Part_I_exploration

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1 Part I - Ford GoBike System Data Exploration

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2.1 Introduction

This dataset includes information about individual rides made in a bike-sharing system covering the greater San Francisco Bay area.

We will be analysing the dataset to see how different features change over time, accross various rides and to see if there are relationships between them. We start with preliminary wrangling and move on to univariate, bivariate and then multivariate exploration. Then we summarise our findings.

2.2 Preliminary Wrangling

[1]:
```
# 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
from datetime import datetime

%matplotlib inline
```

Let's load our dataset and start withh a non-visual analysis to see if we need to do some cleaning or tidying.

[2]:
```
df = pd.read_csv("201902-fordgobike-tripdata.csv")
```

[3]:
```
df
```

[3]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitude	start_station_longitude	end_station_id	end_station_name	end_station_latitude
0	52185	2019-02-28 17:32:10.1450	2019-03-01 08:01:55.9750	21.0	Montgomery St BART Station (Market St at 2nd St)	37.789625	-122.400811	13.0	Commercial St at Montgomery St	37.794231
1	42521	2019-02-28 18:53:21.7890	2019-03-01 06:42:03.0560	23.0	The Embarcadero at Steuart St	37.791464	-122.391034	81.0	Berry St at 4th St	37.775880
2	61854	2019-02-28 12:13:13.2180	2019-03-01 05:24:08.1460	86.0	Market St at Dolores St	37.769305	-122.426826	3.0	Powell St BART Station (Market St at 4th St)	37.786375
3	36490	2019-02-28 17:54:26.0100	2019-03-01 04:02:36.8420	375.0	Grove St at Masonic Ave	37.774836	-122.446546	70.0		
4	1585	2019-02-28 23:54:18.5490	2019-03-01 00:20:44.0740	7.0	Frank H Ogawa Plaza	37.804562	-122.271738	222.0		
…	…	…	…	…	…	…	…	…	…	…
183407	480	2019-02-01 00:04:49.7240	2019-02-01 00:12:50.0340	27.0	Beale St at Harrison St	37.788059	-122.391865	324.0		
183408	313	2019-02-01 00:05:34.7440	2019-02-01 00:10:48.5020	21.0	Montgomery St BART Station (Market St at 2nd St)	37.789625	-122.400811	66.0		
183409	141	2019-02-01 00:06:05.5490	2019-02-01 00:08:27.2200	278.0	The Alameda at Bush St	37.331932	-121.904888	277.0		
183410	139	2019-02-01 00:05:34.3600	2019-02-01 00:07:54.2870	220.0	San Pablo Ave at MLK Jr Way	37.811351	-122.273422	216.0		
183411	271	2019-02-01 00:00:20.6360	2019-02-01 00:04:52.0580	24.0	Spear St at Folsom St	37.789677	-122.390428	37.0		

```
3                            Central Ave at Fell St             37.773311
4                             10th Ave at E 15th St             37.792714
…                                               …                  …
183407          Union Square (Powell St at Post St)             37.788300
183408                        3rd St at Townsend St             37.778742
183409                   Morrison Ave at Julian St              37.333658
183410                    San Pablo Ave at 27th St              37.817827
183411                         2nd St at Folsom St              37.785000

        end_station_longitude  bike_id   user_type  member_birth_year  \
0                  -122.402923     4902    Customer             1984.0
1                  -122.393170     2535    Customer                NaN
2                  -122.404904     5905    Customer             1972.0
3                  -122.444293     6638  Subscriber             1989.0
4                  -122.248780     4898  Subscriber             1974.0
…                         …       …          …                 …
183407             -122.408531     4832  Subscriber             1996.0
183408             -122.392741     4960  Subscriber             1984.0
183409             -121.908586     3824  Subscriber             1990.0
183410             -122.275698     5095  Subscriber             1988.0
183411             -122.395936     1057  Subscriber             1989.0

       member_gender bike_share_for_all_trip
0               Male                      No
1                NaN                      No
2               Male                      No
3              Other                      No
4               Male                     Yes
…               …                        …
183407          Male                      No
183408          Male                      No
183409          Male                     Yes
183410          Male                      No
183411          Male                      No

[183412 rows x 16 columns]
```

Looking at the data types and checking for null/missing values.

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             183412 non-null  int64
 1   start_time               183412 non-null  object
```

```
 2   end_time                 183412 non-null  object
 3   start_station_id         183215 non-null  float64
 4   start_station_name       183215 non-null  object
 5   start_station_latitude   183412 non-null  float64
 6   start_station_longitude  183412 non-null  float64
 7   end_station_id           183215 non-null  float64
 8   end_station_name         183215 non-null  object
 9   end_station_latitude     183412 non-null  float64
 10  end_station_longitude    183412 non-null  float64
 11  bike_id                  183412 non-null  int64
 12  user_type                183412 non-null  object
 13  member_birth_year        175147 non-null  float64
 14  member_gender            175147 non-null  object
 15  bike_share_for_all_trip  183412 non-null  object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

We do not have missing data for some of the features but we do for some like the station_id. Since we have complete data for the station longitude and latitude, we can get the missing station ids and the station names by finding matching longitudes and latitudes of those non-null values (This will be necessary if we need them for our analysis).

We will also get the descriptive statistics of the numeric features.

[5]:
```
df.describe()
```

[5]:

	duration_sec	start_station_id	start_station_latitude	\
count	183412.000000	183215.000000	183412.000000	
mean	726.078435	138.590427	37.771223	
std	1794.389780	111.778864	0.099581	
min	61.000000	3.000000	37.317298	
25%	325.000000	47.000000	37.770083	
50%	514.000000	104.000000	37.780760	
75%	796.000000	239.000000	37.797280	
max	85444.000000	398.000000	37.880222	

	start_station_longitude	end_station_id	end_station_latitude	\
count	183412.000000	183215.000000	183412.000000	
mean	-122.352664	136.249123	37.771427	
std	0.117097	111.515131	0.099490	
min	-122.453704	3.000000	37.317298	
25%	-122.412408	44.000000	37.770407	
50%	-122.398285	100.000000	37.781010	
75%	-122.286533	235.000000	37.797320	
max	-121.874119	398.000000	37.880222	

	end_station_longitude	bike_id	member_birth_year
count	183412.000000	183412.000000	175147.000000

```
mean          -122.352250    4472.906375       1984.806437
std              0.116673    1664.383394         10.116689
min           -122.453704      11.000000       1878.000000
25%           -122.411726    3777.000000       1980.000000
50%           -122.398279    4958.000000       1987.000000
75%           -122.288045    5502.000000       1992.000000
max           -121.874119    6645.000000       2001.000000
```

There is an inconsistency in the statistical data of the duration feature. This may be due to wrong data that we can drop. We can also calculate the correct duration by subtracting the start_time from end_time and comparing the result with what we have in the duration_sec column.

2.2.1 Data Cleaning

We identify some dirty and untidy data issues as below: 1. start_station_id and end_station_id are float (should be int) 2. member_birth_year is float (should be int) 3. Missing data 4. data type for date 5. The max duration_sec is unexpectedly way above the 75th percentile (also compared to other percentiles).

We will be creating copies of our data as we clean it, so we can save the versions as we go

[6]:
```
df_copy = df.copy()
```

First, we convert the `start_time` and `end_time` to pandas datetime

[7]:
```
df_copy['start_time'] = pd.to_datetime(df_copy['start_time'])
df_copy['end_time'] = pd.to_datetime(df_copy['end_time'])
```

We are missing `start_station_id` and `end_station_id` for 197 rows. Let's see if we can get stations with same longititude and latitude, with station ids.

[8]:
```
null_stations = df_copy[df_copy.start_station_id.isna()]
null_stations
```

[8]:
```
        duration_sec              start_time                 end_time  \
475             1709 2019-02-28 20:55:53.932 2019-02-28 21:24:23.738
1733            1272 2019-02-28 18:32:34.273 2019-02-28 18:53:46.727
3625             142 2019-02-28 17:10:46.529 2019-02-28 17:13:09.431
4070             585 2019-02-28 16:28:45.934 2019-02-28 16:38:31.332
5654             509 2019-02-28 12:30:17.131 2019-02-28 12:38:46.329
…                …                         …                        …
176154          1447 2019-02-02 12:03:04.544 2019-02-02 12:27:12.267
179730           309 2019-02-01 12:59:45.969 2019-02-01 13:04:55.426
179970           659 2019-02-01 12:17:37.675 2019-02-01 12:28:37.014
180106          2013 2019-02-01 11:33:55.147 2019-02-01 12:07:28.940
181201           312 2019-02-01 09:26:34.803 2019-02-01 09:31:46.921

        start_station_id start_station_name  start_station_latitude  \
475                  NaN                NaN                   37.40
```

```
1733                  NaN                NaN                    37.40
3625                  NaN                NaN                    37.41
4070                  NaN                NaN                    37.39
5654                  NaN                NaN                    37.40
…                     …                  …                      …
176154                NaN                NaN                    37.40
179730                NaN                NaN                    37.40
179970                NaN                NaN                    37.41
180106                NaN                NaN                    37.40
181201                NaN                NaN                    37.40

        start_station_longitude  end_station_id end_station_name  \
475                      -121.94             NaN              NaN
1733                     -121.94             NaN              NaN
3625                     -121.95             NaN              NaN
4070                     -121.93             NaN              NaN
5654                     -121.92             NaN              NaN
…                          …                 …                …
176154                   -121.93             NaN              NaN
179730                   -121.94             NaN              NaN
179970                   -121.96             NaN              NaN
180106                   -121.94             NaN              NaN
181201                   -121.93             NaN              NaN

        end_station_latitude  end_station_longitude  bike_id   user_type  \
475                    37.40                -121.93     4211    Customer
1733                   37.41                -121.96     4174  Subscriber
3625                   37.41                -121.96     4283  Subscriber
4070                   37.40                -121.92     4089  Subscriber
5654                   37.39                -121.93     4089  Subscriber
…                      …                    …       …        …
176154                 37.40                -121.93     4249    Customer
179730                 37.40                -121.93     4249    Customer
179970                 37.41                -121.94     4092  Subscriber
180106                 37.40                -121.94     4251    Customer
181201                 37.40                -121.93     4208  Subscriber

        member_birth_year member_gender bike_share_for_all_trip
475                1991.0        Female                     No
1733               1980.0          Male                     No
3625               1988.0          Male                     No
4070               1984.0          Male                    Yes
5654               1984.0          Male                    Yes
…                   …           …                       …
176154             1984.0          Male                     No
179730             1987.0        Female                     No
179970             1999.0        Female                     No
```

```
180106             1990.0        Female                       No
181201             1987.0          Male                       No

[197 rows x 16 columns]
```

We will pick the latitudes and see if we can get the station ids from other rides

