Part_I_exploration

February 25, 2023

1 Part I - Ford Bike Dataset Exploration Title

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1.2 Introduction

The Ford GoBike dataset contains anonymized trip data for the bike-sharing system from June 2017 to April 2019.

However, I decided to only use the data in the year 2018 (January 2018 to December 2018).

The data includes information on individual bike rides such as trip duration, start and end time, start and end station, bike ID, and user type. Additionally, demographic data such as age, gender, and membership type is provided for some users.

- `duration_sec`: The duration of the bike ride in seconds
- `start_time`: The date and time the bike ride started
- `end_time`: The date and time the bike ride ended
- `start_station_id`: The ID number of the station where the ride started
- `start_station_name`: The name of the station where the ride started
- `start_station_latitude`: The latitude of the station where the ride started
- `start_station_longitude`: The longitude of the station where the ride started
- `end_station_id`: The ID number of the station where the ride ended
- `end_station_name`: The name of the station where the ride ended
- `end_station_latitude`: The latitude of the station where the ride ended
- `end_station_longitude`: The longitude of the station where the ride ended
- `bike_id`: The ID number of the bike used in the ride
- `user_type`: The type of user, either "Subscriber" (members with monthly or annual memberships) or "Customer" (casual riders who - `purchase` a single ride or day pass)
- `member_birth_year`: The birth year of the user (for subscribers only)
- `member_gender`: The gender of the user (for subscribers only)

These columns provide information on the duration and location of the bike ride, the bike and station used, and some demographic information on the users.

1.2.1 Extra Packages

We will be calculating the distance between the start and end stations. To install this package, run the following command in the terminal:

```
pip install haversine
```

[ ]:
```
%pip install haversine
```

```
Requirement already satisfied: haversine in /Users/rellikakisyula/iCloud-
Drive/Documents/Classes/Python/Data-Analysis/data_analysis/lib/python3.9/site-
packages (2.7.0)

[notice] A new release of pip
available: 22.3.1 -> 23.0.1
[notice] To update, run:
pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

1.2.2 Importing Packages

[ ]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

%matplotlib inline
# import the haversine package
from haversine import haversine
```

1.2.3 Base Color

The base color for this project is `#1F77B4`.

[ ]:
```
base_color = sb.color_palette()[0]
```

1.2.4 Downloading the Dataset

I manually downloaded the datasets from the System Data | Bay Wheels | Lyft page. The datasets were in the form of a zip file. I extracted the zip files and saved the csv files in the `data` folder as this notebook. The zip files are in `data/zip_files` folder.

1.2.5 Unzipping the Dataset

Imagine you have zip files stored in `./data/zip_files`with names like 201801-fordgobike-tripdata.csv.zip, 201802-fordgobike-tripdata.csv.zip, etc. You can use the following code to extract all the zip files into the `./data/data_files` folder.

[ ]:
```
# Unzip zip files in the data/zip_files folder into the data/data_files folder
import zipfile
import os

# create a list of all zip files in the zip_files folder
zip_files = os.listdir('./data/zip_files')
```

```
# loop through the list of zip files
for zip_file in zip_files:
    # create a full path to the zip file
    zip_path = './data/zip_files/' + zip_file
    # extract the zip file to the data folder
    with zipfile.ZipFile(zip_path, 'r') as zip_ref:
        zip_ref.extractall('./data/data_files')
```

Note: The code above is adapted from How to unzip multiple files in a folder using Python?

Note: The folder `data/data_files` is not included in the repository because it contains the extracted csv files. These csv files can be generated by running the code above.

1.2.6 Combining the Datasets

I combined the datasets into one csv file by reading all the csv files in the `./data/data_files` folder into an individual pandas dataframe. I then saved the combined those individual dataframe into a csv file in the `data` folder as `bike_data.csv`.

[ ]:
```
# Read the data files from the data/data_files folder
january = pd.read_csv('./data/data_files/201801-fordgobike-tripdata.csv')
january.sample(5)
```

[ ]:
```
       duration_sec                start_time                  end_time  \
40135          1570  2018-01-20 15:19:13.0290  2018-01-20 15:45:23.2580
52908           381  2018-01-16 20:25:55.5880  2018-01-16 20:32:17.2260
40240           484  2018-01-20 15:10:02.0280  2018-01-20 15:18:06.1850
12490          1552  2018-01-29 08:55:26.1800  2018-01-29 09:21:18.7880
92451           350  2018-01-02 09:38:22.3660  2018-01-02 09:44:12.9570

       start_station_id                   start_station_name  \
40135               193         Grand Ave at Santa Clara Ave
52908               182             19th Street BART Station
40240                 7                  Frank H Ogawa Plaza
12490               145                 29th St at Church St
92451               324  Union Square (Powell St at Post St)

       start_station_latitude  start_station_longitude  end_station_id  \
40135               37.812744              -122.247215             186
52908               37.809013              -122.268247             196
40240               37.804562              -122.271738             179
12490               37.743684              -122.426806              17
92451               37.788300              -122.408531              21

                             end_station_name  end_station_latitude  \
40135                    Lakeside Dr at 14th St              37.801319
```

```
52908                        Grand Ave at Perkins St             37.808894
40240                      Telegraph Ave at 27th St             37.816073
12490  Embarcadero BART Station (Beale St at Market St)             37.792251
92451  Montgomery St BART Station (Market St at 2nd St)             37.789625

       end_station_longitude  bike_id   user_type  member_birth_year  \
40135            -122.262642     3475  Subscriber             1987.0
52908            -122.256460     3477  Subscriber             1986.0
40240            -122.267886     2673  Subscriber             1980.0
12490            -122.397086     1068  Subscriber             1980.0
92451            -122.400811     3668  Subscriber             1986.0

      member_gender bike_share_for_all_trip
40135        Female                      No
52908        Female                      No
40240          Male                     Yes
12490          Male                      No
92451          Male                      No
```

[ ]:
```
september = pd.read_csv('./data/data_files/201809-fordgobike-tripdata.csv')
september.sample(5)
```

[ ]:
```
        duration_sec                start_time                  end_time  \
49506           2040  2018-09-23 10:51:56.5990  2018-09-23 11:25:56.7880
87990            838  2018-09-17 16:38:15.2530  2018-09-17 16:52:14.1830
17672            348  2018-09-27 18:13:36.0380  2018-09-27 18:19:24.5470
17464            829  2018-09-27 18:20:24.9930  2018-09-27 18:34:14.0470
154120          1280  2018-09-06 21:38:27.9980  2018-09-06 21:59:48.9640

        start_station_id              start_station_name  \
49506               33.0        Golden Gate Ave at Hyde St
87990                8.0    The Embarcadero at Vallejo St
17672              350.0              8th St at Brannan St
17464              251.0  California St at University Ave
154120              78.0               Folsom St at 9th St

        start_station_latitude  start_station_longitude  end_station_id  \
49506                37.781650              -122.415408            33.0
87990                37.799953              -122.398525            30.0
17672                37.771431              -122.405787            49.0
17464                37.870555              -122.279720           244.0
154120               37.773717              -122.411647           105.0

                               end_station_name  end_station_latitude  \
49506                Golden Gate Ave at Hyde St             37.781650
87990   San Francisco Caltrain (Townsend St at 4th St)             37.776598
17672                         S Park St at 3rd St             37.780760
```

```
17464                    Shattuck Ave at Hearst Ave          37.873748
154120                        16th St at Prosper St          37.764285

        end_station_longitude  bike_id   user_type  member_birth_year  \
49506             -122.415408     1646  Subscriber             1968.0
87990             -122.395282     1056  Subscriber             1972.0
17672             -122.394989     3358    Customer             1979.0
17464             -122.268648     3028  Subscriber             1993.0
154120            -122.431804     2644  Subscriber             1987.0

       member_gender bike_share_for_all_trip
49506           Male                      No
87990           Male                      No
17672           Male                      No
17464           Male                      No
154120        Female                     Yes
```

Instead of reading the data files one by one, we can use a for loop to read all the files

[ ]:

```
# create a list of all data files in the data_files folder
data_files = os.listdir('./data/data_files')
```

[ ]:

```
# Function to loop through the data files and read them into a dataframe
def read_data_files( data_files):
    # create an empty list to store the dataframes
    dataframe_list = []
    # loop through the list of data files
    for data_file in data_files:
        # ignore if it is not a csv file
        if data_file[-3:] != 'csv':
            continue
        # create a full path to the data file
        data_path = './data/data_files/' + data_file
        # read the data file and append it to the list of dataframes
        dataframe_list.append(pd.read_csv(data_path))
    # return the list of dataframes
    return dataframe_list
```

[ ]:

```
dataframes = read_data_files(data_files)
# concatenate the dataframes into one dataframe
bike_data = pd.concat(dataframes, ignore_index=True)
```

[ ]:

```
bike_data.sample(5)
```

[ ]:

```
         duration_sec                start_time                  end_time  \
1267154           448  2018-08-25 13:48:18.5770  2018-08-25 13:55:47.5120
1771867           113  2018-04-23 17:07:25.9330  2018-04-23 17:09:19.3930
```

```
1607743          934  2018-10-02 18:53:50.3960  2018-10-02 19:09:24.6740
1206760         1077  2018-07-04 22:29:47.2840  2018-07-04 22:47:44.5170
1539946          313  2018-10-12 18:17:50.4570  2018-10-12 18:23:03.7000

         start_station_id              start_station_name  \
1267154               8.0   The Embarcadero at Vallejo St
1771867              64.0            5th St at Brannan St
1607743              73.0          Pierce St at Haight St
1206760               8.0   The Embarcadero at Vallejo St
1539946             141.0  Valencia St at Cesar Chavez St

         start_station_latitude  start_station_longitude  end_station_id  \
1267154               37.799953              -122.398525            15.0
1771867               37.776754              -122.399018            67.0
1607743               37.771793              -122.433708            16.0
1206760               37.799953              -122.398525             5.0
1539946               37.747998              -122.420219           121.0

                                          end_station_name  \
1267154  San Francisco Ferry Building (Harry Bridges Pl…
1771867  San Francisco Caltrain Station 2  (Townsend St…
1607743                          Steuart St at Market St
1206760       Powell St BART Station (Market St at 5th St)
1539946                                 Mission Playground

         end_station_latitude  end_station_longitude  bike_id   user_type  \
1267154             37.795392            -122.394203     2025    Customer
1771867             37.776639            -122.395526      774  Subscriber
1607743             37.794130            -122.394430     4324  Subscriber
1206760             37.783899            -122.408445      720    Customer
1539946             37.759210            -122.421339     3062  Subscriber

         member_birth_year member_gender bike_share_for_all_trip
1267154             1998.0        Female                      No
1771867             1983.0          Male                      No
1607743             1990.0          Male                      No
1206760             1994.0          Male                      No
1539946             1984.0          Male                      No
```

[ ]:
```
bike_data.shape
```

[ ]: (1863721, 16)

To confirm if all the rows of each dataset was added onto the dataframe, lets check the number of rows in the combined dataframe and the sum of the number of rows in each individual dataframe.

```
[ ]: number_of_rows = []
# Loop through the list of dataframes and print the shape of each dataframe
for dataframe in dataframes:
    print(dataframe.shape)
    number_of_rows.append(dataframe.shape[0])
print(number_of_rows)
# Confirm that sum of the number of rows in each dataframe is equal to the␣
↪number of rows in the concatenated dataframe
sum(number_of_rows) == bike_data.shape[0]
```

```
(106718, 16)
(134135, 16)
(186217, 16)
(195968, 16)
(179125, 16)
(131363, 16)
(94802, 16)
(199222, 16)
(192162, 16)
(201458, 16)
(111382, 16)
(131169, 16)
[106718, 134135, 186217, 195968, 179125, 131363, 94802, 199222, 192162, 201458,
111382, 131169]
```

```
[ ]: True
```

1.3 Data Preparation

The following are the changes made to the dataset before saving it: 1. Get the distance travelled from the coordinates using `haversine` package 2. Get the age of the users from the `member_birth_year` column 3. Extract the hour, day, month and year from the `start_time`

1.3.1 1: Calcultate distance travelled using the `haversine` package

I decided to find the distance the riders rode. I used the Haversine formula to calculate the distance between the start and end points of the ride.

```
[ ]: # Create a new column `distance` which is the distance between the start and␣
↪end station
bike_data['distance'] = bike_data.apply(lambda x:␣
↪haversine((x['start_station_latitude'], x['start_station_longitude']),
                                                                          ␣
↪(x['end_station_latitude'], x['end_station_longitude'])), axis=1)
```

1.3.2 2: Calculate the age of the users

[ ]:
```
# Create a new column `member_age` which is the difference between the 2018 and␣
↪`member_birth_year`
bike_data['member_age'] = 2018 - bike_data.member_birth_year
# Select the column member_birth_year and member_age
bike_data[['member_birth_year', 'member_age']].sample(10)
```

[ ]:
```
         member_birth_year  member_age
1435023             1986.0        32.0
1423155             1978.0        40.0
595063              1977.0        41.0
147380              1990.0        28.0
15032               1983.0        35.0
1423772             1983.0        35.0
1641358             1988.0        30.0
973857              1993.0        25.0
326931              1977.0        41.0
676258              1988.0        30.0
```

1.3.3 Extract the hour, day, month and year from the start_time column

[ ]:
```
bike_data['start_time'] = pd.to_datetime(bike_data['start_time'])
# Extract the month name from the start_time column
bike_data['month_of_year'] = bike_data['start_time'].dt.strftime('%B')

# Extract the day of the week from the start_time column
bike_data['day_of_week'] = bike_data['start_time'].dt.strftime('%A')

# Extract the hour from the start_time column
bike_data['hour'] = bike_data['start_time'].dt.strftime('%H')
```

[ ]:
```
# Select the columns start_time, month, day_of_week, hour
bike_data[['start_time', 'month_of_year', 'day_of_week', 'hour']].sample(10)
```

[ ]:
```
                     start_time month_of_year day_of_week hour
437233  2018-06-29 08:34:20.773          June      Friday   08
528920  2018-06-15 12:48:45.124          June      Friday   12
1229123 2018-08-31 17:14:12.407        August      Friday   17
1649728 2018-03-25 18:23:05.482         March      Sunday   18
1218786 2018-07-02 18:43:28.254          July      Monday   18
841030  2018-12-19 17:12:07.154      December   Wednesday   17
527777  2018-06-15 16:28:44.061          June      Friday   16
96383   2018-02-03 13:14:56.890      February    Saturday   13
618206  2018-06-01 17:40:02.348          June      Friday   17
584271  2018-06-06 22:00:23.834          June   Wednesday   22
```

```
[ ]: # Using the `month_of_year` column, perform a value count
bike_data.month_of_year.value_counts()
```

```
[ ]: October      201458
     July         199222
     June         195968
     August       192162
     September    186217
     May          179125
     November     134135
     December     131363
     April        131169
     March        111382
     February     106718
     January       94802
     Name: month_of_year, dtype: int64
```

1.3.4 Creating period of day (`period_of_day`) column from the `hour` column

As mentioned above, I want to get the period of the day, that is either **Early Morning**, **Morning**, **Afternoon**, **Evening**, **Night**, **Late Night**, **Midnight**. I will use the `start_time` column to extract the hour of the day and then categorize it into the above periods.

```
[ ]: # Using the hour, generate a new column `period_of_day` which is the period of␣
     ↪the day
# Early Morning: 3am - 6am, Morning: 6am - 12pm, Afternoon: 12pm - 3pm, Evening:
     ↪ 3pm - 6pm, Night: 6pm - 9pm, Late Night: 9pm - 12am, Midnight: 12am - 3am
bike_data['period_of_day'] = bike_data['hour'].apply(lambda x: 'Early Morning'␣
     ↪if 3 <= int(x) < 6 else 'Morning' if 6 <= int(x) < 12 else 'Afternoon' if 12␣
     ↪<= int(x) < 15 else 'Evening' if 15 <= int(x) < 18 else 'Night' if 18 <=␣
     ↪int(x) < 21 else 'Late Night' if 21 <= int(x) < 24 else 'Midnight')
```

```
[ ]: # Select the columns start_time, hour, period_of_day
bike_data[['start_time', 'hour', 'period_of_day']].sample(10)
```

```
[ ]:                      start_time hour period_of_day
     1508529 2018-10-17 19:11:00.126   19         Night
     1219224 2018-07-02 18:11:27.517   18         Night
     1786551 2018-04-19 18:35:27.581   18         Night
     166591  2018-11-14 06:56:18.901   06       Morning
     1260694 2018-08-27 08:16:49.245   08       Morning
     573530  2018-06-08 14:20:49.367   14     Afternoon
     1253652 2018-08-28 08:41:03.884   08       Morning
     1617356 2018-10-01 15:00:36.339   15       Evening
     1508588 2018-10-17 19:04:44.449   19         Night
     1330545 2018-08-15 09:02:52.110   09       Morning
```

[ ]:
```
# Use the period_of_day and perform a value count
bike_data.period_of_day.value_counts()
```

[ ]:
```
Morning          669598
Evening          459806
Night            341831
Afternoon        261127
Late Night        96657
Midnight          19815
Early Morning     14887
Name: period_of_day, dtype: int64
```

1.3.5 Saving the `bike_data` dataframe to csv file.

I saved the combined dataframe as `bike_data.csv` in the `data` folder.

```
# Save the combined dataframe as bike_data.csv in the data folder
bike_data.to_csv('data/bike_data.csv', index=False)
```

[ ]:
```
# Save the combined dataframe as bike_data.csv in the data folder
bike_data.to_csv('data/bike_data.csv', index=False)
```

> **Note:** The **file** `data/bike_data.csv` is not included in the repository. The `bike_data.csv` file can be generated by running the code above.

