The Explanation Visualization Project

February 13, 2021

0.1 The visualization Project:

0.1.1 By Mohamed Atef Youssef

0.2 this project is concerning the 201902 Ford go bike trip data.

0.2.1 The works down here are representing my code work and exploration work in addtion to the explanatory work concerning the previous data of ford go bike.

0.2.2 First about this project i engoyed the work here and i know that the project is measured against rubric but i did what appeared interesting to me and followed a trend and it giveme a convincing results in which i hope to be the same for you.

0.2.3 About the data under investigation:

I downloaded the data from the Udacity resources in the same time i tried to use the ford go bike data in the Data Option but the link directed me to the main Ford web site and it was of no use for me.

0.3 The nature of data set and wrangling efforts;

0.3.1 It took me into two stages:

The first wrangling stage according to the nature of the dataset.

The second wrangling stage according to the aim i want to achive and points want to explain.

0.4 The Data Wrangling;

The data consist of 16 column and (seven) of them will be dropped like (start_station_latitude, start_station_longitude).

The trip duration listed in seconds and when dealing with it was not representive so need to be in minutes.

After trasformation the duration in sec column will be dropped.

The null values in the dataset happen in 8688 rows will be removed.

Extracting date and time from start and end time into (four) columns for start and end (time and date).

Changing Start date and End date columns into datetime formate.

Extracting start and end day of the week from start date and end date columns.

Changing the member_birth_year column into (int) to extract the year from.

developing a new column called (age)

```
In [1]: # Importing the necessary liberaries.

        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sb
        import datetime as dt
        import io
        import seaborn as sns
        %matplotlib inline
```

```
In [2]: # importing and opening the dataset of concern.
        df = pd.read_csv('201902-fordgobike-tripdata.csv')
```

```
/opt/conda/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2785: DtypeWarning: Colu
  interactivity=interactivity, compiler=compiler, result=result)
```

0.4.1 The main exploration step for the dataset upon which the wrangling step prepared and pointed out.

```
In [3]: df.head(5)
```

```
Out[3]:    duration_sec                start_time                  end_time  \
        0         52185  2019-02-28 17:32:10.1450  2019-03-01 08:01:55.9750
        1         42521  2019-02-28 18:53:21.7890  2019-03-01 06:42:03.0560
        2         61854  2019-02-28 12:13:13.2180  2019-03-01 05:24:08.1460
        3         36490  2019-02-28 17:54:26.0100  2019-03-01 04:02:36.8420
        4          1585  2019-02-28 23:54:18.5490  2019-03-01 00:20:44.0740

           start_station_id                                start_station_name  \
        0              21.0  Montgomery St BART Station (Market St at 2nd St)
        1              23.0                    The Embarcadero at Steuart St
        2              86.0                          Market St at Dolores St
        3             375.0                          Grove St at Masonic Ave
        4               7.0                              Frank H Ogawa Plaza
```

```
   start_station_latitude start_station_longitude  end_station_id  \
0               37.789625                -122.401            13.0   
1               37.791464                -122.391            81.0   
2               37.769305                -122.427             3.0   
3               37.774836                -122.447            70.0   
4               37.804562                -122.272           222.0   

                             end_station_name end_station_latitude  \
0                Commercial St at Montgomery St              37.7942   
1                           Berry St at 4th St              37.7759   
2  Powell St BART Station (Market St at 4th St)              37.7864   
3                        Central Ave at Fell St              37.7733   
4                         10th Ave at E 15th St              37.7927   

   end_station_longitude  bike_id   user_type  member_birth_year  \
0            -122.402923   4902.0    Customer             1984.0   
1            -122.393170   2535.0    Customer                NaN   
2            -122.404904   5905.0    Customer             1972.0   
3            -122.444293   6638.0  Subscriber             1989.0   
4            -122.248780   4898.0  Subscriber             1974.0   

  member_gender bike_share_for_all_trip  
0          Male                      No  
1           NaN                      No  
2          Male                      No  
3         Other                      No  
4          Male                     Yes  
```