[9]:
```
df_copy[df_copy.start_station_latitude == 37.39]
```

[9]:
```
        duration_sec              start_time                end_time  \
4070             585 2019-02-28 16:28:45.934 2019-02-28 16:38:31.332
45410            605 2019-02-22 12:16:01.730 2019-02-22 12:26:07.725
54603            532 2019-02-21 12:25:53.670 2019-02-21 12:34:46.367
55542            235 2019-02-21 10:02:11.532 2019-02-21 10:06:07.131
61593            768 2019-02-20 17:30:56.074 2019-02-20 17:43:45.070
71838            743 2019-02-19 17:05:20.891 2019-02-19 17:17:44.592
72916           1741 2019-02-19 15:01:18.291 2019-02-19 15:30:19.691
73793            510 2019-02-19 12:33:35.392 2019-02-19 12:42:06.189
79523            712 2019-02-18 17:22:03.999 2019-02-18 17:33:56.667
81568            546 2019-02-18 12:48:09.383 2019-02-18 12:57:16.319
120203           158 2019-02-11 17:20:03.750 2019-02-11 17:22:41.891

        start_station_id start_station_name  start_station_latitude  \
4070                 NaN                NaN                   37.39
45410                NaN                NaN                   37.39
54603                NaN                NaN                   37.39
55542                NaN                NaN                   37.39
61593                NaN                NaN                   37.39
71838                NaN                NaN                   37.39
72916                NaN                NaN                   37.39
73793                NaN                NaN                   37.39
79523                NaN                NaN                   37.39
81568                NaN                NaN                   37.39
120203               NaN                NaN                   37.39

        start_station_longitude  end_station_id end_station_name  \
4070                     -121.93             NaN              NaN
45410                    -121.93             NaN              NaN
54603                    -121.93             NaN              NaN
55542                    -121.93             NaN              NaN
61593                    -121.93             NaN              NaN
71838                    -121.93             NaN              NaN
72916                    -121.92             NaN              NaN
73793                    -121.93             NaN              NaN
79523                    -121.93             NaN              NaN
81568                    -121.93             NaN              NaN
120203                   -121.93             NaN              NaN
```

```
        end_station_latitude  end_station_longitude  bike_id   user_type  \
4070                   37.40                -121.92     4089  Subscriber
45410                  37.40                -121.93     4207  Subscriber
54603                  37.40                -121.93     4207  Subscriber
55542                  37.39                -121.93     4249  Subscriber
61593                  37.40                -121.93     4207  Subscriber
71838                  37.40                -121.93     4207  Subscriber
72916                  37.40                -121.94     4197    Customer
73793                  37.40                -121.93     4207  Subscriber
79523                  37.40                -121.93     4197  Subscriber
81568                  37.40                -121.93     4197  Subscriber
120203                 37.39                -121.93     4249  Subscriber

        member_birth_year member_gender bike_share_for_all_trip
4070               1984.0          Male                     Yes
45410              1986.0          Male                      No
54603              1986.0          Male                      No
55542              1994.0          Male                     Yes
61593              1986.0          Male                      No
71838              1986.0          Male                      No
72916              1985.0        Female                      No
73793              1986.0          Male                      No
79523              1986.0          Male                      No
81568              1986.0          Male                      No
120203             1986.0          Male                      No
```

It looks like they are all null values. Since we do not have a station id of zero, we can fill the missing values with zero. We also need to convert the datatype to integer.

[10]:
```
df_copy.fillna({'start_station_id': 0, 'end_station_id':0}, inplace=True)
```

[11]:
```
df_copy['start_station_id'] = df_copy['start_station_id'].astype('int')
```

[12]:
```
df_copy['end_station_id'] = df_copy['end_station_id'].astype('int')
```

For the `member_birth_year`, let fill the missing values with the mean member_birth_year value (we can fill with zero because that will be unreal and will distort our analysis). Then we convert the datatype to integer.

[13]:
```
mean_birth_year = df_copy.member_birth_year.mean()
mean_birth_year
```

[13]:
```
1984.8064368787361
```

[14]:
```
df_copy.fillna({'member_birth_year': mean_birth_year}, inplace=True)
```

[15]:
```
df_copy['member_birth_year'] = df_copy['member_birth_year'].astype('int')
```

For `member_gender`, we will fill the missing values with "Other". Then we fill missing values for `start_station_name` and `end_station_name` with "None".

[16]:
```
df_copy["member_gender"].fillna("Other", inplace = True)
```

[17]:
```
df_copy["start_station_name"].fillna("None", inplace = True)
df_copy["end_station_name"].fillna("None", inplace = True)
```

We will check if the `duration_sec` column has the correct values, by subtracting `start_time` from `end_time` and comparing the value with what we have in the `duration_sec` column.

[18]:
```
df_copy['duration2'] = (df_copy['end_time'] - df_copy['start_time']).dt.
↪total_seconds().astype('int')
```

[19]:
```
df_copy['equal'] = np.where(df_copy["duration_sec"] == df_copy["duration2"],␣
↪True, False)
```

[20]:
```
df_copy.loc[df_copy['equal']==False].shape
```

[20]:
```
(0, 18)
```

Since we do not have any wrong duration_sec, we will not be updating it. Rather, we would drop the new columns we created.

[21]:
```
df_copy.drop(['duration2', 'equal'], axis=1, inplace=True)
```

Let's add some new columns 'start_year', 'start_month', 'start_day', 'age' so we can do some analysis based on them. We also want to calculate age based on the year the ride was taken. This way, we can know the age of the rider at that time.

[22]:
```
df_copy2 = df_copy.copy()
```

[23]:
```
df_copy2["year"] = df_copy2["start_time"].dt.year
df_copy2["month"] = df_copy2["start_time"].dt.month
df_copy2["week_day"] = df_copy2["start_time"].dt.day_name()
```

[24]:
```
df_copy2["age"] = df_copy2["year"] - df_copy2["member_birth_year"]
df_copy2
```

[24]:

	duration_sec	start_time	end_time	\
0	52185	2019-02-28 17:32:10.145	2019-03-01 08:01:55.975	
1	42521	2019-02-28 18:53:21.789	2019-03-01 06:42:03.056	
2	61854	2019-02-28 12:13:13.218	2019-03-01 05:24:08.146	
3	36490	2019-02-28 17:54:26.010	2019-03-01 04:02:36.842	
4	1585	2019-02-28 23:54:18.549	2019-03-01 00:20:44.074	
…	…	…	…	
183407	480	2019-02-01 00:04:49.724	2019-02-01 00:12:50.034	
183408	313	2019-02-01 00:05:34.744	2019-02-01 00:10:48.502	
183409	141	2019-02-01 00:06:05.549	2019-02-01 00:08:27.220	

```
183410          139 2019-02-01 00:05:34.360 2019-02-01 00:07:54.287
183411          271 2019-02-01 00:00:20.636 2019-02-01 00:04:52.058

        start_station_id                                start_station_name  \
0                     21  Montgomery St BART Station (Market St at 2nd St)
1                     23                      The Embarcadero at Steuart St
2                     86                            Market St at Dolores St
3                    375                            Grove St at Masonic Ave
4                      7                                Frank H Ogawa Plaza
…                    …                                                  …
183407                27                            Beale St at Harrison St
183408                21  Montgomery St BART Station (Market St at 2nd St)
183409               278                             The Alameda at Bush St
183410               220                          San Pablo Ave at MLK Jr Way
183411                24                              Spear St at Folsom St

        start_station_latitude  start_station_longitude  end_station_id  \
0                    37.789625              -122.400811              13
1                    37.791464              -122.391034              81
2                    37.769305              -122.426826               3
3                    37.774836              -122.446546              70
4                    37.804562              -122.271738             222
…                          …                        …               …
183407               37.788059              -122.391865             324
183408               37.789625              -122.400811              66
183409               37.331932              -121.904888             277
183410               37.811351              -122.273422             216
183411               37.789677              -122.390428              37

                                  end_station_name  end_station_latitude  \
0                    Commercial St at Montgomery St             37.794231
1                               Berry St at 4th St             37.775880
2       Powell St BART Station (Market St at 4th St)             37.786375
3                             Central Ave at Fell St             37.773311
4                              10th Ave at E 15th St             37.792714
…                                                …                    …
183407          Union Square (Powell St at Post St)             37.788300
183408                        3rd St at Townsend St             37.778742
183409                    Morrison Ave at Julian St             37.333658
183410                     San Pablo Ave at 27th St             37.817827
183411                          2nd St at Folsom St             37.785000

        end_station_longitude  bike_id   user_type  member_birth_year  \
0                -122.402923     4902    Customer               1984
1                -122.393170     2535    Customer               1984
2                -122.404904     5905    Customer               1972
3                -122.444293     6638  Subscriber               1989
```

```
4                -122.248780     4898  Subscriber                1974
…                      …       …          …                    …
183407           -122.408531     4832  Subscriber                1996
183408           -122.392741     4960  Subscriber                1984
183409           -121.908586     3824  Subscriber                1990
183410           -122.275698     5095  Subscriber                1988
183411           -122.395936     1057  Subscriber                1989

       member_gender bike_share_for_all_trip  year  month  week_day  age
0               Male                     No  2019      2  Thursday   35
1              Other                     No  2019      2  Thursday   35
2               Male                     No  2019      2  Thursday   47
3              Other                     No  2019      2  Thursday   30
4               Male                    Yes  2019      2  Thursday   45
…                …                      …    …       …       …  …
183407          Male                     No  2019      2    Friday   23
183408          Male                     No  2019      2    Friday   35
183409          Male                    Yes  2019      2    Friday   29
183410          Male                     No  2019      2    Friday   31
183411          Male                     No  2019      2    Friday   30

[183412 rows x 20 columns]
```

[25]:
```
df_copy2.describe()
```

[25]:
```
        duration_sec  start_station_id  start_station_latitude  \
count  183412.000000     183412.000000           183412.000000
mean      726.078435        138.441569               37.771223
std      1794.389780        111.811012                0.099581
min        61.000000          0.000000               37.317298
25%       325.000000         47.000000               37.770083
50%       514.000000        104.000000               37.780760
75%       796.000000        239.000000               37.797280
max     85444.000000        398.000000               37.880222

       start_station_longitude  end_station_id  end_station_latitude  \
count            183412.000000   183412.000000         183412.000000
mean               -122.352664      136.102780             37.771427
std                   0.117097      111.544544              0.099490
min                -122.453704        0.000000             37.317298
25%                -122.412408       44.000000             37.770407
50%                -122.398285      100.000000             37.781010
75%                -122.286533      235.000000             37.797320
max                -121.874119      398.000000             37.880222

       end_station_longitude        bike_id  member_birth_year      year  \
count          183412.000000  183412.000000      183412.000000  183412.0
```

```
mean             -122.352250    4472.906375        1984.770097    2019.0
std                 0.116673    1664.383394           9.887534       0.0
min              -122.453704      11.000000        1878.000000    2019.0
25%              -122.411726    3777.000000        1981.000000    2019.0
50%              -122.398279    4958.000000        1987.000000    2019.0
75%              -122.288045    5502.000000        1992.000000    2019.0
max              -121.874119    6645.000000        2001.000000    2019.0
```

```
          month            age
count  183412.0  183412.000000
mean        2.0      34.229903
std         0.0       9.887534
min         2.0      18.000000
25%         2.0      27.000000
50%         2.0      32.000000
75%         2.0      38.000000
max         2.0     141.000000
```

Let's create the age_group column but we will create a copy of our current dataset to preserve the cleaning we've done so far.