1.4 Preliminary Wrangling

> Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

[ ]:
```
# Read the bike_data.csv file into a dataframe
combined_bike_data = pd.read_csv('data/bike_data.csv')
combined_bike_data.sample(5)
```

[ ]:
```
         duration_sec               start_time                  end_time  \
1231274          2675  2018-08-31 11:24:46.659  2018-08-31 12:09:22.6340
8174              536  2018-02-27 08:12:39.992  2018-02-27 08:21:36.8300
1310768           431  2018-08-18 09:57:10.970  2018-08-18 10:04:22.7610
770504           1411  2018-05-06 15:31:20.274  2018-05-06 15:54:51.9120
1508289           351  2018-10-17 19:57:02.204  2018-10-17 20:02:53.8040

         start_station_id                                start_station_name  \
1231274              77.0                               11th St at Natoma St
8174                 15.0  San Francisco Ferry Building (Harry Bridges Pl…
1310768             271.0                                     San Pablo Park
770504               72.0                                 Page St at Scott St
1508289             284.0  Yerba Buena Center for the Arts (Howard St at …

         start_station_latitude  start_station_longitude  end_station_id  \
```

```
1231274                 37.773507              -122.416040             14.0
8174                    37.795392              -122.394203             81.0
1310768                 37.855783              -122.283127            241.0
770504                  37.772406              -122.435650             15.0
1508289                 37.784872              -122.400876             61.0

                                              end_station_name  \
1231274                                   Clay St at Battery St
8174                                         Berry St at 4th St
1310768                                      Ashby BART Station
770504   San Francisco Ferry Building (Harry Bridges Pl…
1508289                                     Howard St at 8th St

         end_station_latitude  …   user_type  member_birth_year  \
1231274             37.795001  …    Customer             1988.0
8174                37.775880  …  Subscriber             1982.0
1310768             37.852477  …  Subscriber             1973.0
770504              37.795392  …  Subscriber             1982.0
1508289             37.776513  …  Subscriber             1987.0

        member_gender  bike_share_for_all_trip  distance member_age  \
1231274          Male                       No  2.776100       30.0
8174             Male                       No  2.171537       36.0
1310768          Male                       No  1.191899       45.0
770504         Female                       No  4.449675       36.0
1508289          Male                       No  1.305494       31.0

         month_of_year  day_of_week hour period_of_day
1231274         August       Friday   11       Morning
8174          February      Tuesday    8       Morning
1310768         August     Saturday    9       Morning
770504             May       Sunday   15       Evening
1508289        October    Wednesday   19         Night

[5 rows x 22 columns]
```

1.4.1 What is the structure of your dataset?

[ ]:
```python
# Check the shape of the data
combined_bike_data.shape
```

[ ]:
```
(1863721, 22)
```

[ ]:
```python
# Get general information about the dataframe, including the number of non-null
↪values in each column
combined_bike_data.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1863721 entries, 0 to 1863720
Data columns (total 22 columns):
 #   Column                   Non-Null Count    Dtype
---  ------                   --------------    -----
 0   duration_sec             1863721 non-null  int64
 1   start_time               1863721 non-null  object
 2   end_time                 1863721 non-null  object
 3   start_station_id         1851950 non-null  float64
 4   start_station_name       1851950 non-null  object
 5   start_station_latitude   1863721 non-null  float64
 6   start_station_longitude  1863721 non-null  float64
 7   end_station_id           1851950 non-null  float64
 8   end_station_name         1851950 non-null  object
 9   end_station_latitude     1863721 non-null  float64
 10  end_station_longitude    1863721 non-null  float64
 11  bike_id                  1863721 non-null  int64
 12  user_type                1863721 non-null  object
 13  member_birth_year        1753003 non-null  float64
 14  member_gender            1753354 non-null  object
 15  bike_share_for_all_trip  1863721 non-null  object
 16  distance                 1863721 non-null  float64
 17  member_age               1753003 non-null  float64
 18  month_of_year            1863721 non-null  object
 19  day_of_week              1863721 non-null  object
 20  hour                     1863721 non-null  int64
 21  period_of_day            1863721 non-null  object
dtypes: float64(9), int64(3), object(10)
memory usage: 312.8+ MB
```

I have observed the following properties about the dataset: - The `start_time`, `end_time` are of object type, I will convert them to datetime type so it will be possible to perform analysis - The dataset contains some missing values in the `start_station_id`, `start_station_name`, `end_station_id`, and `end_station_name` columns. I will drop the rows with missing values.

[ ]:
```
# View descriptive statistics for numeric variables
combined_bike_data.describe()
```

[ ]:
```
       duration_sec  start_station_id  start_station_latitude  \
count  1.863721e+06      1.851950e+06            1.863721e+06
mean   8.573026e+02      1.196744e+02            3.776678e+01
std    2.370379e+03      1.003976e+02            1.057689e-01
min    6.100000e+01      3.000000e+00            3.726331e+01
25%    3.500000e+02      3.300000e+01            3.777106e+01
50%    5.560000e+02      8.900000e+01            3.778107e+01
75%    8.720000e+02      1.860000e+02            3.779625e+01
max    8.636600e+04      3.810000e+02            4.551000e+01
```

	start_station_longitude	end_station_id	end_station_latitude
count	1.863721e+06	1.851950e+06	1.863721e+06
mean	-1.223492e+02	1.181730e+02	3.776690e+01
std	1.654634e-01	1.004403e+02	1.056483e-01
min	-1.224737e+02	3.000000e+00	3.726331e+01
25%	-1.224114e+02	3.000000e+01	3.777106e+01
50%	-1.223974e+02	8.800000e+01	3.778127e+01
75%	-1.222865e+02	1.830000e+02	3.779728e+01
max	-7.357000e+01	3.810000e+02	4.551000e+01

	end_station_longitude	bike_id	member_birth_year	distance
count	1.863721e+06	1.863721e+06	1.753003e+06	1.863721e+06
mean	-1.223487e+02	2.296851e+03	1.983088e+03	1.590931e+00
std	1.650597e-01	1.287733e+03	1.044289e+01	1.028364e+00
min	-1.224737e+02	1.100000e+01	1.881000e+03	0.000000e+00
25%	-1.224094e+02	1.225000e+03	1.978000e+03	8.675446e-01
50%	-1.223971e+02	2.338000e+03	1.985000e+03	1.374592e+00
75%	-1.222894e+02	3.333000e+03	1.991000e+03	2.087456e+00
max	-7.357000e+01	6.234000e+03	2.000000e+03	6.530934e+01

	member_age	hour
count	1.753003e+06	1.863721e+06
mean	3.491204e+01	1.351437e+01
std	1.044289e+01	4.742223e+00
min	1.800000e+01	0.000000e+00
25%	2.700000e+01	9.000000e+00
50%	3.300000e+01	1.400000e+01
75%	4.000000e+01	1.700000e+01
max	1.370000e+02	2.300000e+01

The dataset contains 1863721 rows and 16 columns. In the **data preparation** section, I added 6 more columns name `member_age`, `distance`, `hour`, `period_of_day`, `day_of_week` and `month_of_year`. The features are described above. - **trip duration**: This includes columns for the duration of the bike ride in seconds, the date and time the bike ride started, and the date and time the bike ride ended. - **start station**: This includes columns for the ID number of the station where the ride started, the name of the station where the ride started, and the latitude and longitude of the station where the ride started. - **end station**: This includes columns for the ID number of the station where the ride ended, the name of the station where the ride ended, and the latitude and longitude of the station where the ride ended. - **bike**: This includes columns for the ID number of the bike used in the ride. - **customer data**: This includes information such as if the person who rented the bike was a customer or subscriber. It also states information of the person who rented such as date of birth, gender, age, and membership type.

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

1. Based on the Ford GoBike dataset, I can explore when and where most trips are taken as the dataset includes information on the start time and location of each ride. This information can help me identify popular starting points and times for the bike-sharing system. I will start by analyzing the `start_station_name`. I will then use `start_station_latitude` and `start_station_longitude` columns to calculate the distance of travel. Doing so, I will be able to get a better understanding of when and where the most trips originate.

2. In addition to identifying popular starting points and times, I am also interested in exploring the characteristics of the riders such as age, sex, and user type. This can be done by analyzing the `member_birth_year`, `member_gender`, and `user_type` columns. Understanding the demographics of the riders can help me identify patterns in bike usage and preferences.

3. I am also interested in exploring the time of the day, that is either **morning**, **afternoon**, **evening** or **night**. Understanding the time of the day can help me identify patterns in bike usage and preferences. Moreover, I want to explore the day of the week and month of the year. Understanding the day of the week and month of the year can help me identify patterns in bike usage and preferences.

4. Finally, I plan to analyze the duration of the trips for each starting point and time. This information can help me understand how long riders typically use the bikes for and whether there are any patterns or trends in trip duration based on the starting location or time. Overall, I am looking forward to exploring this dataset and gaining insights into the usage patterns of the Ford GoBike system.

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

To observe the points mentioned above, we can use the following features of the Ford GoBike dataset: 1. To identify the popular starting points and times, we can use the start_time, start_station_id, start_station_name, start_station_latitude, and start_station_longitude columns. 2. To explore the characteristics of the riders, we can use the member_birth_year, member_gender, and user_type columns. 3. To explore the time of the day, the day of the week and month of the year, we can `hour`, `period_of_day`, `day_of_week`, `month_of_year` columns we extracted from the `start_time` column in our **data perparation phase**. 4. To analyze the duration of the trips for each starting point and time, we can use the duration_sec column, as well as the start_time and start_station_id columns to match up each ride's duration with its starting point and time.

By examining these features of the dataset, we can gain insights into when and where most trips are taken, the characteristics of the riders, and the duration of the trips for each starting point and time. These insights can help us understand usage patterns and preferences, and identify opportunities for improving the Ford GoBike system.

Expectations before univariate, bivariate, and multivariate exploration

1. I expect that the most popular starting points and times will be in the morning and afternoon, and that the most popular starting points will be near the city center.
2. I expect that young riders will be more that the older riders who are subscribers
3. Comparing the subscribers and customers, I expect that the subscribers will be more than the customers.
4. Concerning the genders, I expect that males will be more frequent riders than the female riders

1.5 Data Wrangling

1.5.1 Data Assessment

[ ]:
```python
# Lets see the top 5 rows
combined_bike_data.head()
```

[ ]:
```
   duration_sec                start_time                  end_time  \
0           598  2018-02-28 23:59:47.097  2018-03-01 00:09:45.1870
1           943  2018-02-28 23:21:16.495  2018-02-28 23:36:59.9740
2         18587  2018-02-28 18:20:55.190  2018-02-28 23:30:42.9250
3         18558  2018-02-28 18:20:53.621  2018-02-28 23:30:12.4500
4           885  2018-02-28 23:15:12.858  2018-02-28 23:29:58.6080

   start_station_id                                 start_station_name  \
0             284.0  Yerba Buena Center for the Arts (Howard St at …
1               6.0                      The Embarcadero at Sansome St
2              93.0                       4th St at Mission Bay Blvd S
3              93.0                       4th St at Mission Bay Blvd S
4             308.0                                   San Pedro Square

   start_station_latitude  start_station_longitude  end_station_id  \
0               37.784872              -122.400876           114.0
1               37.804770              -122.403234           324.0
2               37.770407              -122.391198            15.0
3               37.770407              -122.391198            15.0
4               37.336802              -121.894090           297.0

                                    end_station_name  end_station_latitude  \
0                          Rhode Island St at 17th St             37.764478
1                 Union Square (Powell St at Post St)             37.788300
2  San Francisco Ferry Building (Harry Bridges Pl…              37.795392
3  San Francisco Ferry Building (Harry Bridges Pl…              37.795392
4                              Locust St at Grant St             37.322980

   …   user_type  member_birth_year member_gender  bike_share_for_all_trip  \
0  …  Subscriber             1988.0          Male                       No
1  …    Customer             1987.0          Male                       No
2  …    Customer             1986.0        Female                       No
```

```
3  …    Customer             1981.0         Male                      No
4  …  Subscriber             1976.0       Female                     Yes

   distance member_age  month_of_year  day_of_week hour period_of_day
0  2.272573       30.0       February    Wednesday   23    Late Night
1  1.889595       31.0       February    Wednesday   23    Late Night
2  2.790685       32.0       February    Wednesday   18         Night
3  2.790685       37.0       February    Wednesday   18         Night
4  1.630600       42.0       February    Wednesday   23    Late Night

[5 rows x 22 columns]
```

[ ]:

```
# Lets see the last 10 columns
combined_bike_data.tail(5)
```

[ ]:

```
         duration_sec               start_time                 end_time  \
1863716           887  2018-04-01 00:00:08.163  2018-04-01 00:14:55.5710
1863717           387  2018-04-01 00:08:06.367  2018-04-01 00:14:33.9940
1863718           480  2018-04-01 00:06:21.281  2018-04-01 00:14:21.4600
1863719           503  2018-04-01 00:04:36.805  2018-04-01 00:13:00.1020
1863720           192  2018-04-01 00:02:03.827  2018-04-01 00:05:16.4430

         start_station_id                                 start_station_name  \
1863716             194.0                      Lakeshore Ave at Trestle Glen Rd
1863717              30.0        San Francisco Caltrain (Townsend St at 4th St)
1863718              44.0   Civic Center/UN Plaza BART Station (Market St …
1863719             100.0                                Bryant St at 15th St
1863720             176.0                                MacArthur BART Station

         start_station_latitude  start_station_longitude  end_station_id  \
1863716               37.811081              -122.243268           215.0
1863717               37.776598              -122.395282            79.0
1863718               37.781074              -122.411738            21.0
1863719               37.767100              -122.410662            93.0
1863720               37.828410              -122.266315           215.0

                                    end_station_name  \
1863716                       34th St at Telegraph Ave
1863717                            7th St at Brannan St
1863718  Montgomery St BART Station (Market St at 2nd St)
1863719                   4th St at Mission Bay Blvd S
1863720                       34th St at Telegraph Ave

         end_station_latitude  …   user_type  member_birth_year  \
1863716             37.822547  …  Subscriber             1988.0
1863717             37.773492  …  Subscriber             1995.0
1863718             37.789625  …    Customer             1984.0
```

```
1863719          37.770407  …  Subscriber           1984.0
1863720          37.822547  …    Customer           1984.0

        member_gender  bike_share_for_all_trip  distance member_age  \
1863716          Male                      Yes  2.392783       30.0
1863717        Female                       No  0.814323       23.0
1863718          Male                       No  1.351422       34.0
1863719        Female                       No  1.749894       34.0
1863720          Male                       No  0.651878       34.0

         month_of_year  day_of_week hour period_of_day
1863716          April       Sunday    0      Midnight
1863717          April       Sunday    0      Midnight
1863718          April       Sunday    0      Midnight
1863719          April       Sunday    0      Midnight
1863720          April       Sunday    0      Midnight

[5 rows x 22 columns]
```

