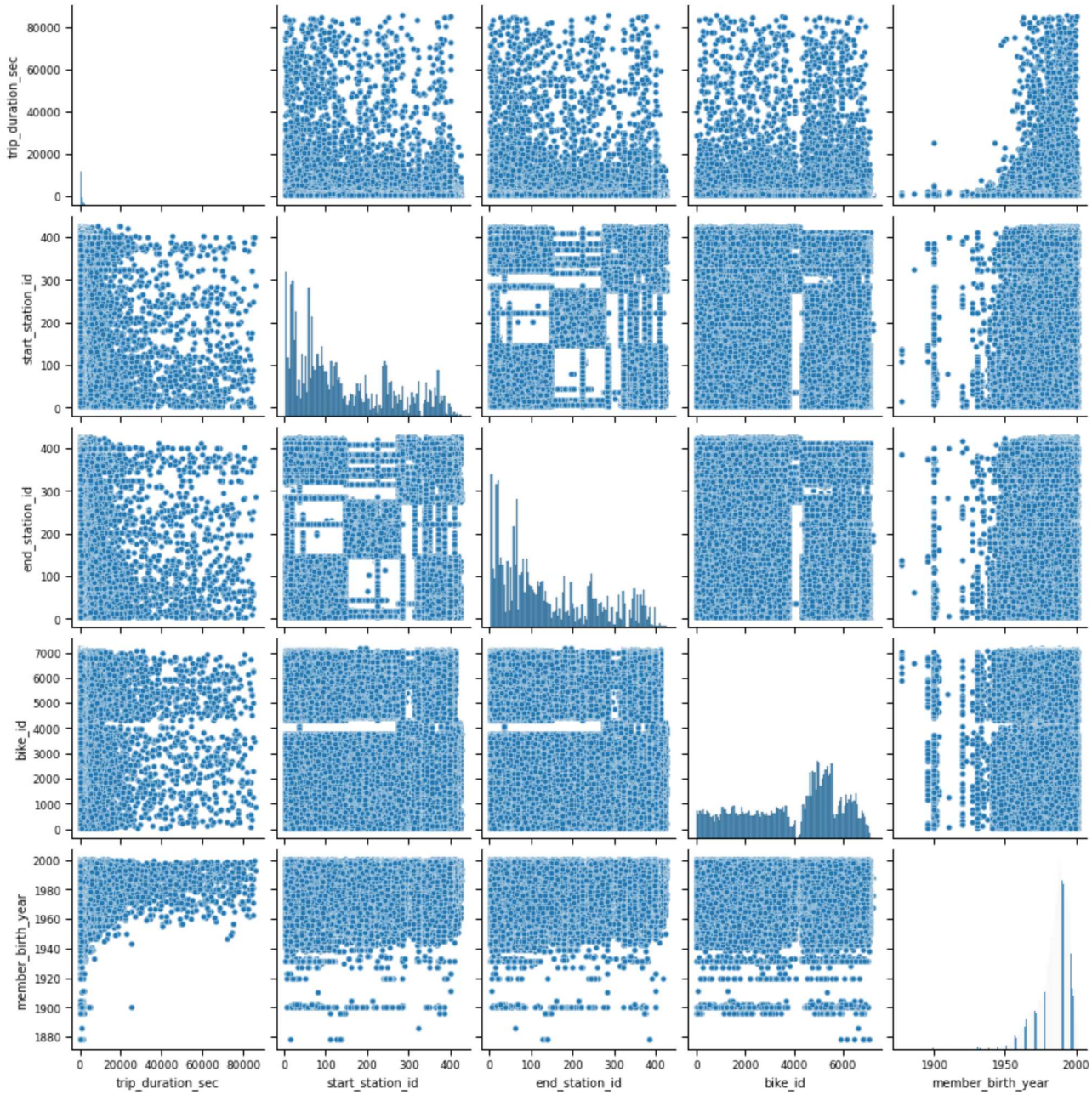
```
data_corr = data.corr()
data_corr
plt.figure(figsize=(8,6))
sns.set_context('paper')

sns.heatmap(data_corr, annot=True, cmap='Blues', fmt='.0%')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f43cc990990>
```