[26]:
```
df_copy3 = df_copy2.copy()
```

[27]:
```
bins= [13,25,45,65,85]
labels = ['13-24','25-44', '45-64', '65-84']
df_copy3['age_group'] = pd. cut(df_copy3['age'], bins=bins, labels=labels,␣
 ↪right=False)
df_copy3
```

[27]:
```
        duration_sec              start_time                 end_time  \
0              52185 2019-02-28 17:32:10.145 2019-03-01 08:01:55.975
1              42521 2019-02-28 18:53:21.789 2019-03-01 06:42:03.056
2              61854 2019-02-28 12:13:13.218 2019-03-01 05:24:08.146
3              36490 2019-02-28 17:54:26.010 2019-03-01 04:02:36.842
4               1585 2019-02-28 23:54:18.549 2019-03-01 00:20:44.074
…                …                       …                       …
183407           480 2019-02-01 00:04:49.724 2019-02-01 00:12:50.034
183408           313 2019-02-01 00:05:34.744 2019-02-01 00:10:48.502
183409           141 2019-02-01 00:06:05.549 2019-02-01 00:08:27.220
183410           139 2019-02-01 00:05:34.360 2019-02-01 00:07:54.287
183411           271 2019-02-01 00:00:20.636 2019-02-01 00:04:52.058

        start_station_id                                start_station_name  \
0                     21  Montgomery St BART Station (Market St at 2nd St)
1                     23                      The Embarcadero at Steuart St
2                     86                            Market St at Dolores St
3                    375                            Grove St at Masonic Ave
```

```
4                      7                              Frank H Ogawa Plaza
…                    …                                                …
183407                27                            Beale St at Harrison St
183408                21  Montgomery St BART Station (Market St at 2nd St)
183409               278                              The Alameda at Bush St
183410               220                          San Pablo Ave at MLK Jr Way
183411                24                               Spear St at Folsom St

        start_station_latitude  start_station_longitude  end_station_id  \
0                    37.789625              -122.400811              13
1                    37.791464              -122.391034              81
2                    37.769305              -122.426826               3
3                    37.774836              -122.446546              70
4                    37.804562              -122.271738             222
…                          …                        …             …
183407               37.788059              -122.391865             324
183408               37.789625              -122.400811              66
183409               37.331932              -121.904888             277
183410               37.811351              -122.273422             216
183411               37.789677              -122.390428              37

                                  end_station_name  end_station_latitude  \
0                      Commercial St at Montgomery St             37.794231
1                                Berry St at 4th St             37.775880
2       Powell St BART Station (Market St at 4th St)             37.786375
3                             Central Ave at Fell St             37.773311
4                              10th Ave at E 15th St             37.792714
…                                                …                    …
183407           Union Square (Powell St at Post St)             37.788300
183408                          3rd St at Townsend St             37.778742
183409                     Morrison Ave at Julian St             37.333658
183410                      San Pablo Ave at 27th St             37.817827
183411                           2nd St at Folsom St             37.785000

        …  bike_id   user_type member_birth_year  member_gender  \
0       …     4902    Customer              1984           Male
1       …     2535    Customer              1984          Other
2       …     5905    Customer              1972           Male
3       …     6638  Subscriber              1989          Other
4       …     4898  Subscriber              1974           Male
…     …       …         …                …             …
183407  …     4832  Subscriber              1996           Male
183408  …     4960  Subscriber              1984           Male
183409  …     3824  Subscriber              1990           Male
183410  …     5095  Subscriber              1988           Male
183411  …     1057  Subscriber              1989           Male
```

```
       bike_share_for_all_trip  year  month  week_day age  age_group
0                           No  2019      2  Thursday  35      25-44
1                           No  2019      2  Thursday  35      25-44
2                           No  2019      2  Thursday  47      45-64
3                           No  2019      2  Thursday  30      25-44
4                          Yes  2019      2  Thursday  45      45-64
…                        …   …    …       …  ..        …
183407                      No  2019      2    Friday  23      13-24
183408                      No  2019      2    Friday  35      25-44
183409                     Yes  2019      2    Friday  29      25-44
183410                      No  2019      2    Friday  31      25-44
183411                      No  2019      2    Friday  30      25-44

[183412 rows x 21 columns]
```

[28]:
```
df_copy3.age_group.value_counts()
```

[28]:
```
25-44    134014
45-64     24726
13-24     22992
65-84      1491
Name: age_group, dtype: int64
```

Now we'll go on to get the parts of the day these trips were taken.

[29]:
```
# A function to get part of the day from the start_time column
def get_part_of_the_day(hour):
    # if the time is between 5:00 and 11:00, return "morning"
    if 5 <= hour <= 11:
        return "morning"
    # if the time is between 12:00 and 16:00, return "afternoon"
    elif 12 <= hour <= 16:
        return "afternoon"
    # if the time is between 17:00 and 22:00, return "evening"
    elif 17 <= hour <= 22:
        return "evening"
    # else, return night
    else:
        return "night"

df_copy3['part_of_day'] = df_copy3.start_time.apply(lambda x:␣
 ↪get_part_of_the_day(x.hour))
```

Let's drop the columns we won't be working with. Since the year are month are the same, we will drop them as well.

[30]:
```
df_copy3.drop(['start_time', 'end_time', 'member_birth_year',␣
↪'start_station_latitude', 'start_station_longitude', 'end_station_latitude',␣
↪'end_station_longitude', 'year', 'month'], axis=1, inplace=True)
```

[31]:
```
df_copy3
```

[31]:

```
        duration_sec  start_station_id  \
0              52185                21
1              42521                23
2              61854                86
3              36490               375
4               1585                 7
…                …                 …
183407           480                27
183408           313                21
183409           141               278
183410           139               220
183411           271                24

                                    start_station_name  end_station_id  \
0       Montgomery St BART Station (Market St at 2nd St)              13
1                         The Embarcadero at Steuart St              81
2                               Market St at Dolores St               3
3                               Grove St at Masonic Ave              70
4                                   Frank H Ogawa Plaza             222
…                                                   …               …
183407                          Beale St at Harrison St             324
183408  Montgomery St BART Station (Market St at 2nd St)              66
183409                           The Alameda at Bush St             277
183410                     San Pablo Ave at MLK Jr Way              216
183411                           Spear St at Folsom St               37

                                  end_station_name  bike_id   user_type  \
0                    Commercial St at Montgomery St     4902    Customer
1                                 Berry St at 4th St     2535    Customer
2       Powell St BART Station (Market St at 4th St)     5905    Customer
3                           Central Ave at Fell St     6638  Subscriber
4                            10th Ave at E 15th St     4898  Subscriber
…                                                …      …           …
183407          Union Square (Powell St at Post St)     4832  Subscriber
183408                       3rd St at Townsend St     4960  Subscriber
183409                  Morrison Ave at Julian St      3824  Subscriber
183410                   San Pablo Ave at 27th St     5095  Subscriber
183411                        2nd St at Folsom St     1057  Subscriber

       member_gender bike_share_for_all_trip  week_day  age age_group  \
0               Male                     No  Thursday   35     25-44
```

```
1              Other                      No  Thursday   35     25-44
2               Male                      No  Thursday   47     45-64
3              Other                      No  Thursday   30     25-44
4               Male                     Yes  Thursday   45     45-64
…               …                  …       …  …          …
183407          Male                      No    Friday   23     13-24
183408          Male                      No    Friday   35     25-44
183409          Male                     Yes    Friday   29     25-44
183410          Male                      No    Friday   31     25-44
183411          Male                      No    Friday   30     25-44

       part_of_day
0          evening
1          evening
2        afternoon
3          evening
4            night
…              …
183407       night
183408       night
183409       night
183410       night
183411       night

[183412 rows x 13 columns]
```

[32]:
```
df_copy3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 13 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             183412 non-null  int64
 1   start_station_id         183412 non-null  int64
 2   start_station_name       183412 non-null  object
 3   end_station_id           183412 non-null  int64
 4   end_station_name         183412 non-null  object
 5   bike_id                  183412 non-null  int64
 6   user_type                183412 non-null  object
 7   member_gender            183412 non-null  object
 8   bike_share_for_all_trip  183412 non-null  object
 9   week_day                 183412 non-null  object
 10  age                      183412 non-null  int64
 11  age_group                183223 non-null  category
 12  part_of_day              183412 non-null  object
dtypes: category(1), int64(5), object(7)
```

```
memory usage: 17.0+ MB
```

[33]:
```
df_copy3.describe()
```

[33]:
```
         duration_sec  start_station_id  end_station_id        bike_id  \
count  183412.000000     183412.000000   183412.000000  183412.000000
mean      726.078435        138.441569      136.102780    4472.906375
std      1794.389780        111.811012      111.544544    1664.383394
min        61.000000          0.000000        0.000000      11.000000
25%       325.000000         47.000000       44.000000    3777.000000
50%       514.000000        104.000000      100.000000    4958.000000
75%       796.000000        239.000000      235.000000    5502.000000
max     85444.000000        398.000000      398.000000    6645.000000

                 age
count  183412.000000
mean       34.229903
std         9.887534
min        18.000000
25%        27.000000
50%        32.000000
75%        38.000000
max       141.000000
```

From the descriptive analysis above, we see that there is a huge gap between the max duration_sec and the 75th percentile. This may be due to some outliers. To better analyse our data, we we be dropping all rows with durations above 1000.

A huge gap is also seen between the max age and the 75th percentile. We will also drop all rows with age above 80.