[ ]:
```
# Lets see the number of unique values in each column
combined_bike_data.nunique()
```

[ ]:
```
duration_sec                 16709
start_time                 1863584
end_time                   1863610
start_station_id               331
start_station_name             348
start_station_latitude         369
start_station_longitude        370
end_station_id                 331
end_station_name               348
end_station_latitude           370
end_station_longitude          371
bike_id                       5054
user_type                        2
member_birth_year               86
member_gender                    3
bike_share_for_all_trip          2
distance                     19145
member_age                      86
month_of_year                   12
day_of_week                      7
hour                            24
period_of_day                    7
dtype: int64
```

[ ]:
```
# Lets see the number of missing values in each column
combined_bike_data.isnull().sum()
```

[ ]:
```
duration_sec                    0
start_time                      0
end_time                        0
start_station_id            11771
start_station_name          11771
start_station_latitude          0
start_station_longitude         0
end_station_id              11771
end_station_name            11771
end_station_latitude            0
end_station_longitude           0
bike_id                         0
user_type                       0
member_birth_year          110718
member_gender              110367
bike_share_for_all_trip         0
distance                        0
member_age                 110718
month_of_year                   0
day_of_week                     0
hour                            0
period_of_day                   0
dtype: int64
```

[ ]:
```
# Lets see the number of duplicated values in each column
combined_bike_data.duplicated().sum()
```

[ ]:
```
0
```

[ ]:
```
# Lets see a sample of the data frame 5 rows
combined_bike_data.sample(5)
```

[ ]:
```
         duration_sec               start_time                  end_time  \
1569747           993  2018-10-08 18:07:51.185  2018-10-08 18:24:24.5190
361692            589  2018-09-12 09:32:46.681  2018-09-12 09:42:36.2240
779928            298  2018-05-04 11:40:37.797  2018-05-04 11:45:36.2290
163784          13547  2018-11-14 10:13:54.193  2018-11-14 13:59:41.7580
1158152          1740  2018-07-12 11:04:16.918  2018-07-12 11:33:17.8090

         start_station_id                               start_station_name  \
1569747              66.0                              3rd St at Townsend St
361692               43.0  San Francisco Public Library (Grove St at Hyde…
779928                6.0                      The Embarcadero at Sansome St
163784                8.0                      The Embarcadero at Vallejo St
```

```
1158152            49.0                                S Park St at 3rd St

         start_station_latitude  start_station_longitude  end_station_id  \
1569747               37.778742              -122.392741           139.0
361692                37.778768              -122.415929            21.0
779928                37.804770              -122.403234             9.0
163784                37.799953              -122.398525           377.0
1158152               37.780760              -122.394989            66.0

                                        end_station_name  \
1569747          Garfield Square (25th St at Harrison St)
361692   Montgomery St BART Station (Market St at 2nd St)
779928                             Broadway at Battery St
163784                              Fell St at Stanyan St
1158152                             3rd St at Townsend St

         end_station_latitude  …   user_type  member_birth_year  \
1569747             37.751017  …  Subscriber             1990.0
361692              37.789625  …  Subscriber             1975.0
779928              37.798572  …  Subscriber             1989.0
163784              37.771917  …    Customer             1976.0
1158152             37.778742  …  Subscriber             1974.0

        member_gender  bike_share_for_all_trip  distance member_age  \
1569747          Male                       No  3.512900       28.0
361692         Female                       No  1.795210       43.0
779928         Female                       No  0.719818       29.0
163784           Male                       No  5.764730       42.0
1158152          Male                      Yes  0.299046       44.0

         month_of_year  day_of_week hour period_of_day
1569747        October       Monday   18         Night
361692       September    Wednesday    9       Morning
779928             May       Friday   11       Morning
163784        November    Wednesday   10       Morning
1158152           July     Thursday   11       Morning

[5 rows x 22 columns]
```

[ ]:

```
# Lets see the information of the data frame using info() and verbose=True
combined_bike_data.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1863721 entries, 0 to 1863720
Data columns (total 22 columns):
 #   Column                   Dtype
---  ------                   -----
```

```
 0   duration_sec             int64
 1   start_time               object
 2   end_time                 object
 3   start_station_id         float64
 4   start_station_name       object
 5   start_station_latitude   float64
 6   start_station_longitude  float64
 7   end_station_id           float64
 8   end_station_name         object
 9   end_station_latitude     float64
 10  end_station_longitude    float64
 11  bike_id                  int64
 12  user_type                object
 13  member_birth_year        float64
 14  member_gender            object
 15  bike_share_for_all_trip  object
 16  distance                 float64
 17  member_age               float64
 18  month_of_year            object
 19  day_of_week              object
 20  hour                     int64
 21  period_of_day            object
dtypes: float64(9), int64(3), object(10)
memory usage: 312.8+ MB
```

1.5.2 Quality Issues

- The `start_time` and `end_time` are of object type
- The `user_type`, `bike_share_for_all_trip` and `member_gender` are of object type
- The `hour` is of int type
- The dataset contains some missing values in the `start_station_id`, `start_station_name`, `end_station_id`, `end_station_name`, `member_birth_year` and `member_gender` columns

1.5.3 Make a copy of the original dataset

[ ]:
```
# Make the copy of the data frame
cc_bike_data = combined_bike_data.copy()
```

[ ]:
```
cc_bike_data.shape
```

[ ]:
```
(1863721, 22)
```

Define: **ISSUE 1:** Convert the `start_time` and `end_time` to datetime type

Code

```
[ ]: # Convert the `start_time` and `end_time` to datetime type
cc_bike_data['start_time'] = pd.to_datetime(cc_bike_data['start_time'])
cc_bike_data['end_time'] = pd.to_datetime(cc_bike_data['end_time'])
```

Test

```
[ ]: # Test the conversion using info() with verbose=True and show_counts=True
cc_bike_data.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1863721 entries, 0 to 1863720
Data columns (total 22 columns):
 #   Column                   Non-Null Count    Dtype
---  ------                   --------------    -----
 0   duration_sec             1863721 non-null  int64
 1   start_time               1863721 non-null  datetime64[ns]
 2   end_time                 1863721 non-null  datetime64[ns]
 3   start_station_id         1851950 non-null  float64
 4   start_station_name       1851950 non-null  object
 5   start_station_latitude   1863721 non-null  float64
 6   start_station_longitude  1863721 non-null  float64
 7   end_station_id           1851950 non-null  float64
 8   end_station_name         1851950 non-null  object
 9   end_station_latitude     1863721 non-null  float64
 10  end_station_longitude    1863721 non-null  float64
 11  bike_id                  1863721 non-null  int64
 12  user_type                1863721 non-null  object
 13  member_birth_year        1753003 non-null  float64
 14  member_gender            1753354 non-null  object
 15  bike_share_for_all_trip  1863721 non-null  object
 16  distance                 1863721 non-null  float64
 17  member_age               1753003 non-null  float64
 18  month_of_year            1863721 non-null  object
 19  day_of_week              1863721 non-null  object
 20  hour                     1863721 non-null  int64
 21  period_of_day            1863721 non-null  object
dtypes: datetime64[ns](2), float64(9), int64(3), object(8)
memory usage: 312.8+ MB
```

Define **ISSUE 2:** Convert the `user_type`, `bike_share_for_all_trip` and `member_gender` to category type

Code

```
[ ]: # Convert the `user_type`, `bike_share_for_all_trip` and `member_gender` to␣
 ↪category type
cc_bike_data.user_type = cc_bike_data.user_type.astype('category')
```

```
cc_bike_data.bike_share_for_all_trip = cc_bike_data.bike_share_for_all_trip.
 ↪astype('category')
cc_bike_data.member_gender = cc_bike_data.member_gender.astype('category')
```

Test

[ ]:
```
# Test the conversion using info() with verbose=True and show_counts=True
cc_bike_data.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1863721 entries, 0 to 1863720
Data columns (total 22 columns):
 #   Column                   Non-Null Count    Dtype
---  ------                   --------------    -----
 0   duration_sec             1863721 non-null  int64
 1   start_time               1863721 non-null  datetime64[ns]
 2   end_time                 1863721 non-null  datetime64[ns]
 3   start_station_id         1851950 non-null  float64
 4   start_station_name       1851950 non-null  object
 5   start_station_latitude   1863721 non-null  float64
 6   start_station_longitude  1863721 non-null  float64
 7   end_station_id           1851950 non-null  float64
 8   end_station_name         1851950 non-null  object
 9   end_station_latitude     1863721 non-null  float64
 10  end_station_longitude    1863721 non-null  float64
 11  bike_id                  1863721 non-null  int64
 12  user_type                1863721 non-null  category
 13  member_birth_year        1753003 non-null  float64
 14  member_gender            1753354 non-null  category
 15  bike_share_for_all_trip  1863721 non-null  category
 16  distance                 1863721 non-null  float64
 17  member_age               1753003 non-null  float64
 18  month_of_year            1863721 non-null  object
 19  day_of_week              1863721 non-null  object
 20  hour                     1863721 non-null  int64
 21  period_of_day            1863721 non-null  object
dtypes: category(3), datetime64[ns](2), float64(9), int64(3), object(5)
memory usage: 275.5+ MB
```

Define **ISSUE 3:** Convert the hour to object type

Code

[ ]:
```
# Convert `hour` to category type
cc_bike_data.hour = cc_bike_data.hour.astype('object')
```

Test

```
[ ]: # Test the conversion using info() with verbose=True and show_counts=True
cc_bike_data.info(verbose=True, show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1863721 entries, 0 to 1863720
Data columns (total 22 columns):
 #   Column                   Non-Null Count    Dtype
---  ------                   --------------    -----
 0   duration_sec             1863721 non-null  int64
 1   start_time               1863721 non-null  datetime64[ns]
 2   end_time                 1863721 non-null  datetime64[ns]
 3   start_station_id         1851950 non-null  float64
 4   start_station_name       1851950 non-null  object
 5   start_station_latitude   1863721 non-null  float64
 6   start_station_longitude  1863721 non-null  float64
 7   end_station_id           1851950 non-null  float64
 8   end_station_name         1851950 non-null  object
 9   end_station_latitude     1863721 non-null  float64
 10  end_station_longitude    1863721 non-null  float64
 11  bike_id                  1863721 non-null  int64
 12  user_type                1863721 non-null  category
 13  member_birth_year        1753003 non-null  float64
 14  member_gender            1753354 non-null  category
 15  bike_share_for_all_trip  1863721 non-null  category
 16  distance                 1863721 non-null  float64
 17  member_age               1753003 non-null  float64
 18  month_of_year            1863721 non-null  object
 19  day_of_week              1863721 non-null  object
 20  hour                     1863721 non-null  object
 21  period_of_day            1863721 non-null  object
dtypes: category(3), datetime64[ns](2), float64(9), int64(2), object(6)
memory usage: 275.5+ MB
```

Define ISSUE 4: Remove rows where the `start_station_id`, `start_station_name`, `end_station_id`, `end_station_name` have missing values

Code

```
[ ]: # Remove the rows with missing values in column `start_station_id`,␣
      ↪`start_station_name`, `end_station_id`, `end_station_name`
cc_bike_data.dropna(subset=['start_station_id', 'start_station_name',␣
      ↪'end_station_id', 'end_station_name'], inplace=True)
```

Test

```
[ ]: # Test if the rows with missing values in column `start_station_id`,␣
      ↪`start_station_name`, `end_station_id`, `end_station_name` are removed
cc_bike_data.isnull().sum()
```

[ ]:
```
duration_sec                    0
start_time                      0
end_time                        0
start_station_id                0
start_station_name              0
start_station_latitude          0
start_station_longitude         0
end_station_id                  0
end_station_name                0
end_station_latitude            0
end_station_longitude           0
bike_id                         0
user_type                       0
member_birth_year          110394
member_gender              110043
bike_share_for_all_trip         0
distance                        0
member_age                 110394
month_of_year                   0
day_of_week                     0
hour                            0
period_of_day                   0
dtype: int64
```

[ ]:
```
# value count of hour
cc_bike_data.hour.value_counts()
```

[ ]:
```
17    218862
8     206081
18    170124
9     160066
16    142347
19    102765
7     101475
15     96219
12     89340
13     87062
10     83603
14     82670
11     78976
20     65825
21     46466
6      36256
22     30792
23     18510
0      10158
5      10010
```

```
1       5841
2       3679
4       2718
3       2105
Name: hour, dtype: int64
```

1.5.4 Creating an ordered categorical type for the `period_of_day` column, `day_of_week` column and `month_of_year` column

The `period_of_day` column will contain the values which are ordered from **Midnight** **Early Morning** **Morning** **Afternoon** **Evening** **Night** **Late Night**

The `day_of_week` column will contain the values which are ordered from **Monday** **Tuesday** **Wednesday** **Thursday** **Friday** **Saturday** **Sunday**

The `month_of_year` column will contain the values which are ordered from **January** **February** **March** **April** **May** **June** **July** **August** **September** **October** **November** **December**

[ ]:
```
# Convert the period_of_day, day_of_week_name and start_time_month to ordered␣
↪categorical types
ordinal_var_dict = {'period_of_day': ['Midnight', 'Early Morning', 'Morning',␣
↪'Afternoon', 'Evening', 'Night',
                                      'Late Night'],
                    'day_of_week': ['Monday', 'Tuesday', 'Wednesday',␣
↪'Thursday', 'Friday', 'Saturday', 'Sunday'],
                    'month_of_year': ['January', 'February', 'March', 'April',␣
↪'May', 'June', 'July', 'August', 'September',
                                      'October', 'November', 'December'],
                    }
for var in ordinal_var_dict:
    ordered_var = pd.api.types.CategoricalDtype(ordered=True,␣
↪categories=ordinal_var_dict[var])
    cc_bike_data[var] = cc_bike_data[var].astype(ordered_var)
```

[ ]:
```
# value count of hour
cc_bike_data.month_of_year.value_counts()
```

[ ]:
```
October      200102
July         196038
June         193907
August       189250
September    184635
May          179125
November     133651
December     131171
April        131169
March        111382
```

```
February     106718
January       94802
Name: month_of_year, dtype: int64
```