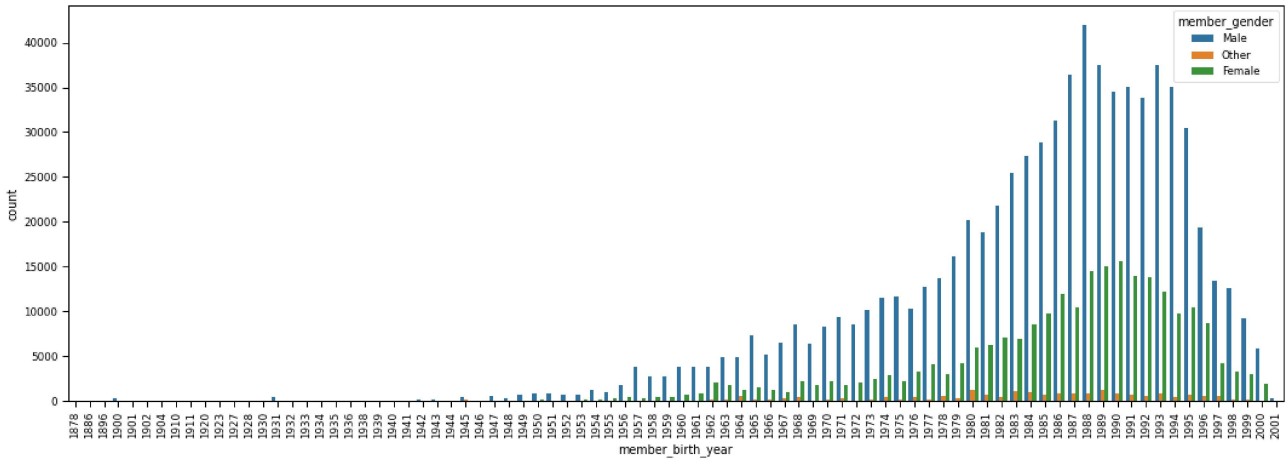

```
#broad look at data distribution
sns.pairplot(data)
```

```
<seaborn.axisgrid.PairGrid at 0x7f43cbdd8650>
```

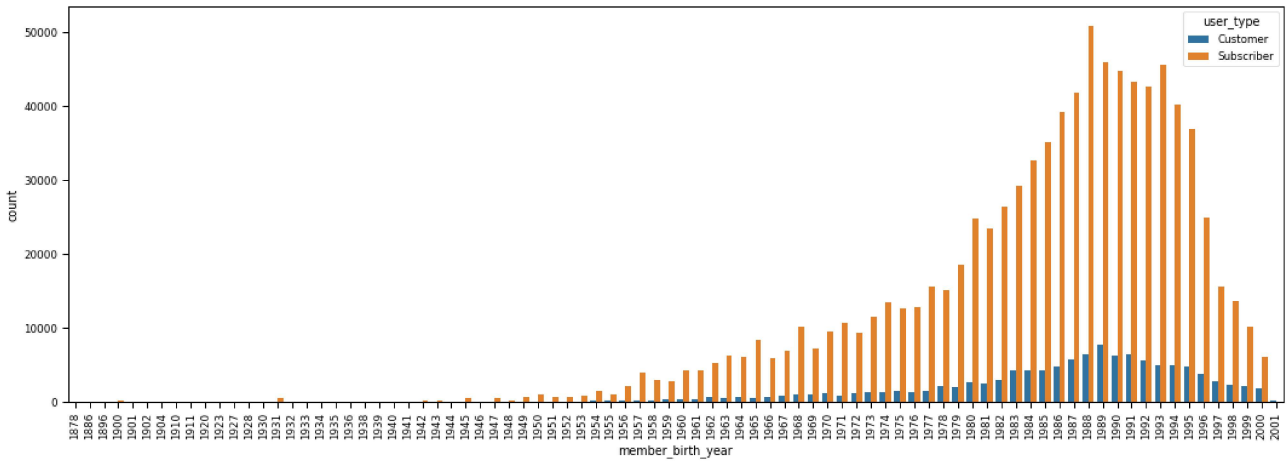



```
#count plot of members DOB
fig_dims = (18, 6)
fig, ax = plt.subplots(figsize=fig_dims)

#ax = axis
plt.xticks(rotation=90)
sns.countplot(x='member_birth_year', hue='member_gender', data=data, ax = ax)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f43c1591e10>
```




```
#count plot with hue
fig_dims = (18, 6)
fig, ax = plt.subplots(figsize=fig_dims)

#ax = axis
plt.xticks(rotation=90)
sns.countplot(x='member_birth_year', hue='user_type', data = data, ax = ax);
```