[34]:
```
df_copy3 = df_copy3.drop(df_copy3[(df_copy3.duration_sec > 1000) | (df_copy3.
  ↪age > 80)].index)
df_copy3.reset_index(drop=True, inplace=True)
df_copy3
```

[34]:
```
        duration_sec  start_station_id  \
0                458               370
1                506                44
2                915               252
3                395               243
4                208               349
…                …                 …
155652           480                27
155653           313                21
155654           141               278
155655           139               220
155656           271                24
```

```
                                    start_station_name  end_station_id  \
0                                    Jones St at Post St              43
1       Civic Center/UN Plaza BART Station (Market St …             343
2                           Channing Way at Shattuck Ave             244
3                            Bancroft Way at College Ave             252
4                                  Howard St at Mary St               60
…                                                     …             …
155652                           Beale St at Harrison St             324
155653   Montgomery St BART Station (Market St at 2nd St)              66
155654                             The Alameda at Bush St             277
155655                          San Pablo Ave at MLK Jr Way             216
155656                               Spear St at Folsom St              37

                                      end_station_name  bike_id  \
0       San Francisco Public Library (Grove St at Hyde…     5318
1                                    Bryant St at 2nd St     5848
2                              Shattuck Ave at Hearst Ave     5101
3                           Channing Way at Shattuck Ave     4786
4                                  8th St at Ringold St     6361
…                                                     …      …
155652               Union Square (Powell St at Post St)     4832
155653                           3rd St at Townsend St     4960
155654                        Morrison Ave at Julian St     3824
155655                         San Pablo Ave at 27th St     5095
155656                              2nd St at Folsom St     1057

         user_type member_gender bike_share_for_all_trip  week_day  age  \
0       Subscriber        Female                     Yes  Thursday   23
1       Subscriber          Male                      No  Thursday   26
2       Subscriber         Other                      No  Thursday   35
3       Subscriber          Male                      No  Thursday   31
4       Subscriber          Male                     Yes  Thursday   26
…            …            …                       …       …  …
155652  Subscriber          Male                      No    Friday   23
155653  Subscriber          Male                      No    Friday   35
155654  Subscriber          Male                     Yes    Friday   29
155655  Subscriber          Male                      No    Friday   31
155656  Subscriber          Male                      No    Friday   30

       age_group part_of_day
0          13-24       night
1          25-44       night
2          25-44       night
3          25-44       night
4          25-44       night
…          …         …
```

```
155652     13-24       night
155653     25-44       night
155654     25-44       night
155655     25-44       night
155656     25-44       night

[155657 rows x 13 columns]
```

[35]:
```
df_copy3.describe()
```

[35]:
```
         duration_sec  start_station_id  end_station_id        bike_id  \
count  155657.000000     155657.000000   155657.000000  155657.000000
mean      482.421947        138.234079      135.109806    4471.634298
std       227.282219        110.129006      109.344129    1659.084499
min        61.000000          0.000000        0.000000      11.000000
25%       299.000000         49.000000       44.000000    3788.000000
50%       453.000000        102.000000       99.000000    4955.000000
75%       648.000000        239.000000      230.000000    5497.000000
max      1000.000000        398.000000      398.000000    6645.000000

                 age
count  155657.000000
mean       34.064539
std         9.546706
min        18.000000
25%        27.000000
50%        32.000000
75%        38.000000
max        80.000000
```

[36]:
```
bike_df = df_copy3
```

2.2.2 What is the structure of your dataset?

After cleaning the dataset, we have 155657 rides in the dataset, with 13 features. Below are the quantitative and the qualitative feature.

Quantitative

1. duration_sec
2. age

Qualitative

1. age_group
2. part_of_day
3. start_station_id
4. start_station_name

5. end_station_id
6. end_station_name
7. bike_id

8. user_type
9. bike_share_for_all_trip
10. member_gender
11. week_day

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

- I am interested in finding out what periods of the day had the most rides as well as the days of the week.
- I also what to know the age group that had the most bike shares.
- I want the explore the rides data for each gender.
- Wich stations are the busiest?
- How long does the average trip take?
- Does the above depend on if a user is a subscriber or customer?

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

- duration_sec
- start_time
- end_time
- start_station_name
- end_station_name
- user_type
- age_group
- member_gender
- part_of_day
- week_day

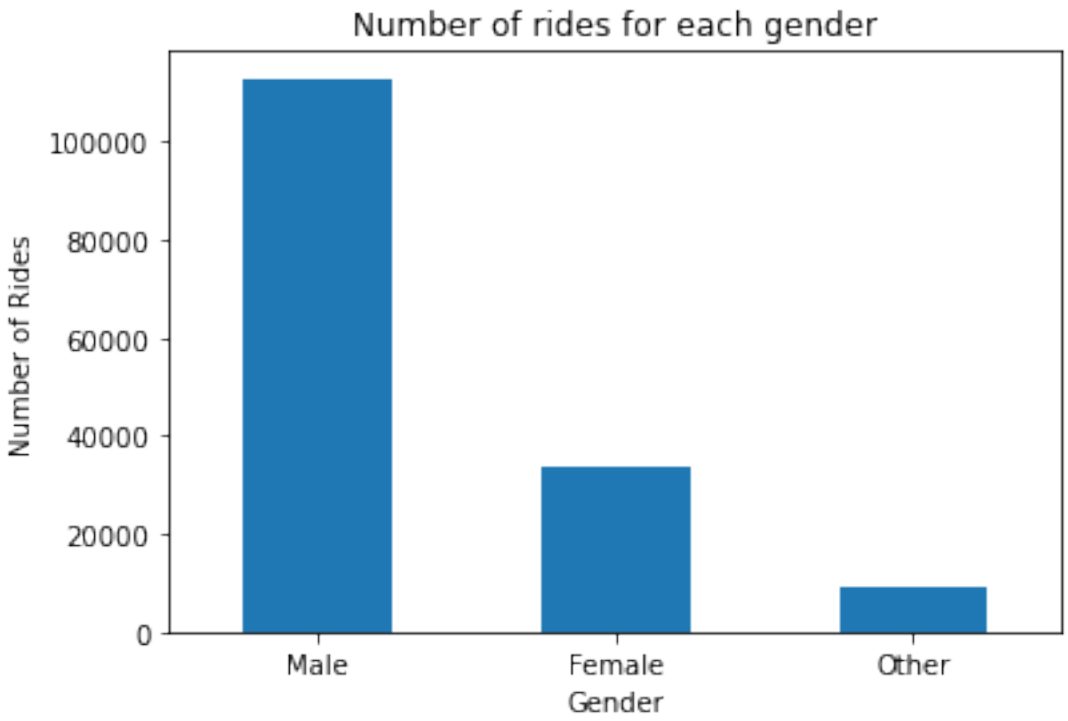
2.3 Univariate Exploration

[37]:
```
# A function for univariate bar charts using pandas value_counts plot
def plot_bar(feature, xlabel, ylabel, title, rot):
    bike_df[feature].value_counts().plot(kind='bar', rot=rot, xlabel=xlabel,␣
 ↪ylabel=ylabel, title=title)
```

2.3.1 Visualization 1: Visualizing ride data for each gender

Visualization

[38]:
```
plot_bar('member_gender', 'Gender', 'Number of Rides', 'Number of rides for␣
 ↪each gender', 0)
```



[39]:
```
bike_df['member_gender'].value_counts(normalize=True)
```

[39]:
```
Male      0.725036
Female    0.215686
Other     0.059278
Name: member_gender, dtype: float64
```

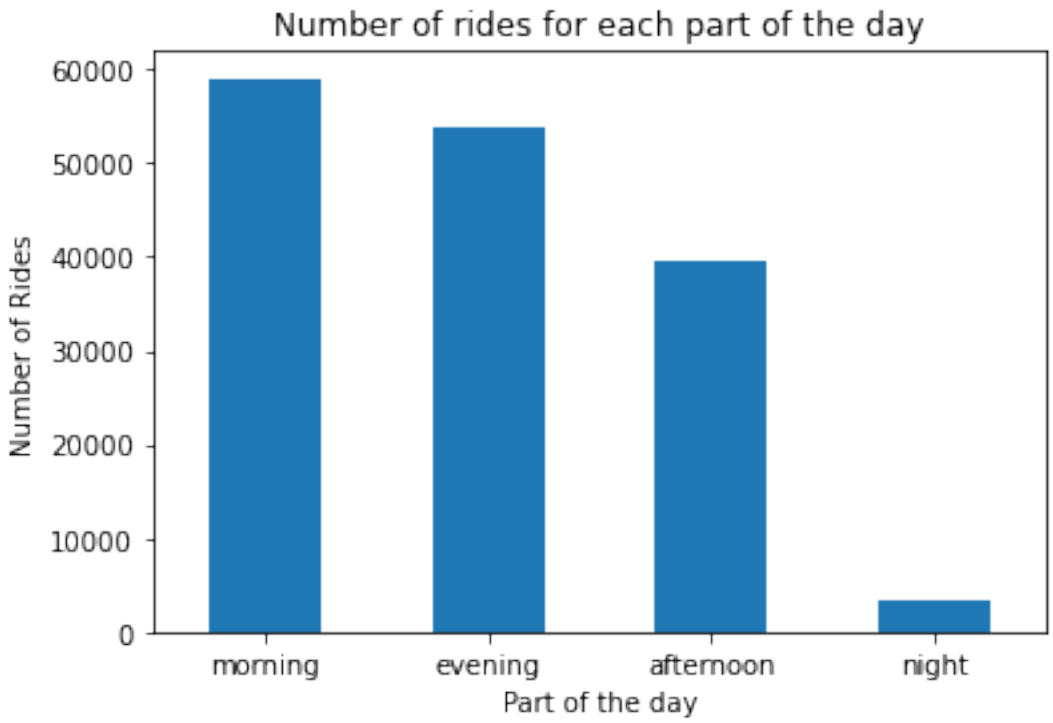
Observation

We have more male than female riders. 72% of the rides are by men. Anyway, we do not know if this has anything to do with the demography (gender ratio) of the population, or if most of the women prefer not to ride.