In [4]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 188280 entries, 0 to 188279
Data columns (total 16 columns):
duration_sec               188280 non-null int64
start_time                 188280 non-null object
end_time                   188280 non-null object
start_station_id           188079 non-null float64
start_station_name         188079 non-null object
start_station_latitude     188280 non-null float64
start_station_longitude    188280 non-null object
end_station_id             188079 non-null float64
end_station_name           188079 non-null object
end_station_latitude       188280 non-null object
end_station_longitude      188279 non-null float64
bike_id                    188279 non-null float64
user_type                  188279 non-null object
member_birth_year          179791 non-null float64
member_gender              179791 non-null object
```

```
bike_share_for_all_trip    188279 non-null object
dtypes: float64(6), int64(1), object(9)
memory usage: 23.0+ MB
```

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

Out[5]:
```
         duration_sec  start_station_id  start_station_latitude  \
count  188280.000000     188079.000000           188280.000000   
mean      725.415041        138.504739               37.795622   
std      1785.963941        111.785818               10.535380   
min        61.000000          3.000000               37.317298   
25%       325.000000         47.000000               37.770407   
50%       514.000000        104.000000               37.780760   
75%       796.000000        239.000000               37.797280   
max     85444.000000        398.000000             4609.000000   

       end_station_id  end_station_longitude        bike_id  member_birth_year  
count   188079.000000          188279.000000  188279.000000      179791.000000  
mean       136.359929            -122.352325    4479.528508        1984.809379  
std        111.549218               0.116540    1664.780452          10.111496  
min          3.000000            -122.453704      11.000000        1878.000000  
25%         44.000000            -122.411726    3787.000000        1980.000000  
50%        100.000000            -122.398279    4962.000000        1987.000000  
75%        235.000000            -122.288045    5510.000000        1992.000000  
max       1987.000000            -121.874119    6645.000000        2001.000000  
```

In [6]:
```
df.dtypes
```

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

0.5 The main step of dataset cleaning by making copy from Datafram.

0.6 And starting the wrangling and cleaning step to give tiddy and clean dataset.

In [7]:
```
# Mking a copy of the datefram.
df_copy = df
```

In [8]:
```
df_copy.shape
```

Out[8]:
```
(188280, 16)
```

In [9]:
```
# Dropping the un necessary columns.
df_copy.drop(['start_station_id', 'start_station_latitude', 'start_station_longitude', '
            , 'end_station_longitude', 'bike_id'], inplace=True, axis = 1)
```

In [10]:
```
# transfering the seconds into minutes.
df_copy['duration_min']=df_copy['duration_sec']/60
```

In [11]:
```
# Droping the duration _sec column.
df_copy.drop(['duration_sec'], inplace=True, axis = 1)
```

In [12]:
```
# configuring the data set to make sure of the changing.
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 188280 entries, 0 to 188279
Data columns (total 9 columns):
start_time                 188280 non-null object
end_time                   188280 non-null object
start_station_name         188079 non-null object
end_station_name           188079 non-null object
user_type                  188279 non-null object
member_birth_year          179791 non-null float64
member_gender              179791 non-null object
bike_share_for_all_trip    188279 non-null object
duration_min               188280 non-null float64
dtypes: float64(2), object(7)
memory usage: 12.9+ MB
```

In [13]:
```
df_copy.shape
```

Out[13]:
```
(188280, 9)
```

0.6.1 Find out the null or Nan in the data set and dropping them.

In [14]:
```
df_copy.isnull().sum()
```

Out[14]:
```
start_time                  0
end_time                    0
start_station_name        201
```