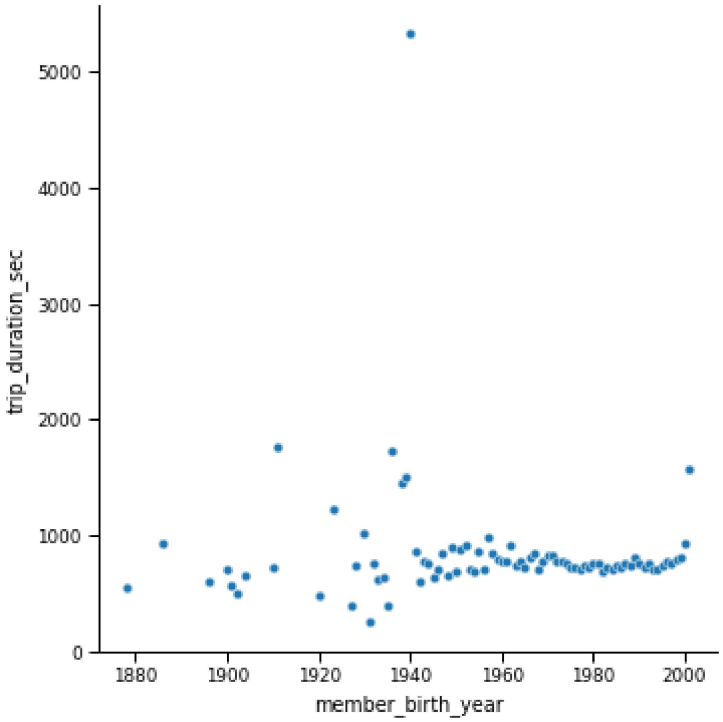


The above two graphs show the count of DOB, plotted with their gender and their user type. There seems to be a skew that leans to the left in both cases. Though, I feel it is important to note that there is no way to know the unique count of age to determine unique number of users. Though, this representation can give an idea of which age demogrpahic the bike share is most popular with.

```
_dims = (12, 3)
```

```
erage trip duration by member birth year
a.groupby(['member_birth_year']).mean().pipe(lambda data: sns.relplot(data=data, x="member
```

```
<seaborn.axisgrid.FacetGrid at 0x7f43b98c2650>
```