2.3.2 Visualization 2: What part of the day are the most rides taken?

Visualization

[40]:
```
plot_bar('part_of_day', 'Part of the day', 'Number of Rides', 'Number of rides␣
↪for each part of the day', 0)
```



[41]:
```
bike_df['part_of_day'].value_counts(normalize=True)
```

[41]:
```
morning      0.379051
evening      0.345375
afternoon    0.254283
night        0.021290
Name: part_of_day, dtype: float64
```

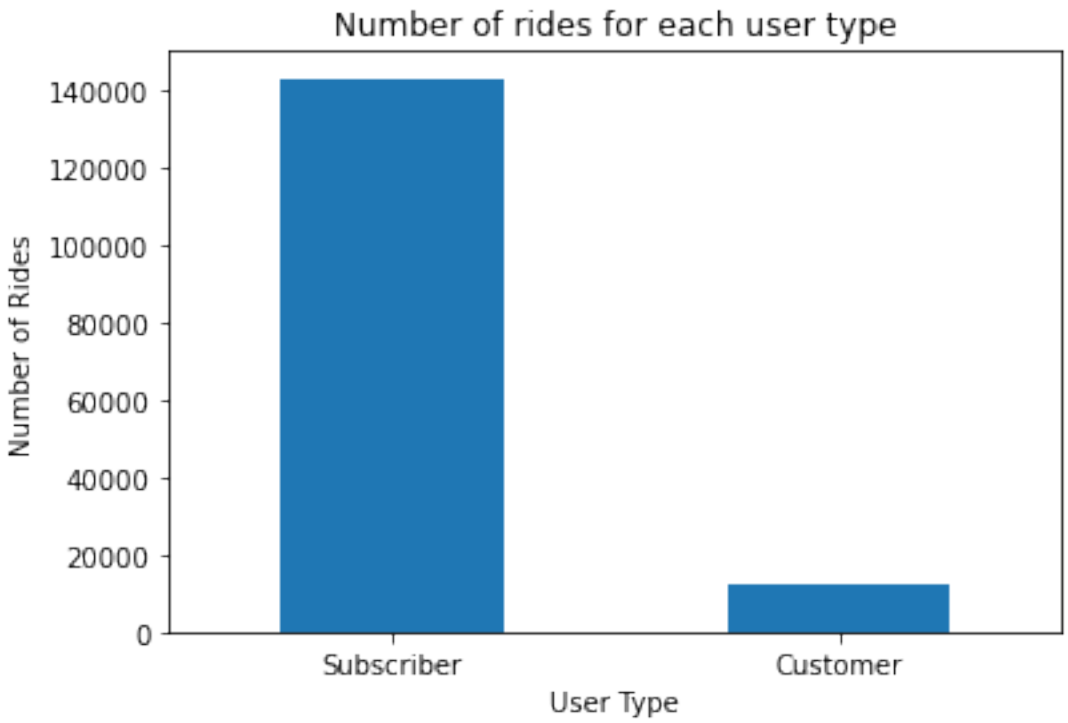
Observation

Most of the rides started in the morning. We have just 2% of the rides starting at night.

2.3.3 Visualization 3: How much of the rides are from each user-type?

Visualization

[42]:
```
plot_bar('user_type', 'User Type', 'Number of Rides', 'Number of rides for each␣
↪user type', 0)
```



[43]:
```
bike_df['user_type'].value_counts(normalize=True)
```

[43]:
```
Subscriber    0.918918
Customer      0.081082
Name: user_type, dtype: float64
```

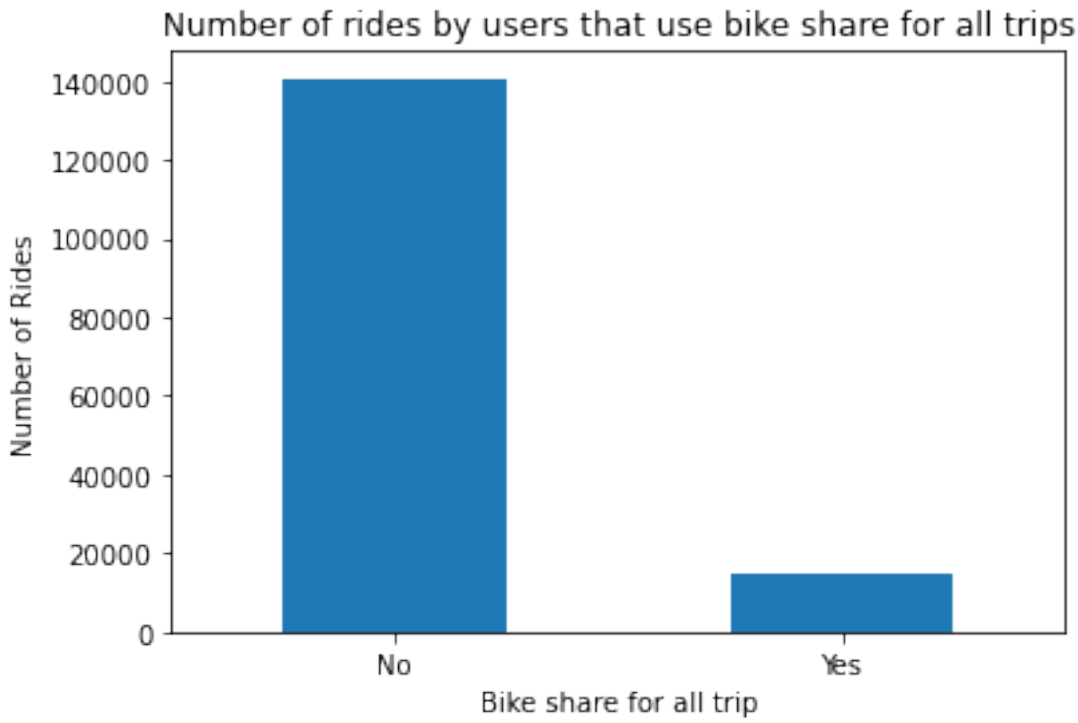
Observation

92% of the rides are from subscribers while the rest are customers

2.3.4 Visualization 4: What percentage of the rides are from users who use bike share for all their trips?

Visualization

[44]:
```
plot_bar('bike_share_for_all_trip', 'Bike share for all trip', 'Number of␣
↪Rides', 'Number of rides by users that use bike share for all trips', 0)
```



[45]:
```
bike_df['bike_share_for_all_trip'].value_counts(normalize=True)
```

[45]:
```
No     0.903923
Yes    0.096077
Name: bike_share_for_all_trip, dtype: float64
```

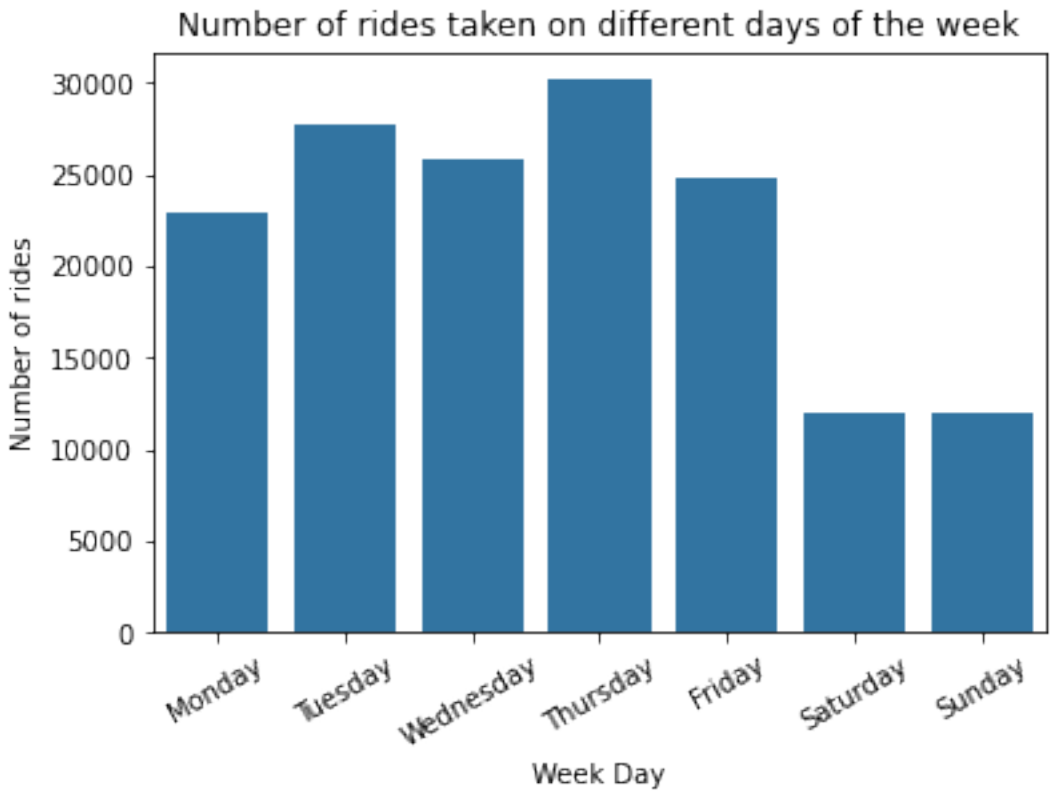
Observation

90% of the rides are from subscribers

2.3.5 Visualization 5: What percentage of the rides were taken at the different days of the week?

Visualization

[46]:
```
days= ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
 ↪'Sunday']
color = sb.color_palette()[0]
sb.countplot(data=bike_df, x='week_day', order=days, color=color)
plt.xticks(rotation=30)
plt.xlabel('Week Day')
plt.ylabel('Number of rides')
plt.title('Number of rides taken on different days of the week')
plt.show()
```



Observation

Most rides are taken between Monday and Friday and the least taken on Saturday and Sunday

2.3.6 Visualization 6: Analysis of the top 10 busiest stations, using the start station column.

[47]:
```
bike_df.start_station_name.value_counts(ascending=False).head(10)
```

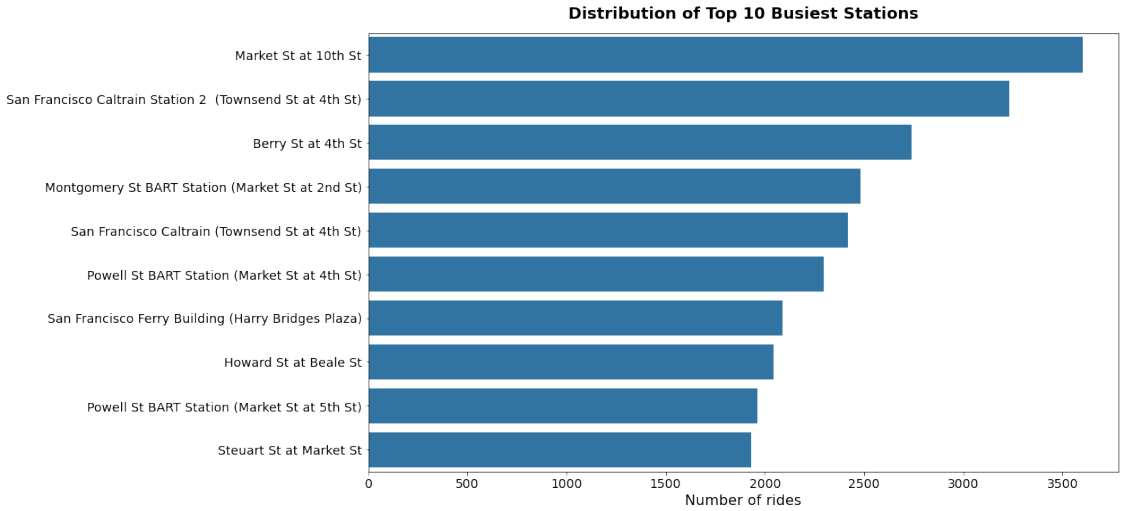
[47]:
```
Market St at 10th St                                   3602
San Francisco Caltrain Station 2  (Townsend St at 4th St)    3232
Berry St at 4th St                                     2738
Montgomery St BART Station (Market St at 2nd St)       2484
San Francisco Caltrain (Townsend St at 4th St)         2417
Powell St BART Station (Market St at 4th St)           2296
San Francisco Ferry Building (Harry Bridges Plaza)     2090
Howard St at Beale St                                  2045
Powell St BART Station (Market St at 5th St)           1962
Steuart St at Market St                                1930
Name: start_station_name, dtype: int64
```

[48]:
```
busiest_stations = bike_df.start_station_name.value_counts(ascending=False).
↪head(10).index
busiest_stations
```

[48]:
```
Index(['Market St at 10th St',
       'San Francisco Caltrain Station 2  (Townsend St at 4th St)',
       'Berry St at 4th St',
       'Montgomery St BART Station (Market St at 2nd St)',
       'San Francisco Caltrain (Townsend St at 4th St)',
       'Powell St BART Station (Market St at 4th St)',
       'San Francisco Ferry Building (Harry Bridges Plaza)',
       'Howard St at Beale St', 'Powell St BART Station (Market St at 5th St)',
       'Steuart St at Market St'],
      dtype='object')
```

Visualization

[49]:
```
color = sb.color_palette()[0]
plt.figure(figsize=(15,9))
sb.countplot(data=bike_df, y='start_station_name', order=busiest_stations,␣
↪orient = 'h', color=color)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.xlabel('Number of rides', fontsize=16)
plt.ylabel('')
plt.title('Distribution of Top 10 Busiest Stations', fontsize=18, y=1.02,␣
↪weight="bold")
plt.show()
```



Observation

The buusiest station is the 'Market St at 10th St' station with 3602 rides starting from there.