```
end_station_name            201
user_type                     1
member_birth_year          8489
member_gender              8489
bike_share_for_all_trip       1
duration_min                  0
dtype: int64
```

In [15]:
```
is_NaN = df_copy.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = df[row_has_NaN]

print(rows_with_NaN)
```

```
                     start_time                  end_time  \
1       2019-02-28 18:53:21.7890  2019-03-01 06:42:03.0560
13      2019-02-28 23:49:06.0620  2019-03-01 00:04:21.8670
28      2019-02-28 23:43:27.5030  2019-02-28 23:54:18.4510
53      2019-02-28 22:41:16.3620  2019-02-28 23:38:14.3630
65      2019-02-28 23:17:05.8530  2019-02-28 23:32:32.6820
147     2019-02-28 22:46:19.1140  2019-02-28 22:52:31.4770
176     2019-02-28 22:28:50.5140  2019-02-28 22:41:00.8970
220     2019-02-28 22:05:25.5530  2019-02-28 22:29:11.1180
266     2019-02-28 21:53:13.2740  2019-02-28 22:14:56.1730
292     2019-02-28 21:43:04.3630  2019-02-28 22:07:32.6640
323     2019-02-28 21:52:54.9590  2019-02-28 21:57:30.5860
329     2019-02-28 21:45:47.5210  2019-02-28 21:56:02.0820
369     2019-02-28 21:34:04.0330  2019-02-28 21:47:08.2180
371     2019-02-28 21:41:14.0510  2019-02-28 21:46:34.7440
407     2019-02-28 21:32:00.4030  2019-02-28 21:38:22.9040
422     2019-02-28 21:28:29.4510  2019-02-28 21:36:11.4770
456     2019-02-28 21:18:14.9580  2019-02-28 21:28:10.3180
472     2019-02-28 21:16:42.8680  2019-02-28 21:24:39.8500
475     2019-02-28 20:55:53.9320  2019-02-28 21:24:23.7380
513     2019-02-28 21:14:26.2530  2019-02-28 21:19:02.7090
546     2019-02-28 15:05:22.4670  2019-02-28 21:13:29.6710
547     2019-02-28 20:52:59.8810  2019-02-28 21:13:24.1490
559     2019-02-28 21:04:38.5970  2019-02-28 21:11:45.8590
617     2019-02-28 20:38:39.5600  2019-02-28 20:59:38.9710
641     2019-02-28 20:47:29.2170  2019-02-28 20:55:52.1840
703     2019-02-28 20:35:31.5170  2019-02-28 20:45:35.9980
726     2019-02-28 20:40:29.8530  2019-02-28 20:42:59.9050
768     2019-02-28 20:27:34.9640  2019-02-28 20:35:26.9640
777     2019-02-28 20:19:22.6330  2019-02-28 20:33:30.0630
778     2019-02-28 20:24:29.6360  2019-02-28 20:33:27.1260
...                          ...                       ...
187764  2019-02-01 07:30:27.7900  2019-02-01 07:44:06.8310
187772  2019-02-01 07:35:23.2890  2019-02-01 07:43:04.1250
```

```
187787  2019-02-01 07:21:29.5150  2019-02-01 07:41:04.0500
187819  2019-02-01 07:33:59.0810  2019-02-01 07:37:00.3560
187859  2019-02-01 07:12:35.5660  2019-02-01 07:31:51.6390
187887  2019-02-01 07:22:45.2490  2019-02-01 07:28:05.1150
187945  2019-02-01 07:11:09.4440  2019-02-01 07:18:45.1520
187972  2019-02-01 06:53:20.9500  2019-02-01 07:12:17.0780
187980  2019-02-01 06:57:46.6320  2019-02-01 07:09:41.2890
187994  2019-02-01 06:58:52.7650  2019-02-01 07:04:47.0170
187999  2019-02-01 06:58:14.2290  2019-02-01 07:03:50.8770
188003  2019-02-01 06:53:16.7010  2019-02-01 07:02:58.9480
188032  2019-02-01 06:46:56.0210  2019-02-01 06:55:01.8930
188048  2019-02-01 06:47:31.8750  2019-02-01 06:50:38.9200
188062  2019-02-01 06:38:01.6770  2019-02-01 06:46:29.8910
188066  2019-02-01 06:44:03.6380  2019-02-01 06:45:12.4190
188077  2019-02-01 06:36:23.4240  2019-02-01 06:41:29.7440
188080  2019-02-01 06:29:10.9000  2019-02-01 06:40:30.7640
188083  2019-02-01 01:39:13.0980  2019-02-01 06:38:26.6810
188094  2019-02-01 06:25:20.7950  2019-02-01 06:33:50.5210
188149  2019-02-01 05:37:59.0090  2019-02-01 05:49:16.4370
188154  2019-02-01 05:30:42.6840  2019-02-01 05:42:41.7100
188174  2019-02-01 01:03:11.3620  2019-02-01 04:44:03.3210
188178  2019-02-01 03:17:02.2330  2019-02-01 03:41:12.3720
188200  2019-02-01 02:10:37.3200  2019-02-01 02:24:25.6090
188222  2019-02-01 01:35:07.6630  2019-02-01 01:42:36.8780
188224  2019-02-01 01:25:50.3660  2019-02-01 01:39:05.9500
188231  2019-02-01 01:12:24.4200  2019-02-01 01:23:37.6450
188239  2019-02-01 01:08:38.6410  2019-02-01 01:11:54.9490
188270  2019-02-01 00:17:32.2580  2019-02-01 00:19:34.9380