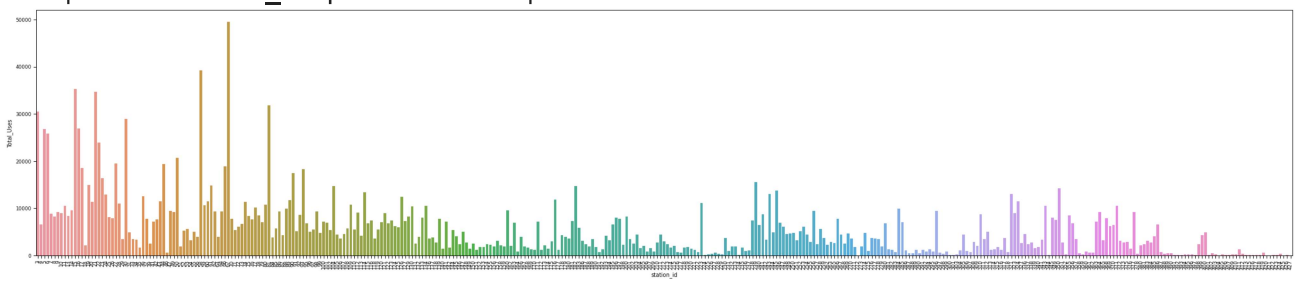


We can see when we plot member_birth_year with average trip duration the average duration of their trip against age.

There seems to be values far below the correlation of the data which suggests possible anomolies in the data regarding member_birth_year.

```
#station popularity
allstations = pd.DataFrame(columns=["Stations"]) # creating new dataframe
allstations = pd.concat([data['start_station_id'], data['end_station_id']])# "concating" t

uniqueid = np.unique(allstations) # Returning all the unique values from the allstation da
stationsusage = pd.DataFrame(columns=["station_id","Total_Uses"]) # new dataframe
for row in uniqueid:
    temp1 = data[data.start_station_id == row]# As start station
    temp2 = data[data.end_station_id == row] # As end station
    tempsum = len(temp1)+len(temp2) # sum
    stationsusage = stationsusage.append({'station_id':row,'Total_Uses':tempsum}, ignore_i

#plot graph
fig_dims = (40, 8)
fig, ax = plt.subplots(figsize=fig_dims)
#ax = axis
plt.xticks(rotation=90)
sns.barplot(data=stationsusage, x='station_id', y='Total_Uses')
```

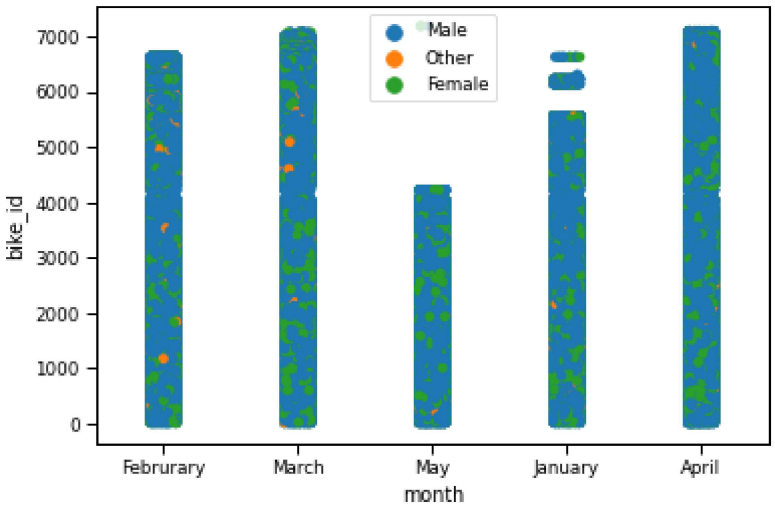
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f43b9822b90>
```



The above graph shows the total uses of a bike station, per its bike ID. I had attempted to plot this with the bike station name but the x axis was illegable. We can see some station have more popularity than others. Specifically double-digit station ID's which where possible placed in key areas with a high flow of people.

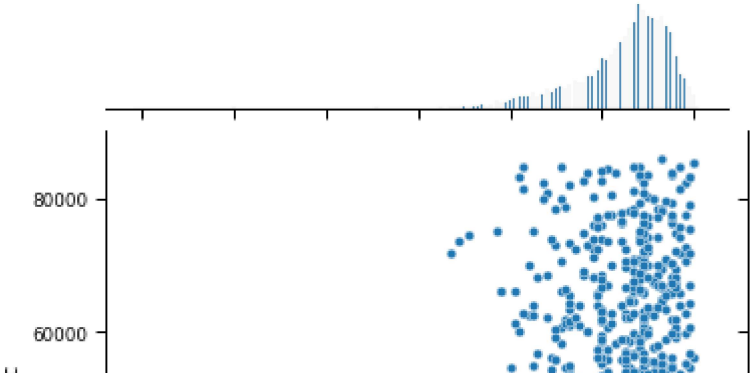
```
#box plot gender, unique users and member age
sns.stripplot(x='month', y='bike_id', data=data, hue='member_gender' )
plt.legend(loc=0)
```