2.3.7 Summary of univariate exploration

From the univariate plots above, we can see that 72% of the riders are male, 92% are subscribers and 90% didn't use bike share for all their trips. There is a significant difference in the number of rides taken at night and those taken at other times of the day. This shows a real life scenario where most people are home or asleep at night. We also see that Mondays to Fridays are the busiest day, which also depicts a real life scenario.

Earlier in the data cleaning section, we noticed an unusual max value for duration, compared to other stats. We had to drop rows with duration above 1000 because of this.

2.4 Bivariate Exploration

[50]:
```
bike_df.head()
```

[50]:

	duration_sec	start_station_id	start_station_name	end_station_id	end_station_name	bike_id	user_type	member_gender	bike_share_for_all_trip	week_day	age	age_group	part_of_day
0	458	370	Jones St at Post St	43	San Francisco Public Library (Grove St at Hyde…	5318	Subscriber	Female	Yes	Thursday	23	13-24	night
1	506	44	Civic Center/UN Plaza BART Station (Market St …	343	Bryant St at 2nd St	5848	Subscriber	Male	No	Thursday	26	25-44	night
2	915	252	Channing Way at Shattuck Ave	244	Shattuck Ave at Hearst Ave	5101	Subscriber	Other	No	Thursday	35	25-44	night
3	395	243	Bancroft Way at College Ave	252	Channing Way at Shattuck Ave	4786	Subscriber	Male	No	Thursday	31	25-44	night
4	208	349	Howard St at Mary St	60	8th St at Ringold St	6361	Subscriber	Male	Yes	Thursday	26	25-44	night

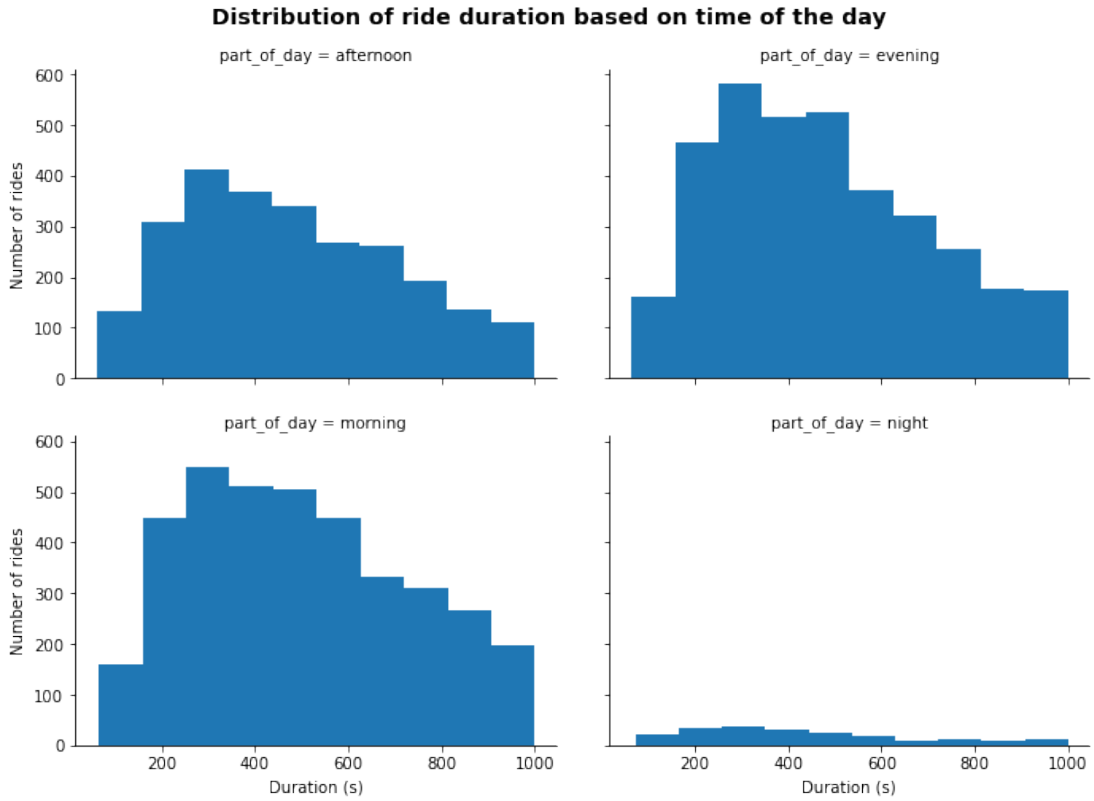
2.4.1 Visualization 7: Analysing ride duration accross the different parts of the day

Visualization

[51]:
```
bike_df.groupby("part_of_day").duration_sec.mean()
```

[51]:
```
part_of_day
afternoon    475.240469
evening      480.700130
morning      492.103030
night        423.765238
Name: duration_sec, dtype: float64
```

[52]:
```
sample_data = bike_df.sample(10000)
g = sb.FacetGrid(data=sample_data, col="part_of_day", col_wrap=2)
g = g.map(plt.hist,"duration_sec")
g.add_legend()
g.set_xlabels('Duration (s)')
g.set_ylabels('Number of rides')
g.fig.set_size_inches(10,7)
g.fig.suptitle('Distribution of ride duration based on time of the day', y=1.
↪02, fontsize=14, weight="bold")
plt.show()
```



Observation

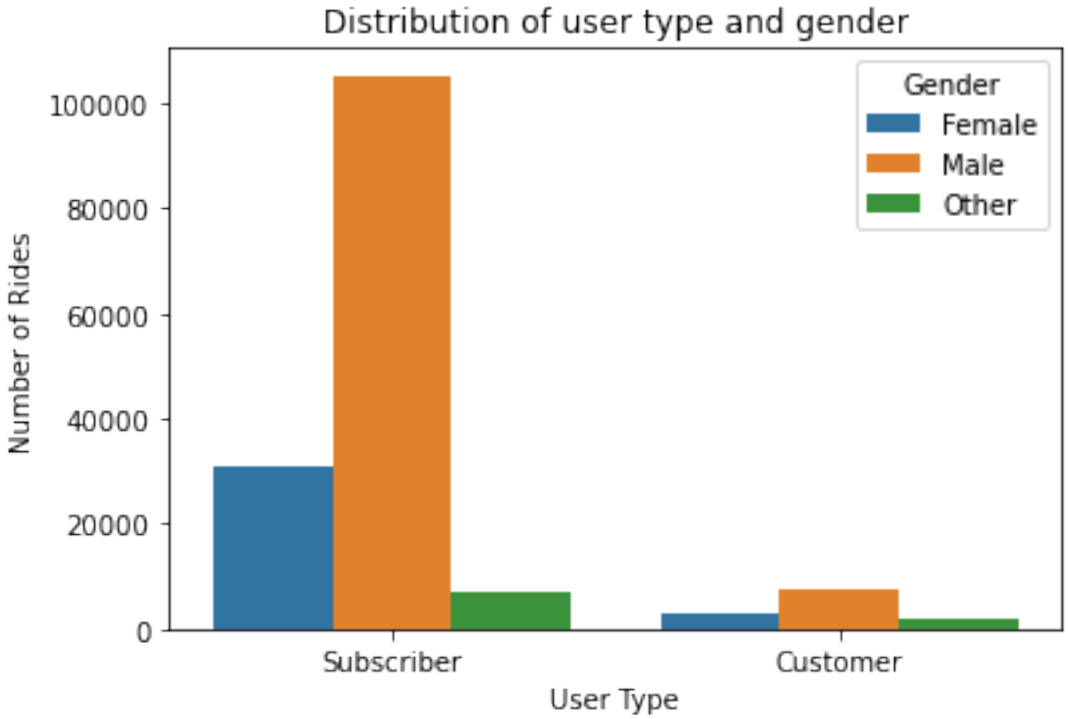
Most people rode for between 200 to 600 seconds irrespective of the time of the day.

2.4.2 Visualization 8: Distribution of User Types and Gender

Visualization

[53]:
```
sb.countplot(data=bike_df, x='user_type', hue='member_gender')
plt.xlabel('User Type')
plt.ylabel('Number of Rides')
plt.legend(title='Gender')

plt.title('Distribution of user type and gender')
plt.show()
```



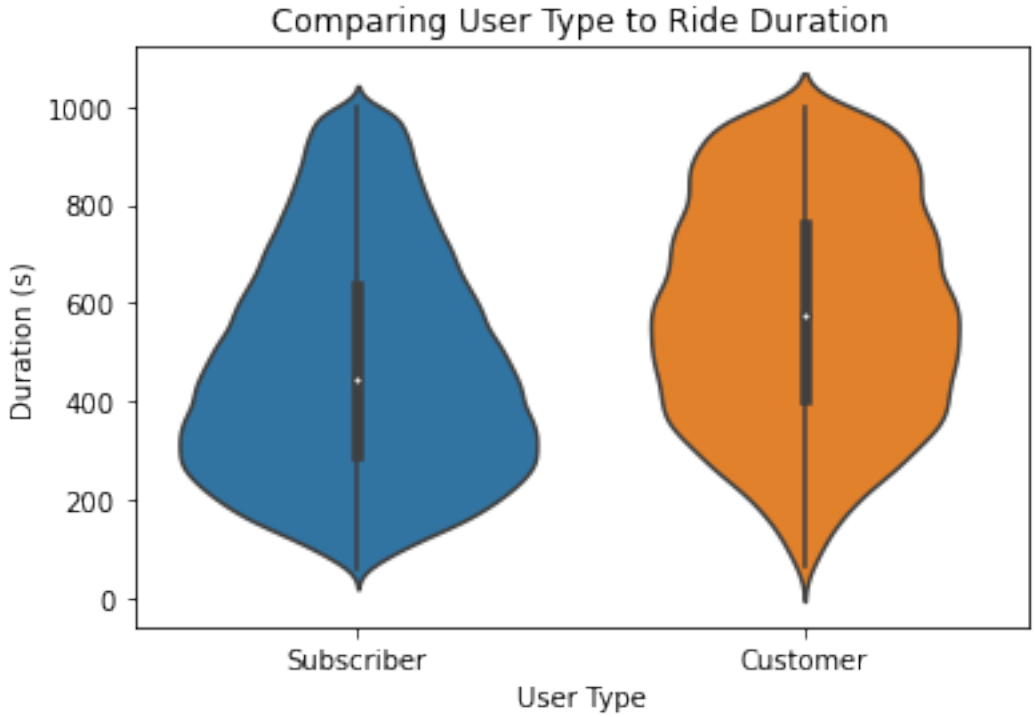
Observation We've already seen that most of the rides are by subscribers and by the male gender. This visualization confirms that by showing the gender ratio of the subscribers.