                                      start_station_name  \
1                            The Embarcadero at Steuart St
13                            Channing Way at Shattuck Ave
28                             University Ave at Oxford St
53                                  Davis St at Jackson St
65                          Commercial St at Montgomery St
147                                     Hyde St at Post St
176                          Channing Way at San Pablo Ave
220                          The Embarcadero at Vallejo St
266                                Grand Ave at Webster St
292                                     5th St at Folsom
323                                              Snow Park
329                                 Valencia St at 16th St
369      Civic Center/UN Plaza BART Station (Market St ...
371                           Channing Way at Shattuck Ave
407                                 2nd St at Townsend St
422                              Webster St at O'Farrell St
456                                    Howard St at 8th St
472                              El Embarcadero at Grand Ave
```

```
475                                                   NaN
513                                 Turk St at Fillmore St
546          Powell St BART Station (Market St at 4th St)
547                         The Embarcadero at Sansome St
559                                   Jones St at Post St
617                               23rd St at Tennessee St
641                               Church St at Duboce Ave
703                                  20th St at Bryant St
726                                Harrison St at 17th St
768      Montgomery St BART Station (Market St at 2nd St)
777                                  16th St Mission BART
778                                  10th St at Fallon St
...                                                   ...
187764                               Laguna St at Hayes St
187772                               Howard St at Beale St
187787                              Derby St at College Ave
187819                                 Berry St at King St
187859                              30th St at San Jose Ave
187887                                 Bay Pl at Vernon St
187945                              Market St at Dolores St
187972                                       Precita Park
187980                              Steuart St at Market St
187994  San Francisco Caltrain Station 2  (Townsend St...
187999                            Cyril Magnin St at Ellis St
188003                               19th St at Florida St
188032                               20th St at Dolores St
188048                                  Irwin St at 8th St
188062                                Jackson St at 5th St
188066                               Hubbell St at 16th St
188077                                    Franklin Square
188080                           Webster St at O'Farrell St
188083                              Market St at Dolores St
188094                                Market St at 10th St
188149                           S Van Ness Ave at Market St
188154                              Beale St at Harrison St
188174                           Raymond Kimbell Playground
188178                            Cyril Magnin St at Ellis St
188200                               Valencia St at 22nd St
188222                           Shattuck Ave at Hearst Ave
188224                                Myrtle St at Polk St
188231                             Market St at Franklin St
188239                                Market St at 10th St
188270                                   18th St at Noe St

                                  end_station_name   user_type  \
1                                   Berry St at 4th St    Customer
13                          Shattuck Ave at Hearst Ave  Subscriber
28                         Channing Way at San Pablo Ave    Customer
```