```
<matplotlib.legend.Legend at 0x7f43b9817110>
```



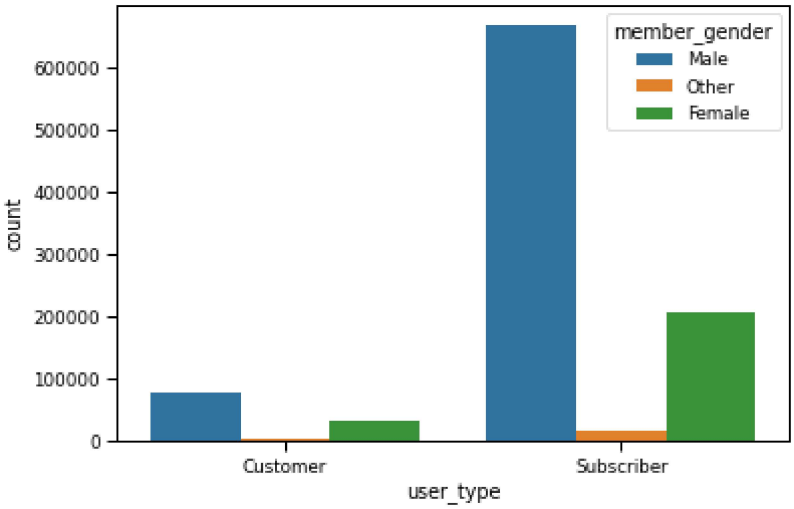

```
#the members age and trip duration
sns.jointplot(x='member_birth_year', y='trip_duration_sec', data=data)
```