2.4.3 Visualization 9: What is correlation between user type and ride duration?

Visualization

[54]:
```
age_duration_plot = sb.violinplot(data=bike_df, x='user_type',␣
↪y='duration_sec');
age_duration_plot.set(title = "Comparing User Type to Ride Duration")
plt.xlabel('User Type')
```

```
plt.ylabel('Duration (s)')
plt.show()
```

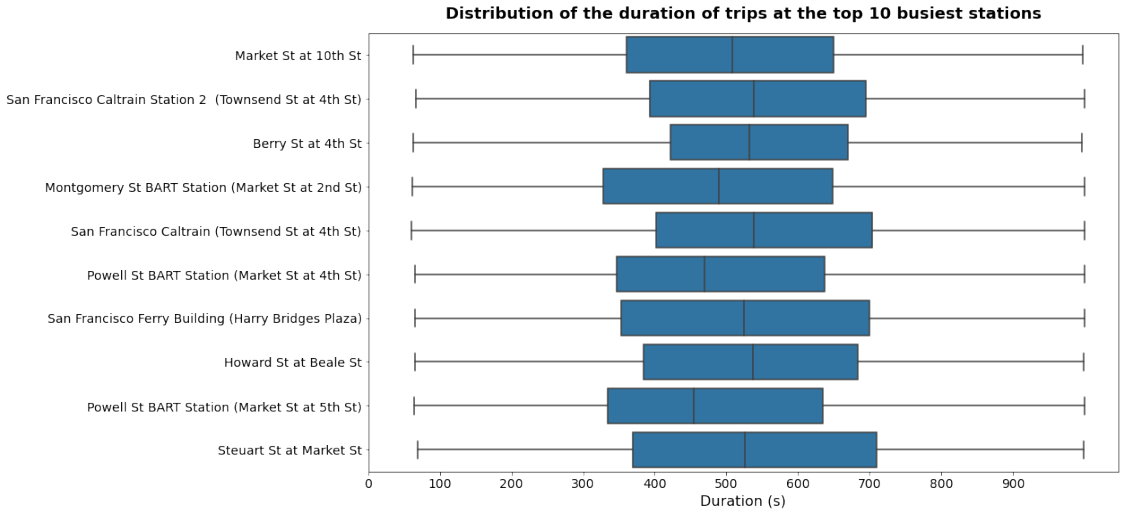


Observation The violin plot above shows that the customers had longer trips on the average.

2.4.4 Visualization 10: The distribution of ride durations for the top 10 busiest stations

Visualization

[55]:
```
color = sb.color_palette()[0]
plt.figure(figsize=(15,9))
sb.boxplot(data=bike_df, x='duration_sec', y='start_station_name',␣
 ↪order=busiest_stations, orient = 'h', color=color)
plt.xticks(ticks=np.arange(0, 1000, step=100), fontsize=14)
plt.yticks(fontsize=14)
plt.xlabel('Duration (s)', fontsize=16)
plt.ylabel('')
plt.title('Distribution of the duration of trips at the top 10 busiest␣
 ↪stations', fontsize=18, y=1.02, weight="bold")
plt.show()
```

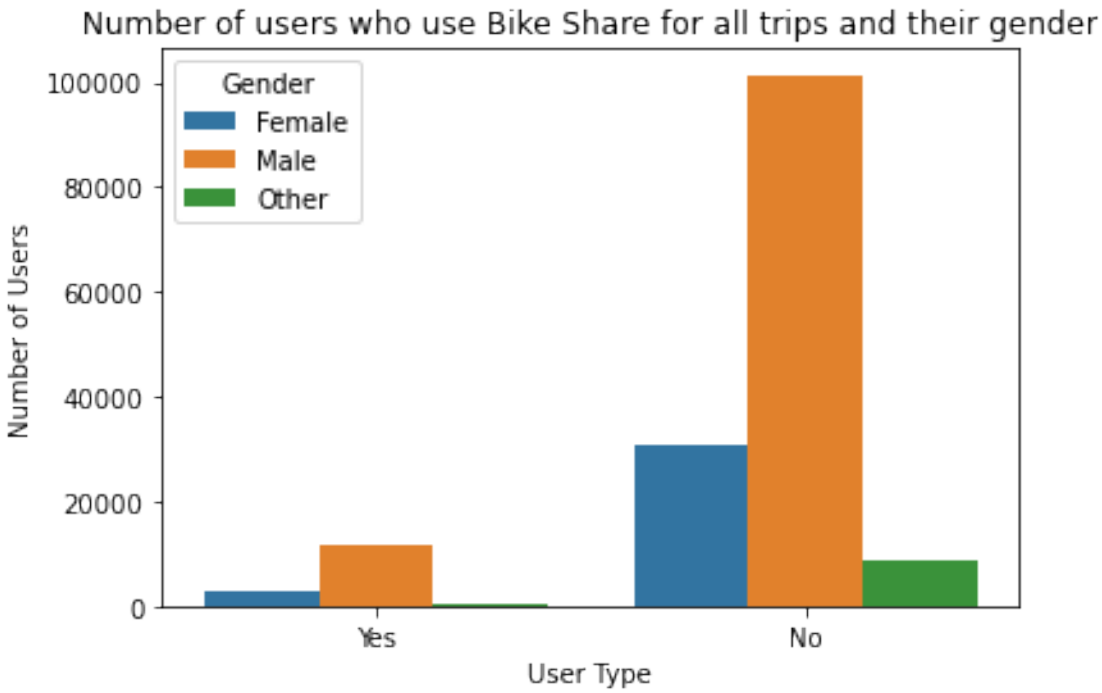


Observation The box plot above shows the duration of rides started at the top 10 busiest stations. It also shows that most of their rides take between 350 to 700 seconds.

2.4.5 Visualization 11: Distribution of the gender of users who use Bike Share for all trips

Visualization

[56]:
```
sb.countplot(data=bike_df, x='bike_share_for_all_trip', hue='member_gender')
plt.xlabel('User Type')
plt.ylabel('Number of Users')
plt.legend(title='Gender')
plt.title('Number of users who use Bike Share for all trips and their gender')
plt.show()
```

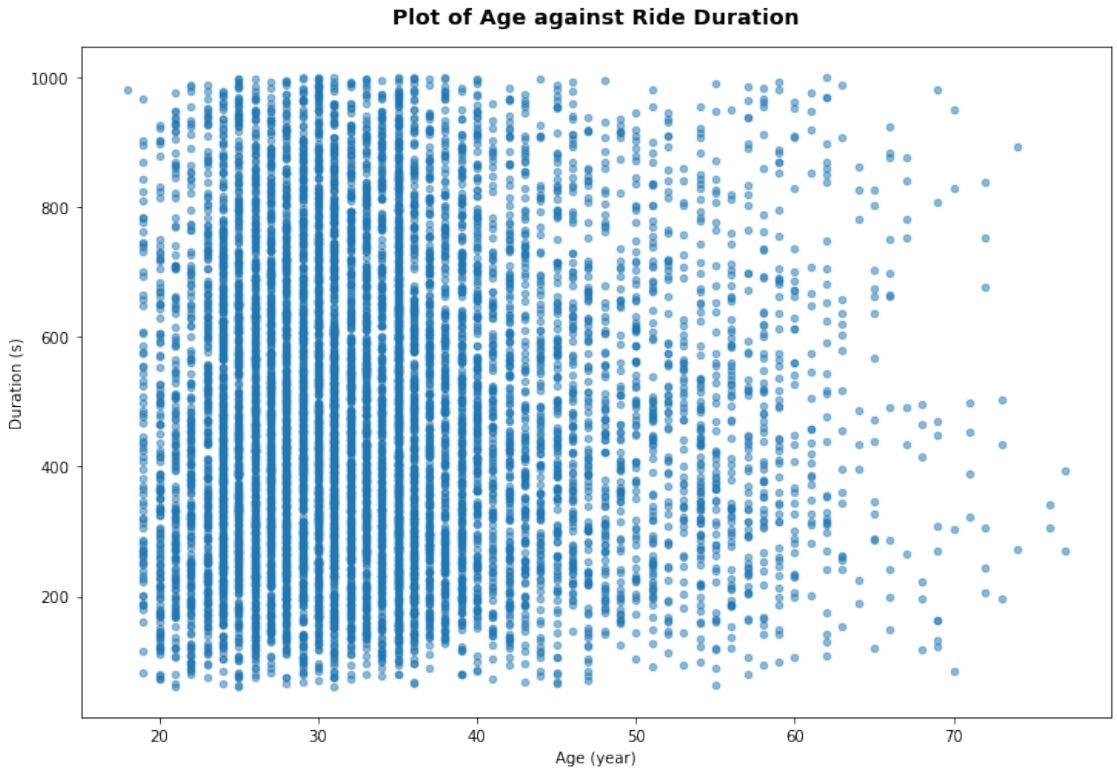


Observation This visualization is in line with previous observations on gender ratio.

2.4.6 Visualization 12: What is correlation between age and ride duration?

Visualization

[57]:
```
sample_data = bike_df.sample(10000)
plt.figure(figsize=(12,8));
plt.scatter( sample_data['age'], sample_data['duration_sec'], alpha=0.5, s=20);
plt.xlabel('Age (year)')
plt.ylabel('Duration (s)')
plt.title('Plot of Age against Ride Duration', y=1.02, fontsize=14,␣
 ↪weight="bold")
plt.show()
```



Observation From the visual above, there is no correlation between age and ride duration. But we can also see that more of the rides are by younger people than older people.