```
53                                Davis St at Jackson St    Customer
65                                  Berry St at 4th St  Subscriber
147     San Francisco Public Library (Grove St at Hyde...    Customer
176                          University Ave at Oxford St    Customer
220                              17th St at Valencia St  Subscriber
266                        Shattuck Ave at Telegraph Ave    Customer
292                        O'Farrell St at Divisadero St    Customer
323                               Grand Ave at Perkins St  Subscriber
329              Garfield Square (25th St at Harrison St)    Customer
369                                 1st St at Folsom St  Subscriber
371                           Shattuck Ave at Hearst Ave    Customer
407       Montgomery St BART Station (Market St at 2nd St)  Subscriber
422                                 Jones St at Post St  Subscriber
456     San Francisco Caltrain Station 2  (Townsend St...  Subscriber
472                             Telegraph Ave at 23rd St    Customer
475                                                  NaN    Customer
513                              Church St at Duboce Ave  Subscriber
546                           Lombard St at Columbus Ave    Customer
547                                 Folsom St at 9th St  Subscriber
559                            Webster St at O'Farrell St  Subscriber
617                                  S Park St at 3rd St    Customer
641                                19th St at Florida St    Customer
703                               29th St at Tiffany Ave    Customer
726                                 20th St at Bryant St  Subscriber
768                        The Embarcadero at Bryant St  Subscriber
777                            Webster St at O'Farrell St    Customer
778                              Grand Ave at Perkins St    Customer
...                                                   ...         ...
187764    Montgomery St BART Station (Market St at 2nd St)  Subscriber
187772                          Washington St at Kearny St  Subscriber
187787                                 Frank H Ogawa Plaza    Customer
187819                                7th St at Brannan St  Subscriber
187859                        O'Farrell St at Divisadero St    Customer
187887                             19th Street BART Station  Subscriber
187945      San Francisco City Hall (Polk St at Grove St)    Customer
187972                                 1st St at Folsom St  Subscriber
187980                                  4th St at 16th St    Customer
187994                             Beale St at Harrison St  Subscriber
187999   Embarcadero BART Station (Beale St at Market St)  Subscriber
188003  San Francisco Caltrain Station 2  (Townsend St...  Subscriber
188032                               Valencia St at 22nd St    Customer
188048                                   4th St at 16th St  Subscriber
188062                             San Jose Diridon Station  Subscriber
188066                                 Irwin St at 8th St  Subscriber
188077                               Hubbell St at 16th St  Subscriber
188080        Powell St BART Station (Market St at 5th St)  Subscriber
188083                          Valencia St at Clinton Park    Customer
188094                               Valencia St at 22nd St  Subscriber
```

```
188149                   Steuart St at Market St  Subscriber
188154                      Market St at 10th St  Subscriber
188174           Commercial St at Montgomery St     Customer
188178                          5th St at Folsom    Customer
188200                      Market St at 10th St    Customer
188222                   Haste St at College Ave    Customer
188224                      20th St at Bryant St  Subscriber
188231                    Valencia St at 22nd St    Customer
188239                  Market St at Franklin St    Customer
188270                      Mission Dolores Park  Subscriber

        member_birth_year member_gender bike_share_for_all_trip  duration_min
1                     NaN           NaN                      No    708.683333
13                    NaN           NaN                      No     15.250000
28                    NaN           NaN                      No     10.833333
53                    NaN           NaN                      No     56.966667
65                    NaN           NaN                      No     15.433333
147                   NaN           NaN                      No      6.200000
176                   NaN           NaN                      No     12.166667
220                   NaN           NaN                      No     23.750000
266                   NaN           NaN                      No     21.700000
292                   NaN           NaN                      No     24.466667
323                   NaN           NaN                      No      4.583333
329                   NaN           NaN                      No     10.233333
369                   NaN           NaN                      No     13.066667
371                   NaN           NaN                      No      5.333333
407                   NaN           NaN                      No      6.366667
422                   NaN           NaN                      No      7.700000
456                   NaN           NaN                      No      9.916667
472                   NaN           NaN                      No      7.933333
475                1991.0        Female                      No     28.483333
513                   NaN           NaN                      No      4.600000
546                   NaN           NaN                      No    368.116667
547                   NaN           NaN                      No     20.400000
559                   NaN           NaN                      No      7.116667
617                   NaN           NaN                      No     20.983333
641                   NaN           NaN                      No      8.366667
703                   NaN           NaN                      No     10.066667
726                   NaN           NaN                      No      2.500000
768                   NaN           NaN                      No      7.866667
777                   NaN           NaN                      No     14.116667
778                   NaN           NaN                      No      8.950000
...                   ...           ...                     ...           ...
187764                NaN           NaN                      No     13.650000
187772                NaN           NaN                      No      7.666667
187787                NaN           NaN                      No     19.566667
187819                NaN           NaN                      No      3.016667
187859                NaN           NaN                      No     19.266667
```