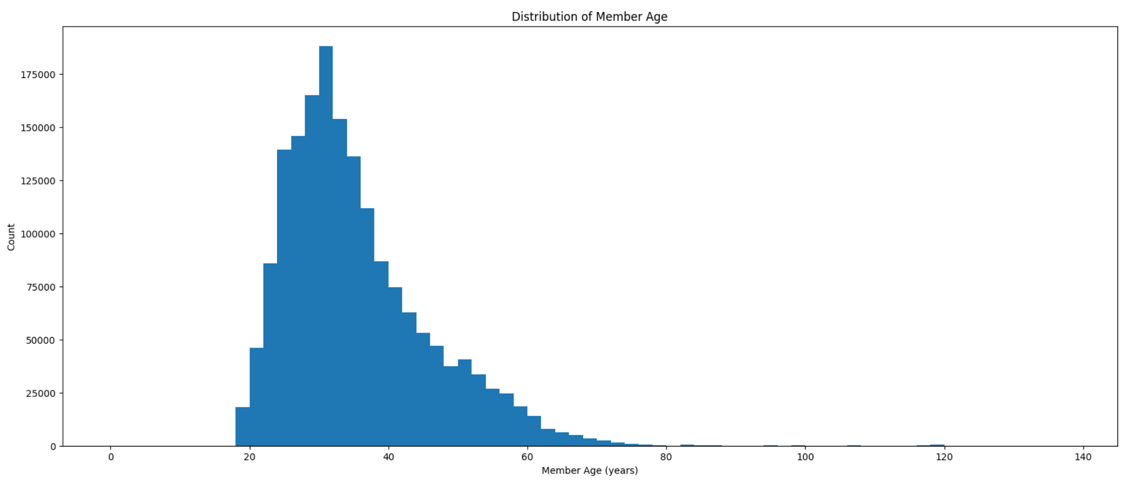
1.6 Univariate Exploration

In this section, investigate distributions of individual variables. If you see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

1. What is the distribution of the age of the users?

[ ]:
```
def plot_histogram(column, title, x_label, binsize=2, y_label='Count'):
    # Use max() to get the size of bins
    binsize = 2
    bins = np.arange(0, cc_bike_data[column].max()+binsize, binsize)
    # Find the distribution of the `member_age` using a histogram
    plt.figure(figsize=[20, 8])
    plt.hist(data=cc_bike_data, x='member_age', bins=bins)
    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title(title);

plot_histogram('member_age', 'Distribution of Member Age', 'Member Age (years)')
```

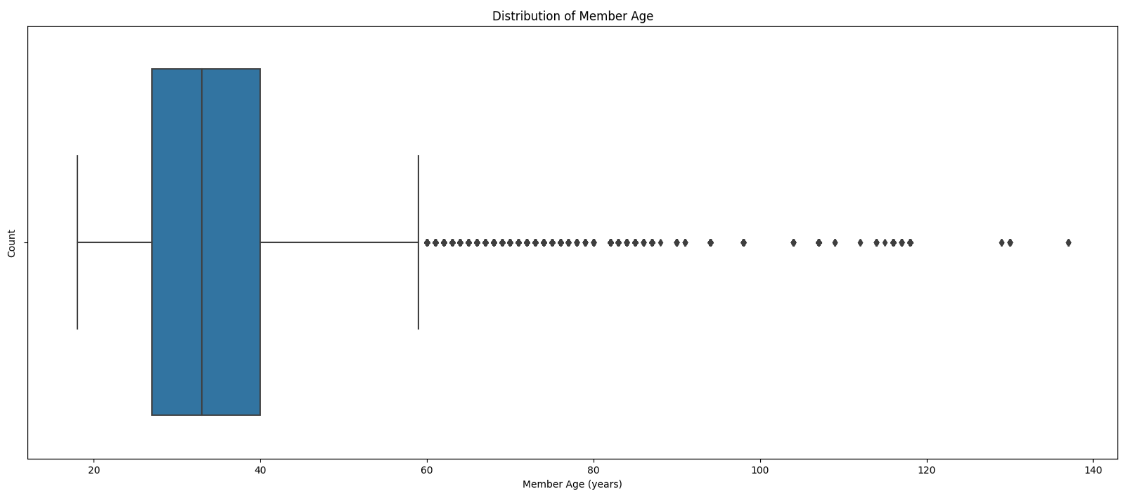


The graph above shows that most riders are between 25 and 40 years old. The distribution is right-skewed, which means that the majority of the riders are young. The distribution is also unimodal, which means that there is one peak in the distribution.

The distribution looks like it contains outliers, which are values that are far from the majority of the data. To confirm this, lets look at the summary statistics of the `member_age` column. We will also look at the boxplot of the `member_age` column.

[ ]:
```python
# Plot the distribution of the `member_age` using a boxplot
def plot_boxplot(column, title, x_label, y_label='Count'):
    # Find the distribution of the `member_age` using a boxplot.
    plt.figure(figsize=[20, 8])
    sb.boxplot(data=cc_bike_data, x=column)
    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title(title);

plot_boxplot('member_age', 'Distribution of Member Age', 'Member Age (years)')
```



Based on the box plot above, we can see that the outliers are from the age of 60 and above.

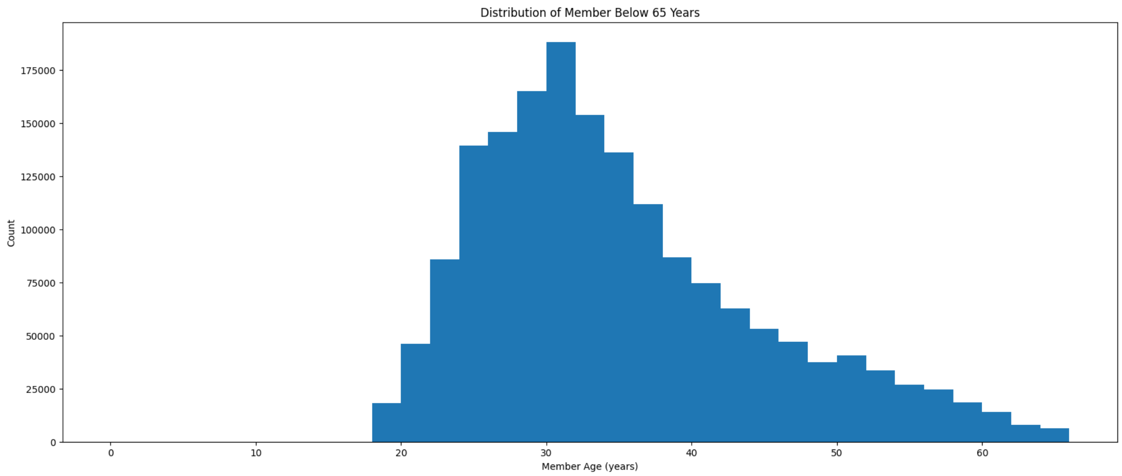
[ ]:
```python
cc_bike_data.query('member_age > 65').shape[0]/ cc_bike_data.shape[0] * 100
```

[ ]: 0.8865250141742488

99% of the riders are between 18 and 65 years old. We will treate any age above 65 as an outlier. We will remove these outliers from the dataset.

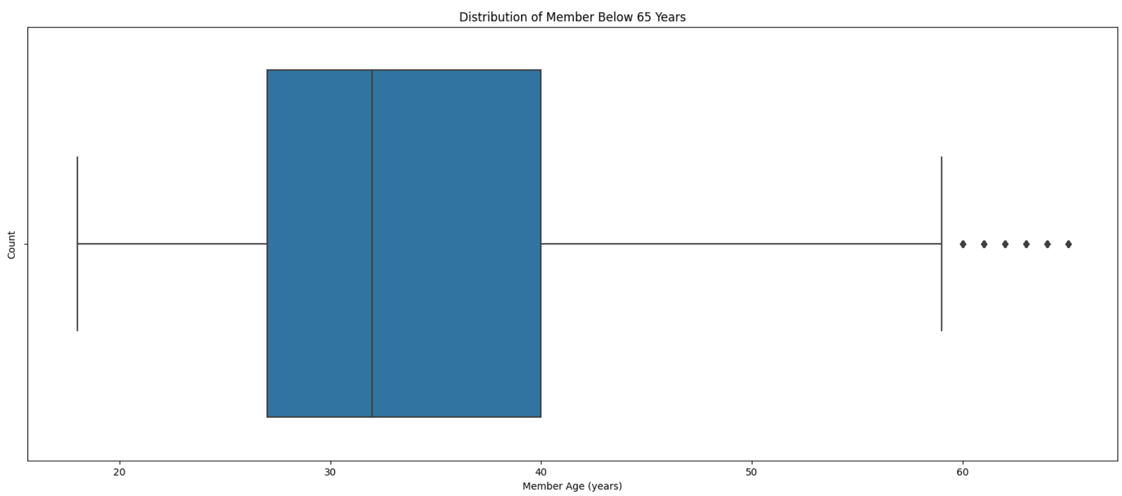
[ ]:
```python
# Select the riders where age is below 60. Assign the result to␣
↪`cc_bike_data_age`
cc_bike_data = cc_bike_data.query('member_age <= 65')
```

[ ]:
```python
# Find the distribution of the `member_age` using a histogram
plot_histogram('member_age', 'Distribution of Member Below 65 Years', 'Member␣
↪Age (years)')
```



In the bivariate exploration, we will explore if the age of the riders has an effect on the distance the riders travel.

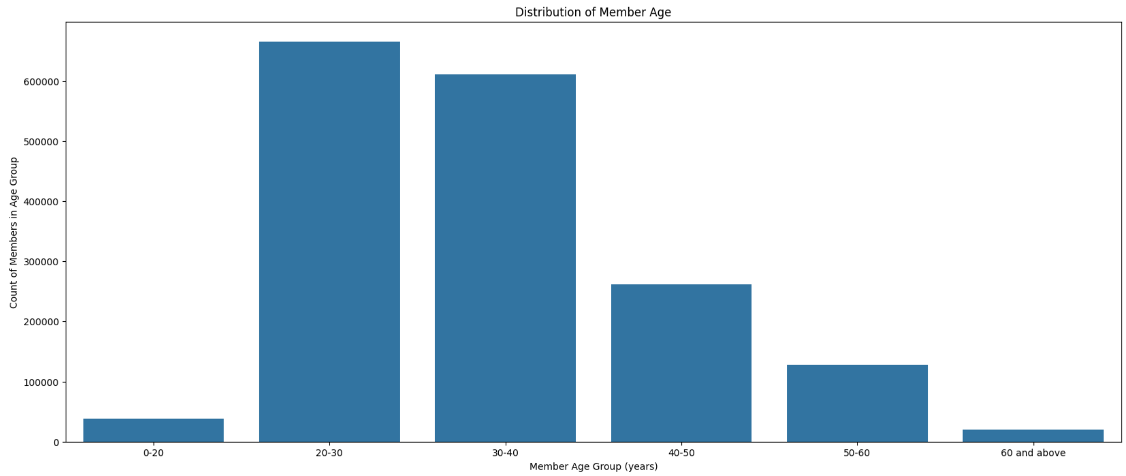
[ ]:
```
# Plot the distribution of the `member_age` using a boxplot
plot_boxplot('member_age', 'Distribution of Member Below 65 Years', 'Member Age␣
↪(years)')
```



Lets perform a cut to get age-group of the users

[ ]:
```
# Perform a cut to divide the `member_age` into 5 bins
cc_bike_data['member_age_group'] = pd.cut(cc_bike_data['member_age'], bins=[0,␣
↪20, 30, 40, 50, 60, 70],
                                          labels=['0-20', '20-30', '30-40',␣
↪'40-50', '50-60', '60 and above'])
```

```
[ ]: # Plot the distribution of the `member_age_group` using a bar chart
plt.figure(figsize=[20, 8])
sb.countplot(data=cc_bike_data, x='member_age_group', color=base_color)
plt.xlabel('Member Age Group (years)')
plt.ylabel('Count of Members in Age Group')
plt.title('Distribution of Member Age');
```



Based on the histogram I created, it seems that the age of the riders in the Ford GoBike dataset ranges from about 18 to 60 years old. I can see that the median age is around 34 years old, and the majority of riders fall between the ages of 27 to 40 years old (the upper quartile). The lower quartile ranges from around 24 to 31 years old.

Using the cut function, I created a new column called `member_age_group` to categorize the riders into five age groups: `0-20`, `20-30`, `30-40`, `40-50`, `50-60` and `60 and above`. The majority of riders fall into the `20-30` age group, which is consistent with the histogram above.

Interestingly, I also noticed that there are several outliers above the upper quartile, indicating that there are a significant number of older riders who are using the bike share system. This suggests that there may be a group of older riders who are using the system for transportation, recreation, or exercise.

However, it's important to note that my analysis is based on the assumptions made from the histogram, and further investigation and analysis may be needed to fully understand the characteristics and behaviors of the riders in the dataset. It's also crucial to consider potential biases in the dataset and to be careful about generalizing these findings to other populations or contexts. **We will explore the the relationship between distribution of (`user_type` and `member_age_group`) and (`user_type` and `member_age_group`)** to understand the demography of riders in age groups.

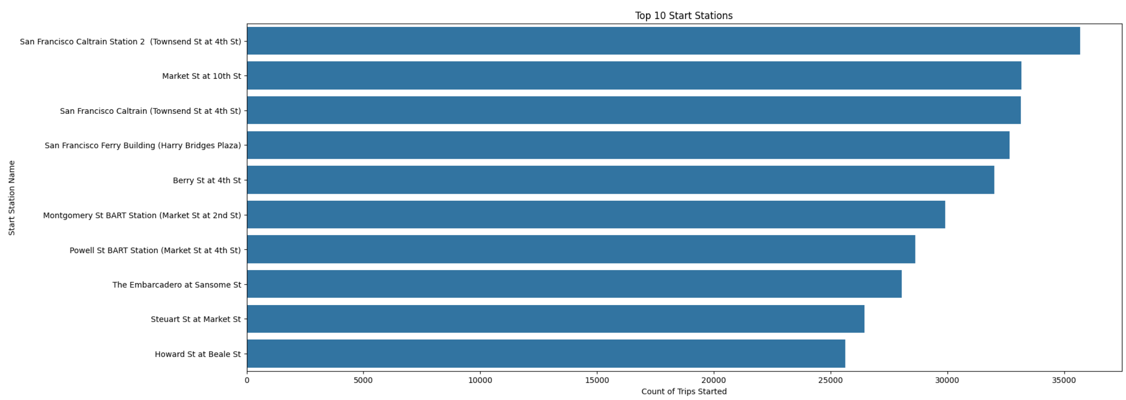
1.6.1 Save the cleaned datasetfor the Part_II_slide_deck.ipynb

```
[ ]: cc_bike_data.to_csv('data/part_II_bike_data.csv', index=False)
```

2. What are top 10 starting points for the bike-sharing system?

```
[ ]: # top 10 start stations
cc_bike_data.start_station_name.value_counts().head(10)

# plot the top 10 start stations
plt.figure(figsize=(20, 8))
sb.countplot(data=cc_bike_data, y='start_station_name', order=cc_bike_data.
 ↪start_station_name.value_counts().head(10).index, color=base_color)
plt.title('Top 10 Start Stations')
plt.xlabel('Count of Trips Started')
plt.ylabel('Start Station Name');
```



We can see that the most popular starting points are **San Francisco Caltrain Station 2 (Townsend St at 4th St)**, **Market St at 10th St** and **San Francisco Caltrain (Townsend St at 4th St)**. These locations may be hubs for transportation, such as train and bus stations, making them convenient and easily accessible starting points for people commuting to work or other destinations.