2.4.7 Visualization 13: Distribution of ride duration by different age groups.

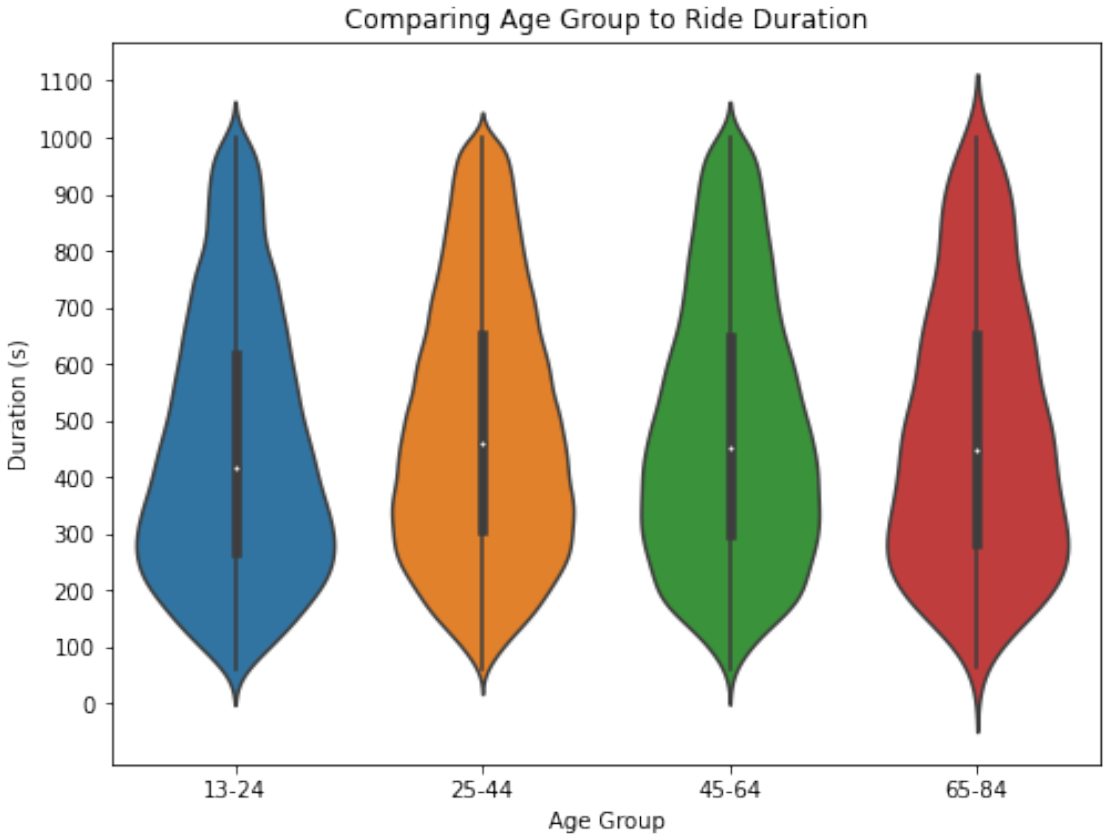
Visualization

[58]:
```
df_groups = bike_df.groupby(['age_group']).duration_sec.mean()
df_groups
```

[58]:
```
age_group
13-24    452.728020
25-44    487.320332
45-64    483.612142
65-84    479.352542
Name: duration_sec, dtype: float64
```

[59]:
```
plt.figure(figsize=(8,6))
age_duration_plot = sb.violinplot(data=bike_df, x='age_group',␣
 ↪y='duration_sec');
age_duration_plot.set(title = "Comparing Age Group to Ride Duration")
plt.yticks(ticks=np.arange(0, 1200, step=100))
plt.xlabel('Age Group')
```

```
plt.ylabel('Duration (s)')
plt.show()
```



Observation The violin plot above shows similar features accross the age groups, with a mean ride duration between 450 and 500 seconds.

2.4.8 Summary of bivariate exploration

The age and the time of the day do not affect the ride duration.

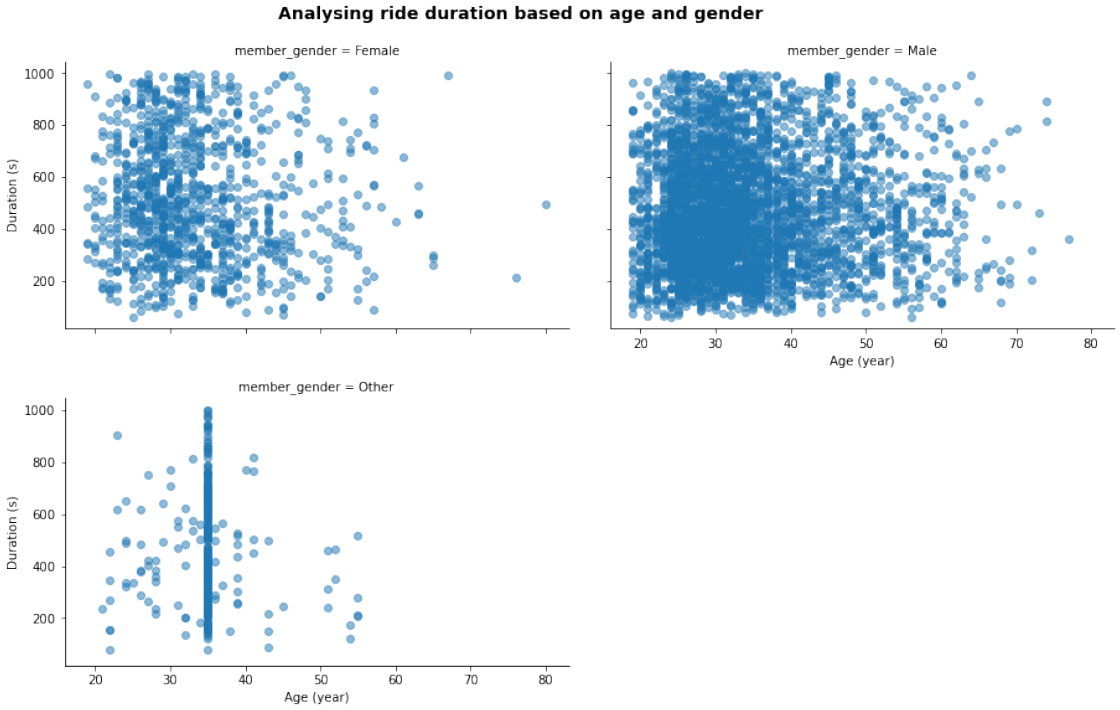
2.5 Multivariate Exploration

2.5.1 Visualization 14: What is the relationship between age, duration and gender?

Visualization

[60]:
```
sample_data = bike_df.sample(5000)
g = sb.FacetGrid(data=sample_data, col="member_gender", col_wrap=2)
g = g.map(plt.scatter,"age","duration_sec", alpha=0.5)
g.set_ylabels('Duration (s)')
g.set_xlabels('Age (year)')
g.fig.set_size_inches(14,8)
```

```
g.fig.suptitle('Analysing ride duration based on age and gender', y=1.02,␣
  ↪fontsize=14, weight="bold")
plt.show()
```



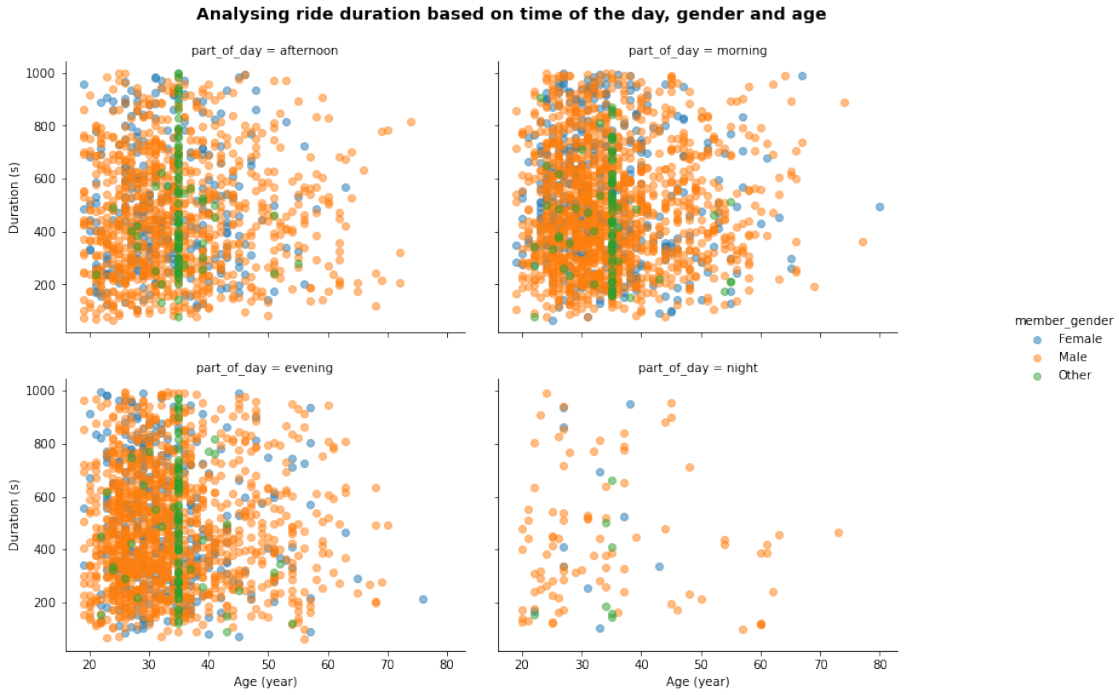
Observation

Age and gender have no relationship with trip duration. This plot also shows that most of the rides were by the male gender.

2.5.2 Visualization 15: What is the relationship between age, duration, gender and part of the day?

Visualization

[61]:
```
g = sb.FacetGrid(data=sample_data, col="part_of_day", hue="member_gender",␣
  ↪col_wrap=2)
g = g.map(plt.scatter,"age","duration_sec", alpha=0.5)
g.add_legend()
g.set_ylabels('Duration (s)')
g.set_xlabels('Age (year)')
g.fig.set_size_inches(14,8)
g.fig.suptitle('Analysing ride duration based on time of the day, gender and␣
  ↪age', y=1.02, fontsize=14, weight="bold")
plt.show()
```



Observation

The part of the day also doesn't show any difference in ride duration. We only have less rides at night.

2.6 Conclusions

The following are the conclusions from the analysis above:

- Most of the rides lasted between 200 to 600 seconds.
- Most rides are by the male gender.
- We have more rides by younger people than older people.
- Most riders are subscribers.
- Saturdays and Sundays have the least number of rides.
- Of all the features we compared to ride duration, none of them affects the ride duration. This may be because the company has a duration range they allow for riders. It may also be that people generally have a limit to how long they can ride a bike before switching to other means of transportation. For instance, taking a bike from the office to the train station and completing the journey by train. We already observed that most riders do not use the bikes for all their trips.