```
<seaborn.axisgrid.JointGrid at 0x7f43b98279d0>
```




```
#count of user_type with split into member_gender
sns.countplot(data=data, x='user_type', hue='member_gender')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f43b5364450>
```



The above chart represents the type of user and the count of how many times a user has used the service in the given 5 month period.

Hypothesis Formulation

From the above graphs, we got some insight about the data. Since this data can be used to make a prediciton based on age group of the user, and if they are a customer or subscriber to understand how much they are likely to use the service and to what capacity, we have to know the attributes that has positive or negative and strong or weak correlation with usage. Here I made several hypotheses regarding to this matter.

First hypothesis

H0 = The younger the user, the more likely they are going to use the service.

Ha = The older the user, the more likely they are going to use the service.

Second hypothesis

H0 = The younger the member, the longer they will use the service.

Ha = The older the member, the longer they will use the service.

Third hypothesis

H0 = Popular stations are more likely to be used by subscribers.

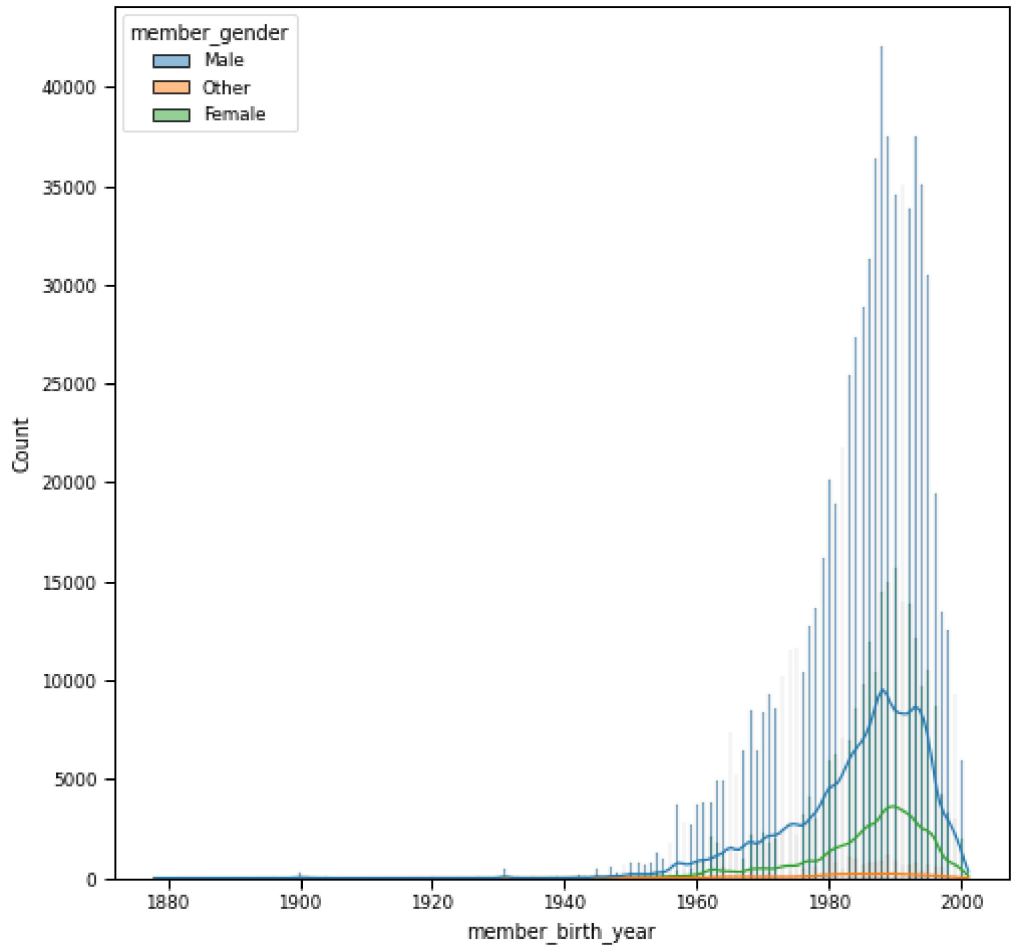
Ha = Popular stations are less likely to be used by subscribers.

Hypothesis Testing & Result

To test the hypothesis, I made a new chart bellow consisting of member_gender attribute, plotted to a historgram. If the hypothesis is true, we should see a left-skewed regression line. Else, if false, a right-skewed regression line. For extra exploration I have added the gender attribute as well.

```
#histogram of age

#plot graph
fig_dims = (8, 8)
fig, ax = plt.subplots(figsize=fig_dims)

sns.histplot(data=data, x="member_birth_year", kde=True, hue="member_gender")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f43b4f93550>
```



As shown above, the majority concesos of users lay around the "1990" area of the chart... While the regression line drops sharply off with anyone younger than 1995, or for anyone who may be older than 1990.

Further to this, we can see the majority of users are mail, however, there regression line is flatter for females as opposed to males. This may indicate that there is a higher likelyhood that the bike-sharing service appeals to a broader age demogaphic for woman than for men.

Summary

For further analysis, I suggest that we can do more insight finding in each variable through feature engineering, for example, reating unique counts of bikes at locations to understand how many times a location may be used. Further to this, involving other data sources such as map data to understand popularity distribution of the bikes and map out rough travel through the trip_duration_sec attribute. Thus, estimating the type of journey a bike may make.

There are some items missing from the dataset that could've been useful, such as time & date, distanc travelled by each bike or even a recalcualted ID per each user, to document multiple uses by the same member, thus understanding customer behaviour.