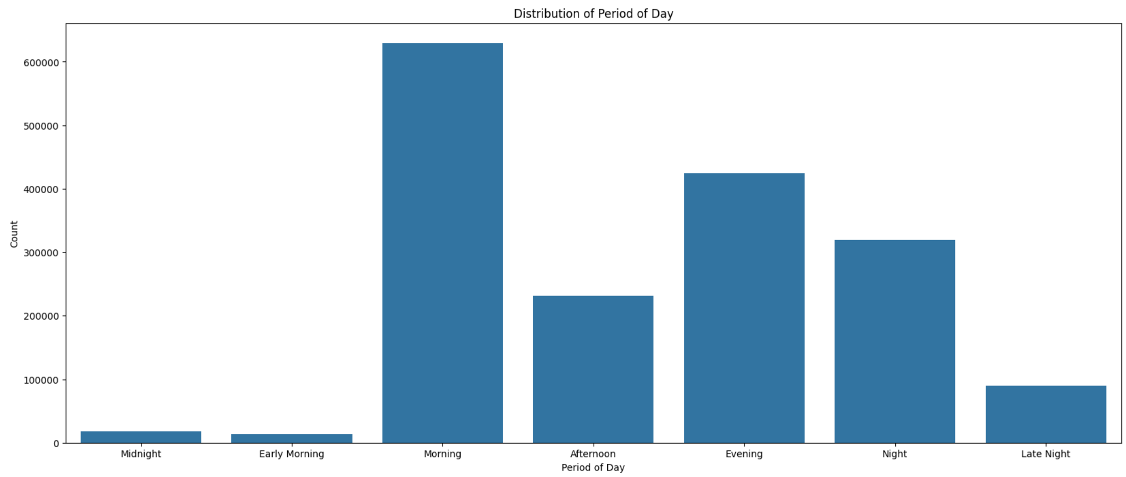
To understand the demography of riders in these top 10 starting points, we will explore the user type (`user_type` and gender `member_gender`) using the bike-sharing system in top 10 starting points.

3. When are most trips taken in terms of time of day (`period_of_day`)

```
[ ]: # Plot the distribution of the `period_of_day` using a countplot
def plot_countplot(column, title, x_label, y_label='Count'):
    plt.figure(figsize=[20, 8])
    sb.countplot(data=cc_bike_data, x=column, color=base_color)
    plt.xlabel(x_label)
    plt.ylabel(y_label)
```

```
    plt.title(title);

plot_countplot('period_of_day', 'Distribution of Period of Day', 'Period of␣
↪Day')
```

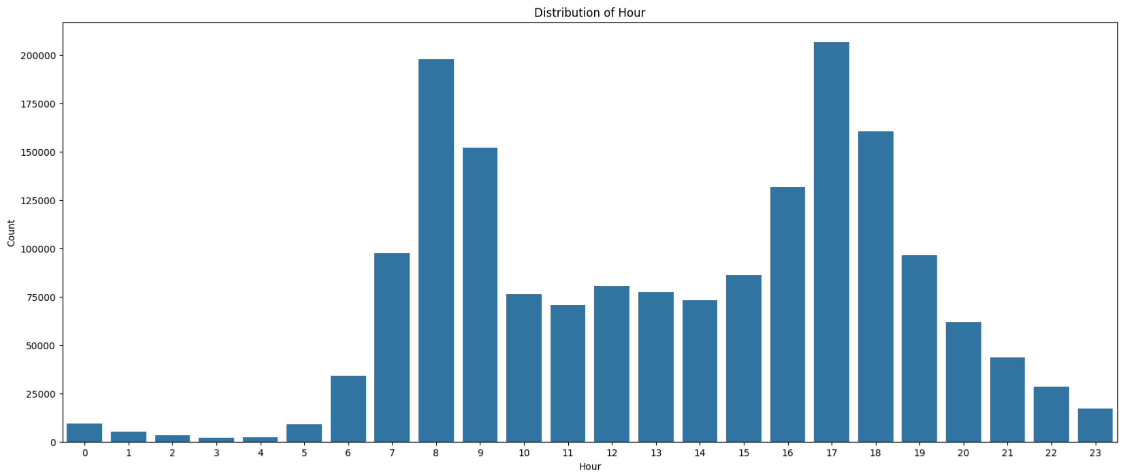


The graph above shows that a large number of rides are taken during the morning and evening hours. Specifically, the 'Morning' period (between 6-11 AM) and 'Evening' period have the highest number of rides, while the 'Midnight' period (between 12AM-3AM) has the lowest number of rides.

This observation suggests that the bike share system is being heavily used by individuals who are commuting to and from work or school during peak morning and evening hours.

However, it's important to note that this analysis is based on the assumptions made from the 'period_of_day' column and that further investigation may be needed to fully understand the reasons behind this pattern. Factors such as weather, local events, and user demographics may also play a role in the trends observed.

[ ]:
```
# Plot the distribution of the hour using a countplot
plot_countplot('hour', 'Distribution of Hour', 'Hour')
```

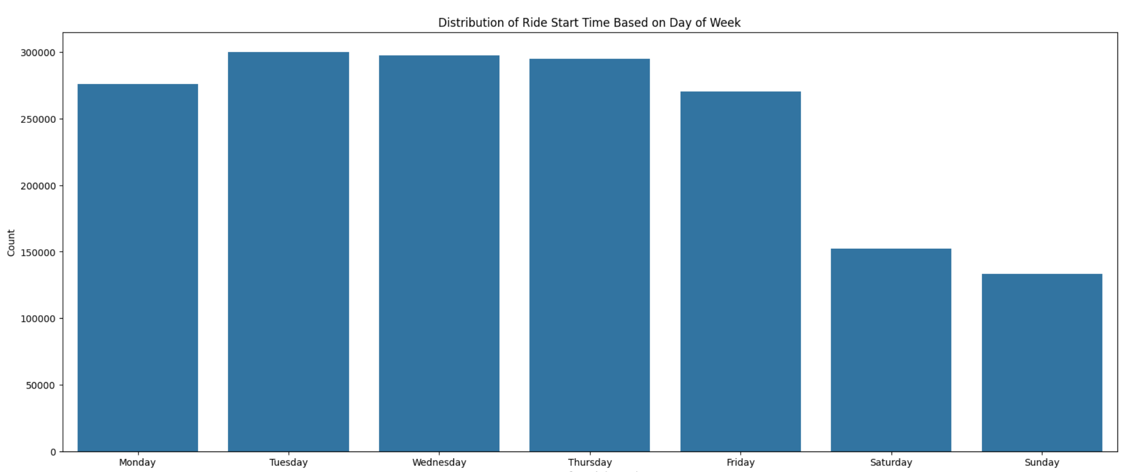


Expanding on the previous observation, it looks that the bike share system is being heavily used at 8 AM and 5 PM. This suggests that the bike share system is being heavily used by individuals who are commuting to and from work or school during peak morning and evening hours.

There is a significant drop in the number of rides starting at 11:00PM to 4:00AM.

4. When are most trips taken in terms of day of week (`days_of_week`)

```
[ ]: # Count plot of `days_of_week_name` bike rides
plt.figure(figsize=[20, 8])
sb.countplot(data=cc_bike_data, x='day_of_week', color=base_color)
plt.xlabel('Day of Week (Name)')
plt.ylabel('Count')
plt.title('Distribution of Ride Start Time Based on Day of Week');
```



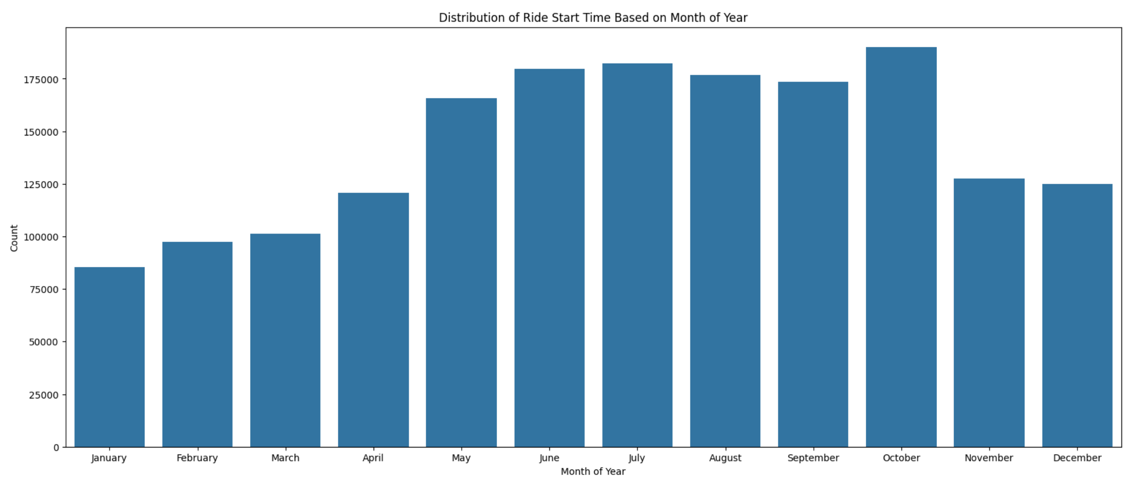
After analyzing the Ford GoBike dataset, I found that most rides are taken during the weekdays. Specifically, the majority of rides occur on Mondays, Tuesdays, Wednesdays, Thursdays, and Fridays, with a noticeable drop in rides on the weekends.

This observation suggests that the bike share system is primarily being used for weekday commuting or transportation, potentially for work or school-related purposes. It may also indicate that riders are less likely to use the bike share system for recreational or leisure activities on the weekends, or that there are other transportation options that are more popular on weekends.

However, it's important to note that there may be other factors that could be contributing to this trend, such as weather, time of year, or local events. Further analysis and investigation may be needed to fully understand the reasons behind this pattern.

5. When are most trips taken in terms of month of the year(`month`)

[ ]:
```
# Count plot of distribution of `month_of_year` bike rides
plt.figure(figsize=[20, 8])
sb.countplot(data=cc_bike_data, x='month_of_year', color=base_color)
plt.xlabel('Month of Year')
plt.ylabel('Count')
plt.title('Distribution of Ride Start Time Based on Month of Year');
```



After analyzing the Ford GoBike dataset, I found that the months with the highest number of rides are May through October, with the highest number of rides occurring in October. This trend suggests that the bike share system is being used more frequently during the warmer months of the year, potentially due to favorable weather conditions and longer daylight hours.

Additionally, the increase in rides during the summer months may also be due to an increase in tourism and outdoor activities during this time, which could lead to more individuals using the bike share system for transportation and recreation.

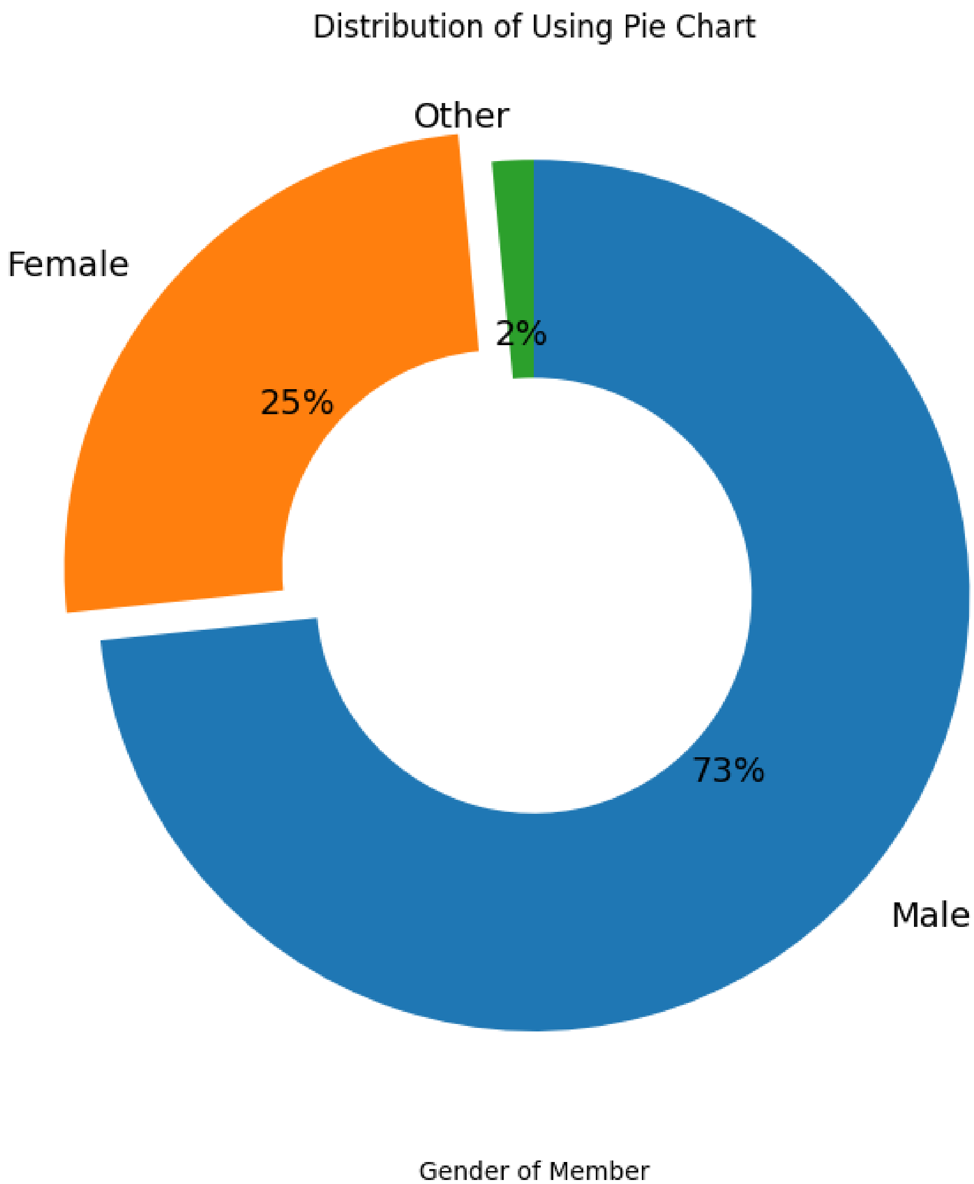
It's important to note that this observation is based on the assumptions made from the data and further investigation may be needed to fully understand the reasons behind this pattern. Factors such as local events, promotional campaigns, and user demographics could also play a role in the trends observed. Nonetheless, this finding can be useful for bike share operators to better understand the ridership patterns and plan for capacity and maintenance during peak seasons.

In the next section, we will explore if there is significant difference between user type through out the year. It will help us understand if there are years which are preferrable for the bike-sharing system for a certain user eg subscribers.

6. What is the distribution of riders based on gender (`member_gender`)?

[ ]:
```
plt.figure(figsize=[20, 8])

# Donut chart of `member_gender` bike rides
member_gender_counts = cc_bike_data["member_gender"].value_counts()
member_gender_counts.plot(kind='pie', autopct='%1.0f%%', startangle=90,␣
↪counterclock=False,
                        wedgeprops={'width':0.5}, textprops={'fontsize': 14},␣
↪explode=[0, 0.1, 0])
plt.xlabel("Gender of Member")
plt.ylabel('')
plt.title('Distribution of Using Pie Chart');
```

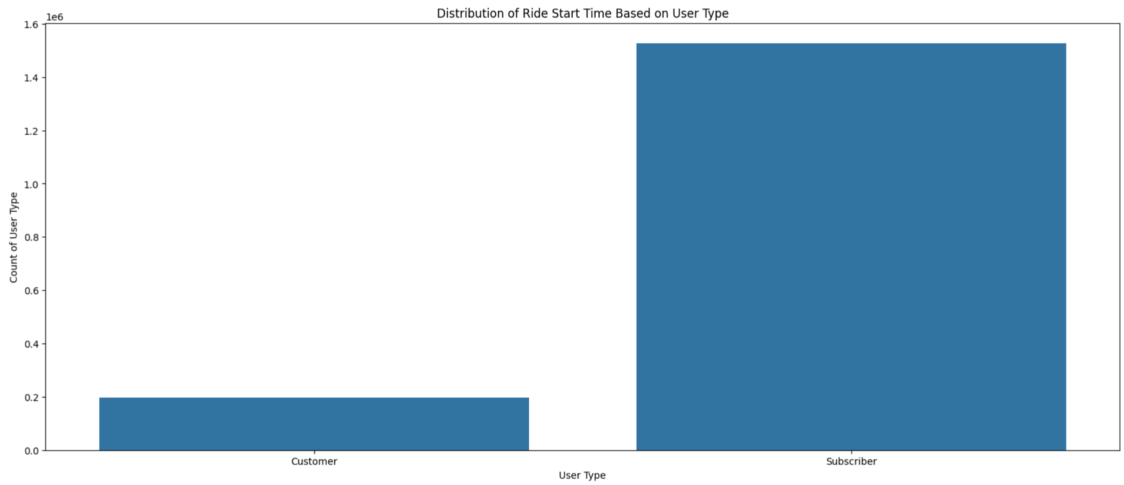


When plotting a donut plot for `member_gender`, it was observed that there were more male riders than female or other gender riders. This observation could be due to a number of factors.