```
187887                    NaN           NaN                          No        5.316667
187945                    NaN           NaN                          No        7.583333
187972                    NaN           NaN                          No       18.933333
187980                    NaN           NaN                          No       11.900000
187994                    NaN           NaN                          No        5.900000
187999                    NaN           NaN                          No        5.600000
188003                    NaN           NaN                          No        9.700000
188032                    NaN           NaN                          No        8.083333
188048                    NaN           NaN                          No        3.116667
188062                    NaN           NaN                          No        8.466667
188066                    NaN           NaN                          No        1.133333
188077                    NaN           NaN                          No        5.100000
188080                    NaN           NaN                          No       11.316667
188083                    NaN           NaN                          No      299.216667
188094                    NaN           NaN                          No        8.483333
188149                    NaN           NaN                          No       11.283333
188154                    NaN           NaN                          No       11.983333
188174                    NaN           NaN                          No      220.850000
188178                    NaN           NaN                          No       24.166667
188200                    NaN           NaN                          No       13.800000
188222                    NaN           NaN                          No        7.483333
188224                    NaN           NaN                          No       13.250000
188231                    NaN           NaN                          No       11.216667
188239                    NaN           NaN                          No        3.266667
188270                    NaN           NaN                          No        2.033333

[8688 rows x 9 columns]
```

In [16]:
```
df_copy.dropna(inplace=True)
```

In [17]:
```
# Dropping Nan confirmation
df_copy.isnull().sum()
```

Out[17]:
```
start_time                 0
end_time                   0
start_station_name         0
end_station_name           0
user_type                  0
member_birth_year          0
member_gender              0
bike_share_for_all_trip    0
duration_min               0
dtype: int64
```

In [18]:
```
# Confirming the removal of null in the data set
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 179592 entries, 0 to 188279
```

```
Data columns (total 9 columns):
start_time                 179592 non-null object
end_time                   179592 non-null object
start_station_name         179592 non-null object
end_station_name           179592 non-null object
user_type                  179592 non-null object
member_birth_year          179592 non-null float64
member_gender              179592 non-null object
bike_share_for_all_trip    179592 non-null object
duration_min               179592 non-null float64
dtypes: float64(2), object(7)
memory usage: 13.7+ MB
```

In [19]:
```
df_copy.head(5)
```

Out[19]:
```
                 start_time                  end_time  \
0  2019-02-28 17:32:10.1450  2019-03-01 08:01:55.9750
2  2019-02-28 12:13:13.2180  2019-03-01 05:24:08.1460
3  2019-02-28 17:54:26.0100  2019-03-01 04:02:36.8420
4  2019-02-28 23:54:18.5490  2019-03-01 00:20:44.0740
5  2019-02-28 23:49:58.6320  2019-03-01 00:19:51.7600

                                start_station_name  \
0  Montgomery St BART Station (Market St at 2nd St)
2                            Market St at Dolores St
3                            Grove St at Masonic Ave
4                                Frank H Ogawa Plaza
5                           4th St at Mission Bay Blvd S