One possible explanation could be that males are generally more likely to use bike sharing services for commuting, exercise, or leisure compared to females. The observation that there are more male riders in the bike sharing service could be due to factors such as differences in usage patterns, marketing, or biases in data collection. It's important to consider these factors when interpreting the results of data analysis.

7. What is the distribution of riders based on user type (`user_type`)?

```
[ ]: # Plot distribution of `user_type` bike rides using countplot
plt.figure(figsize=[20, 8])
sb.countplot(data=cc_bike_data, x='user_type', color=base_color)
plt.xlabel('User Type')
plt.ylabel('Count of User Type')
plt.title('Distribution of Ride Start Time Based on User Type');
```



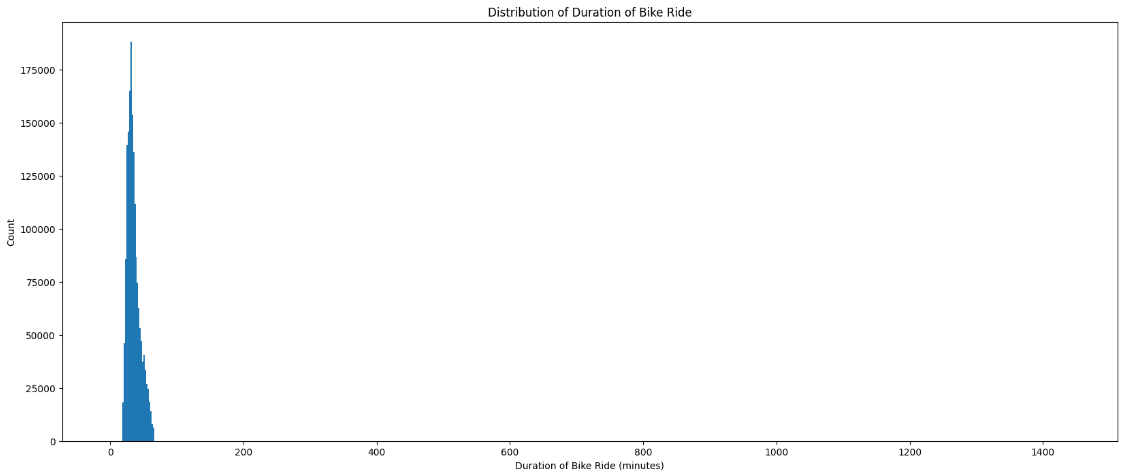
When plotting a countplot for `user_type`, it was observed that there were more subscribers than customers in the bike sharing service. This observation is likely due to the fact that the service is more geared towards long-term users who would benefit from the subscription model. Subscribers may use the service for daily commuting, while customers are more likely to use it for short-term or occasional trips. Additionally, the subscription model may offer discounts or other benefits to encourage users to sign up, which could contribute to the higher number of subscribers.

It's important to note that this observation is based on the specific dataset used for the analysis, and that the results could vary depending on the time period or geographic area being considered. However, in general, the trend of higher numbers of subscribers compared to customers is commonly seen in bike sharing services and other similar subscription-based models.

8. What is the distribution of the duration of the rides? We will convert the `duration_sec` column to minutes and then plot a histogram to see the distribution of the duration of the rides.

```
[ ]: # convert the duration_sec to minutes
cc_bike_data['duration_min'] = cc_bike_data['duration_sec'] / 60
```

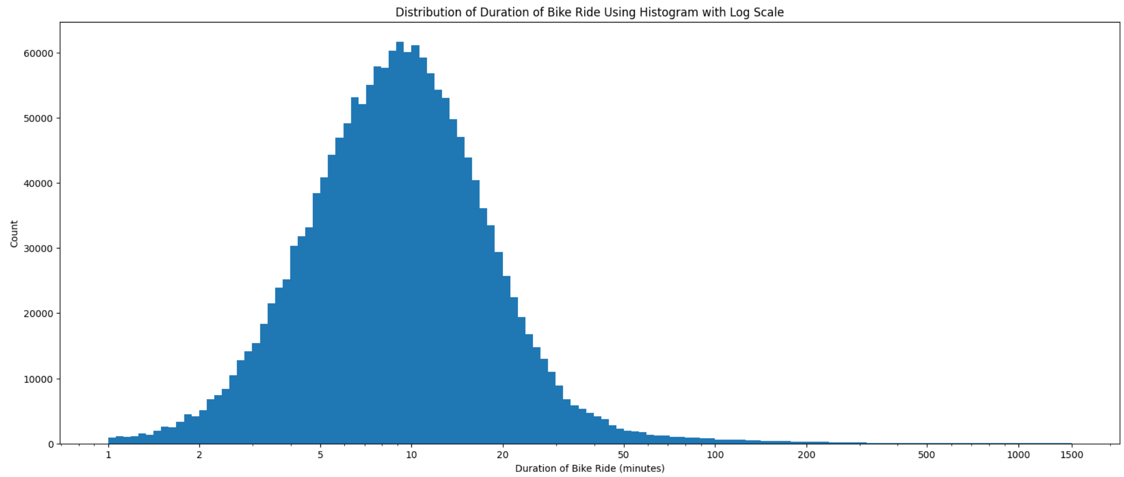
```
[ ]: # Plot the distribution of the `duration_min` using a histogram
plot_histogram('duration_min', 'Distribution of Duration of Bike Ride',␣
 ↪'Duration of Bike Ride (minutes)', 2)
```



Lets perform a `describe()` function on the `duration_min` column to get a better idea of the distribution of the duration of the rides. It appears there are outliers in the data. Lets look use the log transformation to see if we can get a better idea of the distribution.

```
[ ]: def plot_histogram_duration():
         # Plot the distribution of the `duration_min` using a histogram with log␣
      ↪scale
         plt.figure(figsize=[20, 8])
         binsize = .025
         bins = 10 ** np.arange(0, np.log10(cc_bike_data['duration_min'].
      ↪max())+binsize, binsize)
         plt.hist(data=cc_bike_data, x='duration_min', bins=bins)
         plt.xscale('log')
         plt.xticks([1, 2, 5, 10, 20, 50, 100, 200, 500, 1000, 1500], [1, 2, 5, 10,␣
      ↪20, 50, 100, 200, 500, 1000, 1500])
         plt.xlabel('Duration of Bike Ride (minutes)')
         plt.ylabel('Count')
         plt.title('Distribution of Duration of Bike Ride Using Histogram with Log␣
      ↪Scale');

     plot_histogram_duration()
```



For most of the rides, most of the rides are between 5 and 20 minutes. The distribution is right-skewed, which means that the majority of the rides are short. The distribution is also unimodal, which means that there is one peak in the distribution.

Did the people who took long rides go travel long distances? To answer this question, in **bivariate exploration part** we will plot a scatterplot of `duration_min` and `distance` to see if there is a relationship between the duration of the ride and the distance traveled.

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

After conducting a thorough analysis of the dataset, I found several critical variables that are important to understanding the data findings. These variables include the monthly trend of bike riders, age groups of bike riders, gender-wise rides, weekdays, and peak hours. The original dataset contained 1,863,721 bike rides that occurred from January to December 2018, but for simplicity, I limited the data to members who were 80 years old and below.

Based on the analysis, bikes are in high demand between April and October, likely due to the summer season, and ridership drops during the winter months. Weekdays, particularly from Monday to Friday, see more rides than weekends, with 8-9 am and 5-6 pm being the busiest hours for daily bike riders.

Furthermore, the analysis also revealed patterns in gender and age. Males utilized the bike share services more than females, and people in the 20-30 age bracket were more frequent riders than other age groups. These observations highlight important trends in bike usage that can inform decision-making for the bike sharing service

1.6.3 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 wanted to examine the distribution of the ride durations, and discovered it was right-skewed. I applied a log transformation to get a better understanding of the distribution, and although it remained right-skewed, it became more normal than before.

To determine the time of day when most riders are utilizing the bike share system, I created a new column called `period_of_day` that categorizes the start time into 7 periods: 'Midnight', 'Early Morning', 'Morning', 'Afternoon', 'Evening', 'Night', 'Late Night'. Moreover, I created an ordered categorical variable type using `pd.Categorical()` and `ordered=True` to ensure that the periods are ordered correctly.

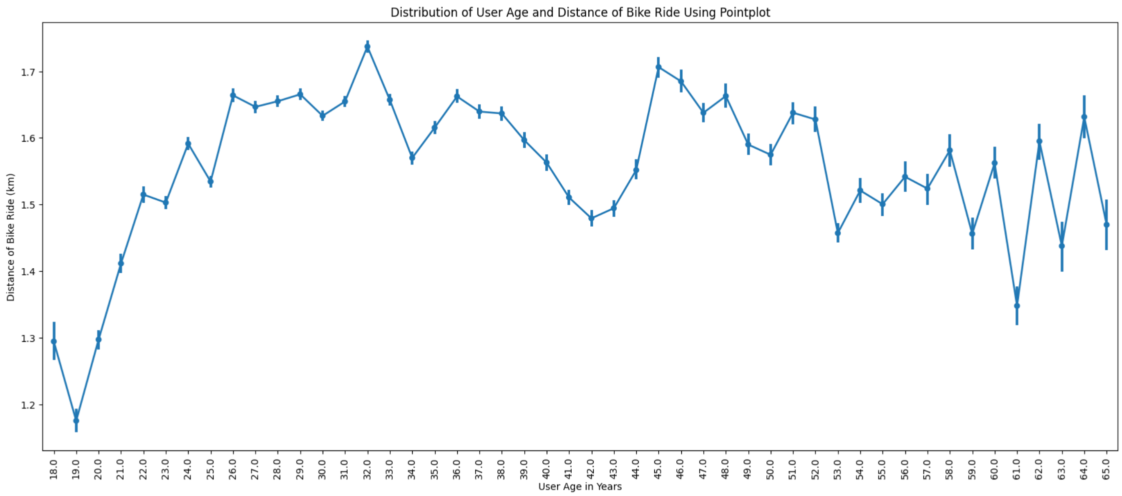
I also created a new column called `month` that categorizes the start time into 12 months: 'January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', 'October', 'November', 'December'. I used the `apply()` function to apply the `lambda` function to the `start_time` column. Moreover, I created an ordered categorical variable type using `pd.Categorical()` and `ordered=True` to ensure that the months are ordered correctly.

1.7 Bivariate Exploration

In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

1. Distribution of members age (`member_age`) and distance traveled (`distance`) in kilometers In the **Univariate Exploration** section, we saw the distribution of age. Does the age affect the distance traveled? Lets see if there is a relationship between the `member_age` and `distance` using a pointplot.

[ ]:
```
# pointplot of `member_age` and `distance`
plt.figure(figsize=(20, 8))
sb.pointplot(data=cc_bike_data, x='member_age', y='distance', scale=.7,␣
 ↪color=base_color)
plt.xlabel('User Age in Years')
plt.ylabel('Distance of Bike Ride (km)')
plt.title('Distribution of User Age and Distance of Bike Ride Using Pointplot')
plt.xticks(rotation=90);
```

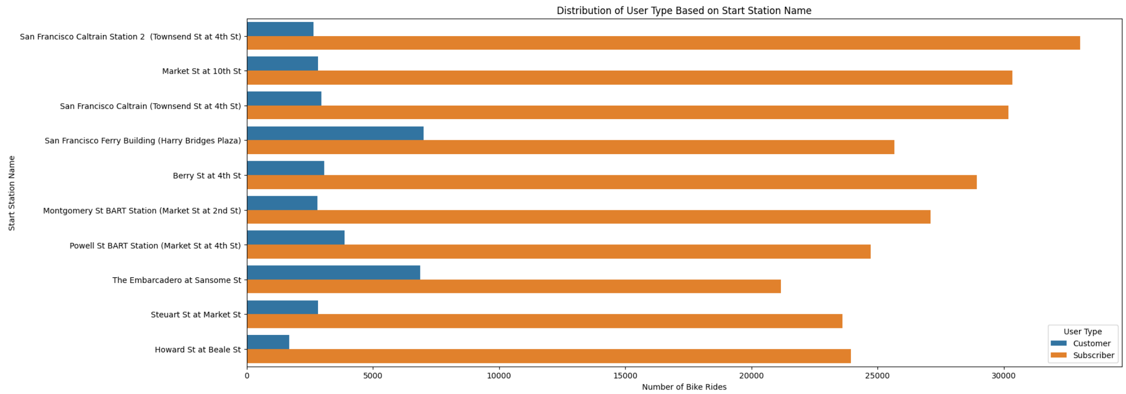


The distribution of the `member_age` and `distance` shows that the majority of the oldest riders had the greatest fluctuation between the shortest and longest distance traveled. This could be due to the fact that the oldest riders are more likely to use the bike share system for recreation and leisure. However, it is worth noting that the distance might not be accurate as the `Haversine` formula does not take into account the routes taken by the riders.

2. What distribution of user type i.e customer or subscribers are using the bike-sharing system in top 10 starting points? In **Univariate Exploration** we saw distrubution of how many riders start their ride in top 10 stations. Now lets see what user type (`user_type` and gender `member_gender`) using the bike-sharing system in top 10 starting points.

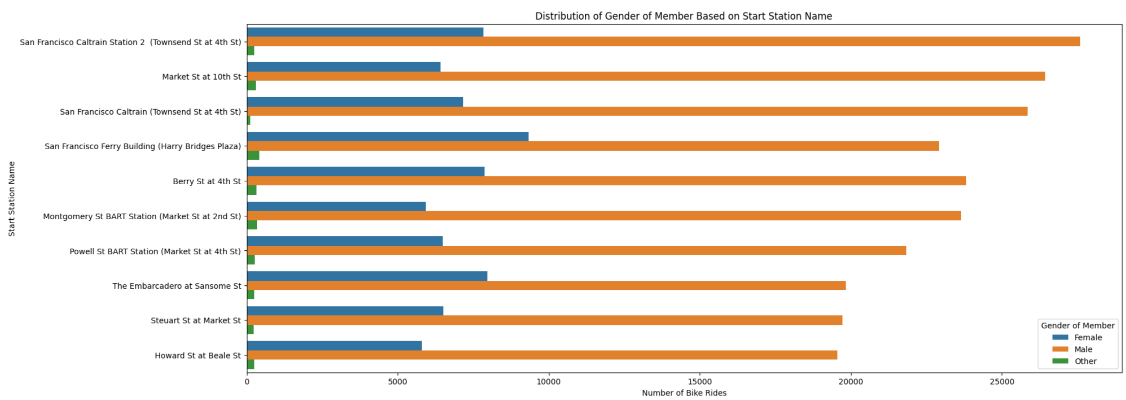
[ ]:
```
def top_stations_data(title, hue, y_label='Start Station Name', x_label='Number of Bike Rides'):
    # Plot the top 10 stations with most number of bike rides
    plt.figure(figsize=[20, 8])
    sb.countplot(data=cc_bike_data, y='start_station_name', hue=hue, order=cc_bike_data.start_station_name.value_counts().iloc[:10].index)
    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title('Distribution of ' + title + ' Based on Start Station Name')
    plt.legend(title=title);
```

[ ]:
```
# clustered bar chart of `user_type` bike rides in the 10 most common `start_station_name`
top_stations_data('User Type', 'user_type')
```



After analysis, we can see that the top 10 starting points are mostly used by subscribers. This is expected as subscribers are more likely to use the bike-sharing system for daily commuting. Customers are more likely to use the bike-sharing system for short-term or occasional trips.

```
[ ]: # clustered bar chart of `member_gender` bike rides in the 10 most common␣
     ↪`start_station_name`
     top_stations_data('Gender of Member', 'member_gender')
```



As we can see, the top 10 starting points, males are frequent riders departing these starting stations. It is possible that males are the primary users of the bike share system for commuting purposes, especially during peak hours. As a result, the top starting points may be locations that are commonly used for commuting.

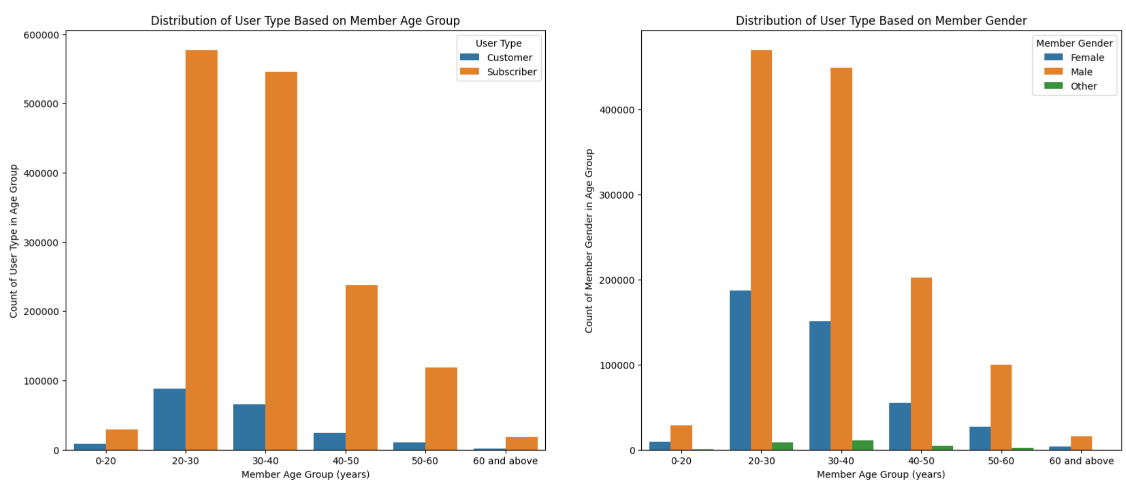
3. What is the relationship between `user_type`/`member_gender` and `member_age_group`? In **Univariate Exploration**, we saw that 73% of riders were males, we also noticed that in age brackets, those in 20-30 years were more frequent riders, let's explore if there in particular gender or user type that is more frequent in the age bracket variables.

```
[ ]: def plot_bivariate_countplot(x_column, y_column, title, x_label, legend, y_label='Count', pallette=None):
         sb.countplot(data=cc_bike_data, x=x_column, hue=y_column, palette=pallette)
         plt.xlabel(x_label)
         plt.ylabel(y_label)
         plt.title(title)
         plt.legend(title=legend);
```

```
[ ]: plt.figure(figsize=[20, 8])

     plt.subplot(1, 2, 1)
     # Plot the relationship between `member_age_group` and `user_type` using a clustered bar chart
     plot_bivariate_countplot('member_age_group',
                              'user_type',
                              'Distribution of User Type Based on Member Age Group',
                              'Member Age Group (years)',
                              'User Type',
                              'Count of User Type in Age Group',
                              )

     plt.subplot(1, 2, 2)
     # Plot the relationship between `member_age_group` and `member_gender` using a clustered bar chart
     plot_bivariate_countplot(
         'member_age_group',
         'member_gender',
         'Distribution of User Type Based on Member Gender',
         'Member Age Group (years)',
         'Member Gender',
         'Count of Member Gender in Age Group',
     )
```

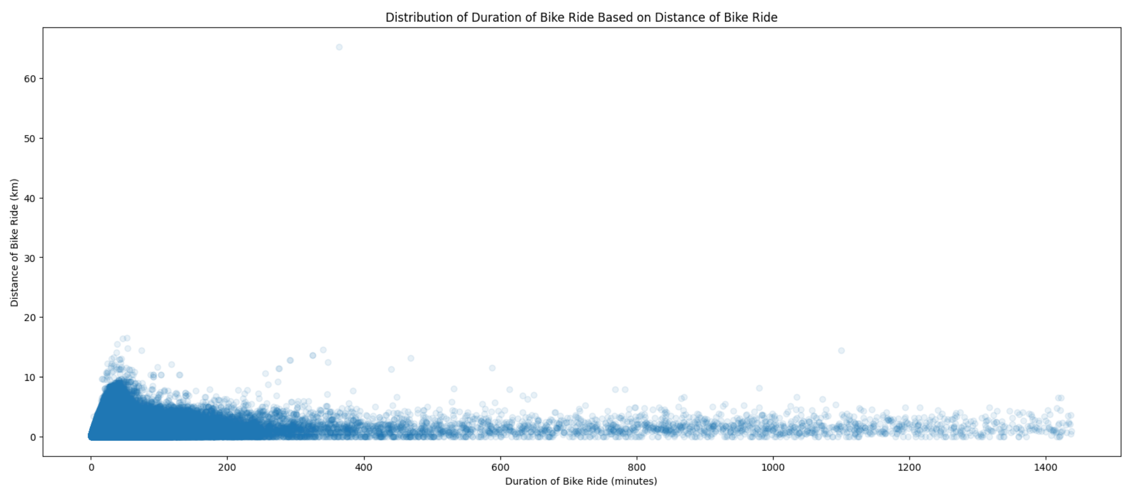


In the above analysis, between `member_age_group` vs `user_type`, we can see that the majority of the users are subscribers. This is expected as the bike sharing service is more geared towards long-term users who would benefit from the subscription model. Subscribers may use the service for daily commuting, while customers are more likely to use it for short-term or occasional trips. Additionally, the subscription model may offer discounts or other benefits to encourage users to sign up, which could contribute to the higher number of subscribers.

Looking at the relationship between `member_age_group` vs `member_gender`, majority of users are male. This is shown in all age brackets.

4. What is the relationship between `duration_min` and `distance`?

[ ]:
```
# Plot the relationship between `duration_min` and `distance_km` using a␣
↪scatter plot
plt.figure(figsize=[20, 8])
sb.regplot(data=cc_bike_data, x='duration_min', y='distance', fit_reg=False,␣
↪scatter_kws={'alpha':0.1})
plt.xlabel('Duration of Bike Ride (minutes)')
plt.ylabel('Distance of Bike Ride (km)')
plt.title('Distribution of Duration of Bike Ride Based on Distance of Bike␣
↪Ride');
```



The relationship between the `duration_min` and the `distance` that the bike was ridden is not clear. Lets investigate the `start_station_id` and `end_station_id` to see if we can get a better idea of the relationship.

[ ]:
```
# Select the subset of data where start station and end station are the same
```

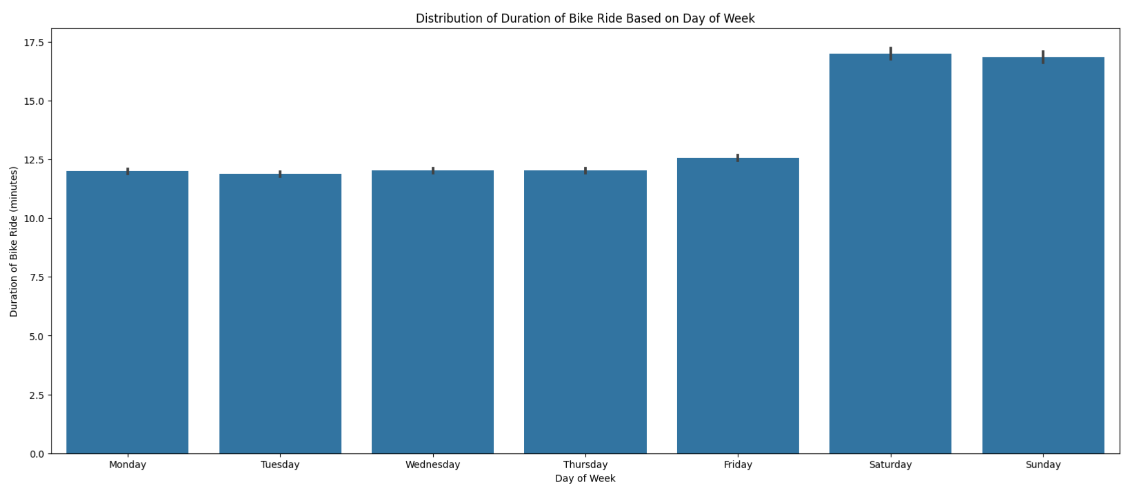
```
same_station = cc_bike_data[cc_bike_data['start_station_id'] ==␣
↪cc_bike_data['end_station_id']]
same_station.shape
```

[ ]: (41305, 24)

We can see that there riders who rode the bike for a long duration but did not travel a long distance. This could be due to the fact that the bike was used for leisure or recreation. However, after investigating the `start_station_id` and `end_station_id`, we can see that some riders rented the bike and then returned it to the same station. Moreover, it is likely some riders who rode for long time returned the bike near or close by the start station. The `Haversine` formula does not take account to such occassion. We would need more data about the routes taken by the riders to get a better idea of the relationship between the `duration_min` and the `distance`.

Lets explore how the duration of the ride appears throughout the week. Did riders rode more on a specific day of the week? Lets see if there is a relationship between the `duration_min` and `day_of_week` using a barplot.

[ ]:
```
plt.figure(figsize=[20, 8])
# barchart of `day_of_week` and `duration_min`
sb.barplot(data=cc_bike_data, x='day_of_week', y='duration_min',␣
↪color=base_color)
plt.xlabel('Day of Week')
plt.ylabel('Duration of Bike Ride (minutes)')
plt.title('Distribution of Duration of Bike Ride Based on Day of Week');
```

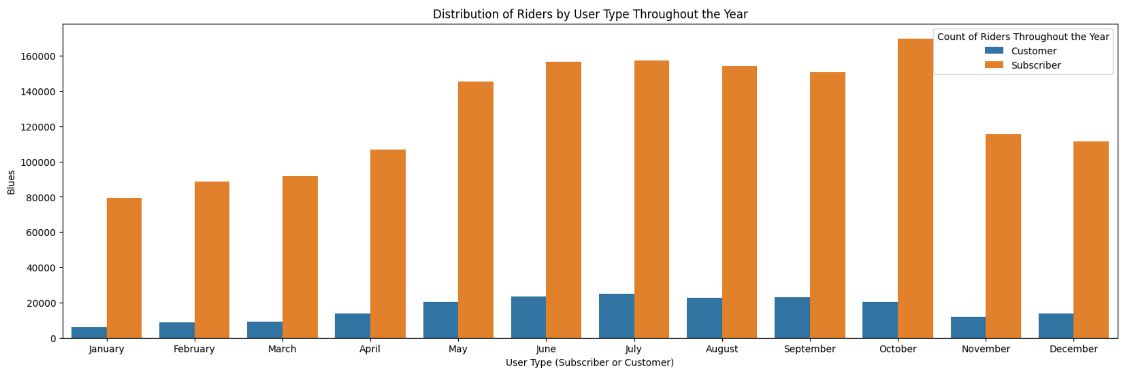


We can see that riders tend to ride for longer duration on weekends. This could be due to the fact that riders are more likely to use the bike share system for leisure and recreation on weekends.

In the following section, we will explore the relationship between the `duration_min` and day_of_week how it varies by user_type.

5. What is the relationship between month_of_year and user_type?

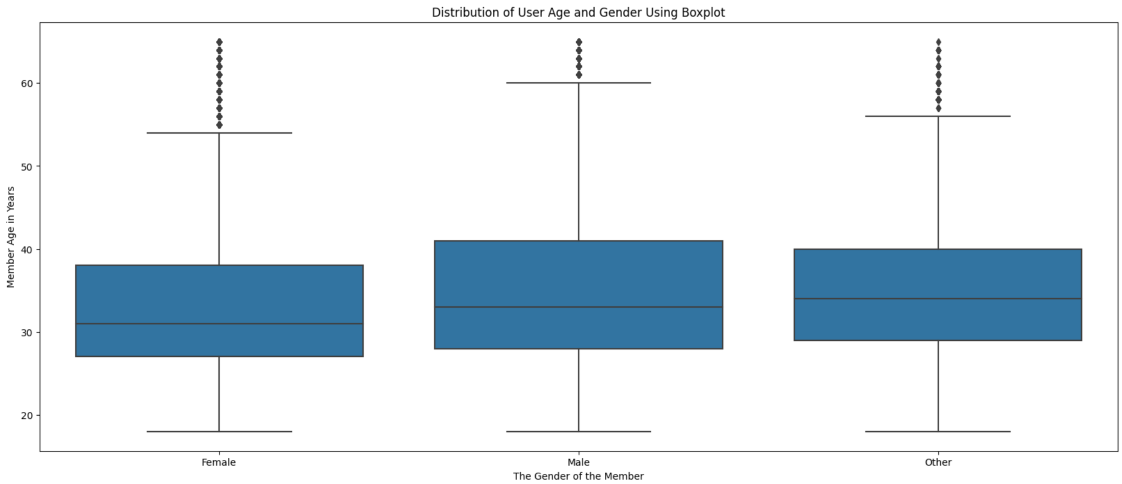
[ ]:
```
# Create a subplot of 2 plots
plt.figure(figsize=(20, 6))
# Plot the relationship between `month_of_year` and `user_type` using a␣
↪clustered bar chart
plot_bivariate_countplot(
    'month_of_year',
    'user_type',
    'Distribution of Riders by User Type Throughout the Year',
    'User Type (Subscriber or Customer)',
    'Count of Riders Throughout the Year',
    'Blues'
)
```



Throughout the year, we can see that subscribers were more frequent riders. This maybe explained by the fact that the subscribers are more likely to use the bike share system for recreation, leisure and daily commuting to work or school even during the winter months.