                              end_station_name   user_type  \
0                Commercial St at Montgomery St    Customer
2  Powell St BART Station (Market St at 4th St)    Customer
3                         Central Ave at Fell St  Subscriber
4                          10th Ave at E 15th St  Subscriber
5                             Broadway at Kearny  Subscriber

   member_birth_year member_gender bike_share_for_all_trip  duration_min
0             1984.0          Male                      No    869.750000
2             1972.0          Male                      No   1030.900000
3             1989.0         Other                      No    608.166667
4             1974.0          Male                     Yes     26.416667
5             1959.0          Male                      No     29.883333
```

Extracting date and time from start and end time into (four) columns for start and end (time and date).

In [20]:
```
df_copy['start_date'] = pd.to_datetime(df_copy['start_time']).dt.date
df_copy['start_time'] = pd.to_datetime(df_copy['start_time']).dt.time
```

```
In [21]: df_copy['end_date'] = pd.to_datetime(df_copy['end_time']).dt.date
         df_copy['end_time'] = pd.to_datetime(df_copy['end_time']).dt.time
```

```
In [22]: df_copy['start_day'] = df_copy['start_date'].apply(lambda r:r.day).astype(int)
         df_copy['end_day'] = df_copy['end_date'].apply(lambda r:r.day).astype(int)

         df_copy.head(5)
```

```
Out[22]:         start_time         end_time  \
         0  17:32:10.145000  08:01:55.975000
         2  12:13:13.218000  05:24:08.146000
         3  17:54:26.010000  04:02:36.842000
         4  23:54:18.549000  00:20:44.074000
         5  23:49:58.632000  00:19:51.760000

                                       start_station_name  \
         0  Montgomery St BART Station (Market St at 2nd St)
         2                           Market St at Dolores St
         3                           Grove St at Masonic Ave
         4                               Frank H Ogawa Plaza
         5                        4th St at Mission Bay Blvd S

                                      end_station_name   user_type  \
         0                Commercial St at Montgomery St    Customer
         2  Powell St BART Station (Market St at 4th St)    Customer
         3                          Central Ave at Fell St  Subscriber
         4                           10th Ave at E 15th St  Subscriber
         5                              Broadway at Kearny  Subscriber

            member_birth_year member_gender bike_share_for_all_trip  duration_min  \
         0             1984.0          Male                      No    869.750000
         2             1972.0          Male                      No   1030.900000
         3             1989.0         Other                      No    608.166667
         4             1974.0          Male                     Yes     26.416667
         5             1959.0          Male                      No     29.883333

            start_date    end_date  start_day  end_day
         0  2019-02-28  2019-03-01         28        1
         2  2019-02-28  2019-03-01         28        1
         3  2019-02-28  2019-03-01         28        1
         4  2019-02-28  2019-03-01         28        1
         5  2019-02-28  2019-03-01         28        1
```

```
In [23]: df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 179592 entries, 0 to 188279
Data columns (total 13 columns):
start_time                 179592 non-null object
```

```
end_time                   179592 non-null object
start_station_name         179592 non-null object
end_station_name           179592 non-null object
user_type                  179592 non-null object
member_birth_year          179592 non-null float64
member_gender              179592 non-null object
bike_share_for_all_trip    179592 non-null object
duration_min               179592 non-null float64
start_date                 179592 non-null object
end_date                   179592 non-null object
start_day                  179592 non-null int64
end_day                    179592 non-null int64
dtypes: float64(2), int64(2), object(9)
memory usage: 19.2+ MB
```

Changing Start date and End date columns into datetime formate.

```
In [24]: df_copy['start_date'] = pd.to_datetime(df_copy['start_date'])
         df_copy['end_date'] = pd.to_datetime(df_copy['end_date'])
```

```
In [25]: df_copy.dtypes
```

```
Out[25]: start_time                           object
         end_time                             object
         start_station_name                   object
         end_station_name                     object
         user_type                            object
         member_birth_year                   float64
         member_gender                        object
         bike_share_for_all_trip              object
         duration_min                        float64
         start_date                   datetime64[ns]
         end_date                     datetime64[ns]
         start_day                             int64
         end_day                               int64
         dtype: object
```

```
In [26]: df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 179592 entries, 0 to 188279
Data columns (total 13 columns):
start_time                 179592 non-null object
end_time                   179592 non-null object
start_station_name         179592 non-null object
end_station_name           179592 non-null object
user_type                  179592 non-null object
member_birth_year          179592 non-null float64
```

```
member_gender              179592 non-null object
bike_share_for_all_trip    179592 non-null object
duration_min               179592 non-null float64
start_date                 179592 non-null datetime64[ns]
end_date                   179592 non-null datetime64[ns]
start_day                  179592 non-null int64
end_day                    179592 non-null int64
dtypes: datetime64[ns](2), float64(2), int64(2), object(7)
memory usage: 19.2+ MB
```

Extracting start and end day of the week from start date and end date columns.