6. Distribution between age (member_age) and gender (member_gender) of Bike Share Users

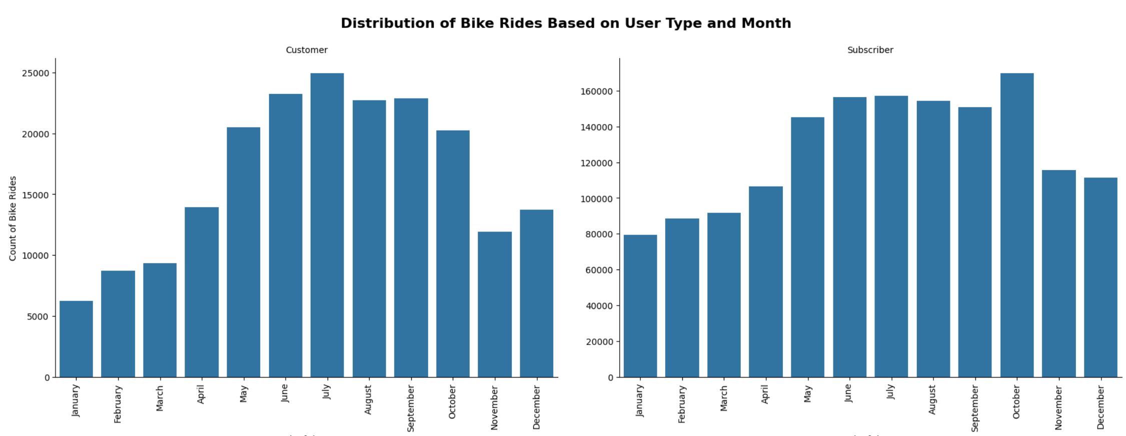
[ ]:
```
# Plot a boxplot of `member_age` and `member_gender` using boxplot
plt.figure(figsize=(20, 8))
sb.boxplot(data=cc_bike_data, x='member_gender', y='member_age',␣
↪color=base_color)
plt.xlabel('The Gender of the Member')
plt.ylabel('Member Age in Years')
plt.title('Distribution of User Age and Gender Using Boxplot');
```



Plotting a box plot of `member_age` against the `member_gender` shows that **male** are more distributed in terms of riders age. The max age for riders is **male** while **female** tend to have more outliers that **other**

7: Distribution of user type (`user_type`) and monthly usage (`month`) of Bike Share System

[ ]:
```
# catplot of `user_type` and `month`
graph =sb.catplot(data=cc_bike_data, x='month_of_year', col='user_type',␣
↪kind='count', sharey = False, sharex=True, color=base_color,
            height=6, aspect=1.5)
graph.set_axis_labels('Month of the Year', 'Count of Bike Rides')
graph.set_titles('{col_name}')
graph.set_xticklabels(rotation=90)
graph.fig.suptitle('Distribution of Bike Rides Based on User Type and Month',␣
↪y=1.05, fontsize=16, fontweight='semibold');
```



Both customer and subscriber types show a seasonal trend in their monthly usage, characterized by an increase in demand during the spring and fall seasons, followed by a decline in the winter. Notably, the month of July records the highest number of usage for customers, while subscribers show the highest usage in October.

1.7.1 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?

> Analysis of the period of the day when the bike share system is used reveals that subscribers tend to use it more during the morning and evening rush hours, and males tend to use it more often. This is expected because subscribers are more likely to use the system for daily commuting.
>
> In the analysis of `user_type` vs `member_age_group` and `user_type` and `member_gender`, we can see that the majority of the users are subscribers. This is because the bike sharing service is more oriented towards long-term users who would benefit from the subscription model. The subscription model may also offer discounts or other benefits, which could contribute to the higher number of subscribers.
>
> The top users of the Bike Share system throughout the week are young people between the ages of 20-30 and 30-40 years, and males. This could be because young people are more likely to use the bike share system for recreation, leisure, and daily commuting to work or school.

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

> Some riders rode the bike for a long duration but did not travel a long distance. This could be because the bike was used for leisure or recreation. However, after investigating the `start_station_id` and `end_station_id`, it is evident that some riders rented the bike and then returned it to the same station. Moreover, some riders who rode for a long time returned the bike near or close to the start station. The `Haversine` formula does not account for such instances. More data about the routes taken by the riders is needed to get a better idea of the relationship between duration_min and distance.

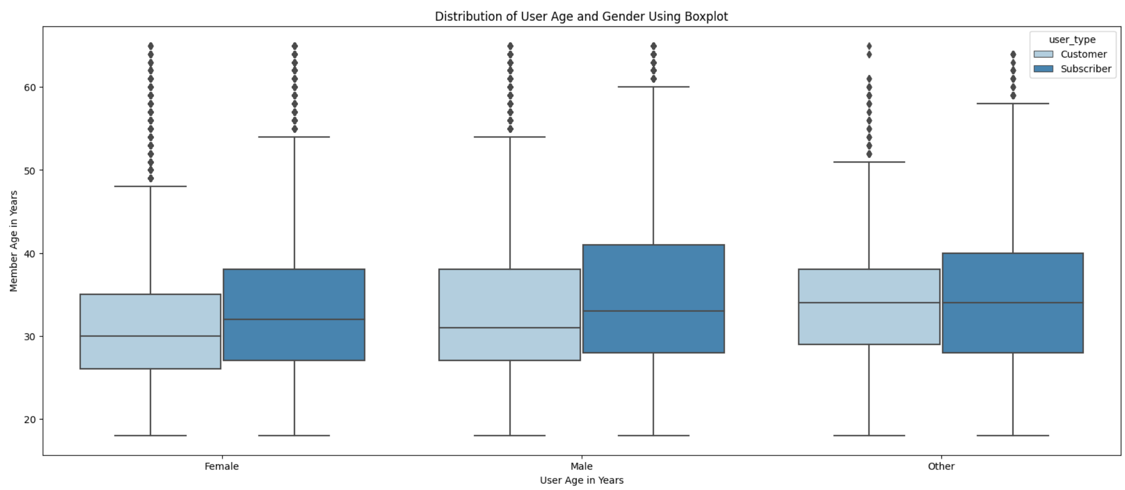
1.8 Multivariate Exploration

> Create plots of three or more variables to investigate your data even further. Make sure that your investigations are justified, and follow from your work in the previous sections.

In this section, I will investigate relationships between three or more variables in the dataset. I will start by looking at the relationships between the following variables: - `user_type` and `member_age` and `member_gender` - `distance` and `member_age` and `member_gender` - `duration_min` and `day_of_week` and `user_type` - `user_type` and `member_age_group` and `member_gender`

1: Relationship and distribution between `user_type` and `member_age` and `member_gender` In the previous section, we saw that the majority of the users are subscribers. We also saw that males are frequent riders than any other genders. In this section, we will explore the distribution of `user_type` and `member_gender` across the age of the riders.

[ ]:
```
# Plot a boxplot of `member_age` and `member_gender` using boxplot
plt.figure(figsize=(20, 8))
sb.boxplot(data=cc_bike_data, x='member_gender', y='member_age',␣
    ↪palette="Blues", hue='user_type')
plt.xlabel('User Age in Years')
plt.ylabel('Member Age in Years')
plt.title('Distribution of User Age and Gender Using Boxplot');
```

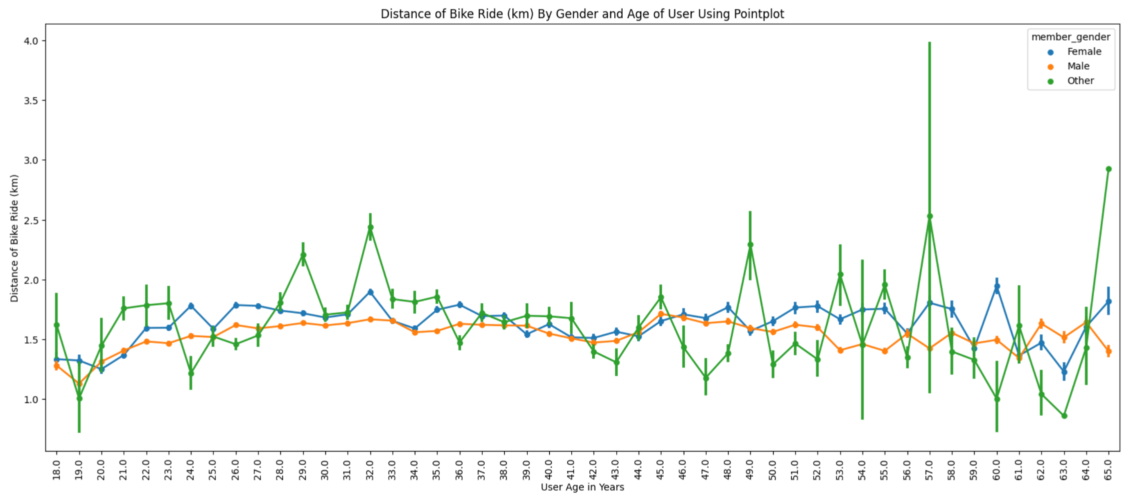


In the plot above, I observed that the **subscriber** category have large interquartile range span than **customer** user type, indicating a wider range of ages within the **subscriber** category. This implies that there is greater age diversity among **subscribers** compared to **customers**. It is also possible that **subscribers** are more likely to use the bike sharing service for daily commuting, which could lead to a wider age range as opposed to **customers** who may use the service more sporadically.

2. Duration of ride (`duration_min`) taken by age (`member_age`), separated by member gender (`member_gender`) In the previous section, we explored how distance and age of the members are related. We saw that the majority of the oldest riders had the greatest fluctuation between the shortest and longest distance traveled. In this section, we will try to if gender affected the distance traveled by riders of different ages.

[ ]:
```
# pointplot of `member_age` and `duration_min` separated by `member_gender`
plt.figure(figsize=(20, 8))
sb.pointplot(data=cc_bike_data, x='member_age', y='distance',␣
    ↪hue='member_gender', scale=.7)
plt.xlabel('User Age in Years')
plt.ylabel('Distance of Bike Ride (km)')
```

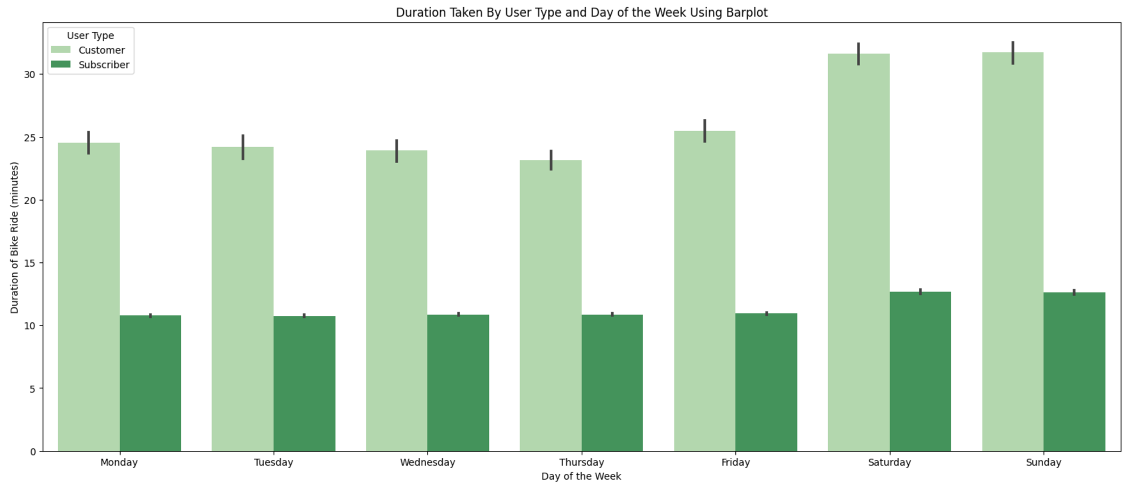
```
plt.title('Distance of Bike Ride (km) By Gender and Age of User Using␣
 ↪Pointplot')
plt.xticks(rotation=90);
```



Interestingly, when we compare the distance travelled by `member_age` and `member_gender`, we see that the **other** gender category had big flactuation from 50 years and older demographic than any other age. The distance was calculated by Haversine formula. The observation that the **other** gender category had bigger fluctuations in distance travelled among the 50 years and older demographic could be due to small sample size. However, it is worth noting that the distance might not be accurate as the `Haversine` formula does not take into account the routes taken by the riders.

3. Duration of rides (`duration_min`) throughout the week (`day_of_week`) separated by `user_type` In the previous section, we explored how the duration of the ride appears throughout the week. We were curious to see if there is a specific day which the riders rode more. In this section, we will explore the relationship between the `duration_min` and `day_of_week` how it varies by `user_type`.

[ ]:
```
# barplot of duration_min and day_of_week, separated by user_type
plt.figure(figsize=(20, 8))
sb.barplot(data=cc_bike_data, x='day_of_week', y='duration_min',␣
 ↪hue='user_type', palette="Greens")
plt.xlabel('Day of the Week')
plt.ylabel('Duration of Bike Ride (minutes)')
plt.title('Duration Taken By User Type and Day of the Week Using Barplot')
plt.legend(title='User Type');
```



It is interesting that the `customer` category has a higher duration of ride on throughout the week than the `subscriber` category. This needs further investigation to see if the `customer` category is made up of tourists or daily commuters and the distance each `customer` rode. Because the `Haversine` formula does not take into account the routes taken by the riders, the distance traveled by the `customer` category may not be accurate.

1.8.1 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?

The interquartile range of the **subscriber** user type exhibits a larger span than that of the **customer** user type, indicating a greater range of ages within the **subscriber** group. This suggests that the **subscriber** group has a higher degree of age diversity in comparison to the **customer** group. It is plausible that the **subscriber** group frequently utilizes the bike-sharing service for daily commuting, leading to a wider age range, as opposed to the **customer** group, which may use the service more sporadically.

An observation was made that the **other** gender category had a higher degree of variability in distance travelled among individuals aged 50 and older than any other age group. This observation could potentially be attributed to the relatively small sample size of the other gender category within the 50 years and older demographic.

1.8.2 Were there any interesting or surprising interactions between features?

It is intriguing to note that the `customer` category exhibits a higher ride duration throughout the week as compared to the `subscriber` category. Further scrutiny is required to ascertain whether the `customer` category constitutes of tourists or daily commuters, and the magnitude of distance covered by each `customer`. It is imperative to acknowledge that the `Haversine` formula, being a geometric method for calculating the great-circle distance between two points on a sphere, does not consider the actual routes taken by the riders. Consequently, the distance traversed by the `customer` category may not be entirely precise.

1.9 Conclusion

In my analysis of the 2018 bike ride data from January to December, I discovered that a total of 1,863,721 bike rides had been taken. However, since there were some outliers in the age data, I narrowed my focus to individuals aged between 18 and 65. From this subset, I found that the age range of 20-30 years old had the most frequent riders, with the majority of riders falling within the 25-40 years old age bracket. Male riders accounted for 73% of the total usage, while female riders accounted for 25%, and those who identified as neither male nor female accounted for around 2%.

An interesting observation from my analysis was that there were more subscribers than customers in the bike sharing service. This could be because the service caters more towards long-term users who can benefit from the subscription model. Additionally, the subscription model may offer discounts or other benefits, which could encourage users to sign up and contribute to the higher number of subscribers.

When looking at the duration of rides taken between January to December 2018, I found that the majority of rides lasted between 5 to 20 minutes, with a right-skewed distribution indicating that most rides were short. This trend suggests that the bike share system is primarily being used for short trips, such as commuting to and from work or school. However, riders tend to ride for longer durations on weekends, potentially using the bike share system for leisure and recreation. Interestingly, the customer category had longer ride durations throughout the week than the subscriber category, which may be because customer category riders use the bike share system more for leisure and recreation.

The most popular starting points for bike rides were found to be the San Francisco Ferry Building (Harry Bridges Plaza), San Francisco Caltrain Station 2 (Townsend St at 4th St), and San Francisco Caltrain (Townsend St at 4th St), which are likely transportation hubs such as train and bus stations, making them convenient and easily accessible starting points for people commuting to work or other destinations.

In terms of time usage, bike rides were heavily used at 8 AM and 5 PM, indicating that individuals are primarily using the bike share system for commuting to and from work or school during peak morning and evening hours. I also discovered that there is a significant drop in the number of rides starting at 11:00 PM to 4:00 AM. Furthermore, the majority of rides were taken during weekdays, suggesting that the bike share system is primarily being used for weekday commuting or transportation, likely for work or school-related purposes.

Finally, bike rentals were found to be in high demand between May and October, with the highest number of rides occurring in October. This trend suggests that the bike share system is being used more frequently during the warmer months of the year, likely due to favorable weather conditions and longer daylight hours. Additionally, the increase in rides during the summer months may be due to an increase in tourism and outdoor activities, leading to more individuals using the bike share system for transportation and recreation.