```
In [27]: df_copy['start_day_of_trip'] = df_copy[['start_date']].apply(lambda x: dt.datetime.strf

In [28]: df_copy['end_day_of_trip'] = df_copy[['end_date']].apply(lambda x: dt.datetime.strftime

In [29]: df_copy.head()
```

```
Out[29]:          start_time         end_time  \
         0  17:32:10.145000  08:01:55.975000
         2  12:13:13.218000  05:24:08.146000
         3  17:54:26.010000  04:02:36.842000
         4  23:54:18.549000  00:20:44.074000
         5  23:49:58.632000  00:19:51.760000

                                           start_station_name  \
         0  Montgomery St BART Station (Market St at 2nd St)
         2                               Market St at Dolores St
         3                               Grove St at Masonic Ave
         4                                   Frank H Ogawa Plaza
         5                            4th St at Mission Bay Blvd S

                                         end_station_name   user_type  \
         0                 Commercial St at Montgomery St    Customer
         2  Powell St BART Station (Market St at 4th St)    Customer
         3                         Central Ave at Fell St  Subscriber
         4                          10th Ave at E 15th St  Subscriber
         5                              Broadway at Kearny  Subscriber

            member_birth_year member_gender bike_share_for_all_trip  duration_min  \
         0             1984.0          Male                      No    869.750000
         2             1972.0          Male                      No   1030.900000
         3             1989.0         Other                      No    608.166667
         4             1974.0          Male                     Yes     26.416667
         5             1959.0          Male                      No     29.883333

           start_date   end_date  start_day   end_day start_day_of_trip end_day_of_trip
```

```
0 2019-02-28 2019-03-01          28          1           Thursday           Friday
2 2019-02-28 2019-03-01          28          1           Thursday           Friday
3 2019-02-28 2019-03-01          28          1           Thursday           Friday
4 2019-02-28 2019-03-01          28          1           Thursday           Friday
5 2019-02-28 2019-03-01          28          1           Thursday           Friday
```

Changing the member_birth_year column into (int) to extract the year from.

```
In [30]: df['member_birth_year'] = pd.to_numeric(df['member_birth_year'])
```

```
In [31]: df['member_birth_year'].astype(int)
```

```
Out[31]: 0          1984
         2          1972
         3          1989
         4          1974
         5          1959
         6          1983
         7          1989
         8          1988
         9          1992
         10         1996
         11         1993
         12         1990
         14         1988
         15         1993
         16         1981
         17         1975
         18         1990
         19         1978
         20         1983
         21         1984
         22         1991
         23         1997
         24         1975
         25         1986
         26         2000
         27         1982
         29         1995
         30         1996
         31         1993
         32         1980
                    ...
         188249     1997
         188250     1988
         188251     1997
         188252     1991
         188253     1945
```

```
188254    1998
188255    1999
188256    1927
188257    1985
188258    1999
188259    1980
188260    1993
188261    1985
188262    1975
188263    1993
188264    1991
188265    1988
188266    1982
188267    1993
188268    1984
188269    1991
188271    2000
188272    1980
188273    1984
188274    1988
188275    1996
188276    1984
188277    1990
188278    1988
188279    1989
Name: member_birth_year, Length: 179592, dtype: int64
```

developing a new column called (age)

```
In [32]: df_copy['age'] = 2019 - df_copy['member_birth_year']
```

```
In [33]: df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 179592 entries, 0 to 188279
Data columns (total 16 columns):
start_time                 179592 non-null object
end_time                   179592 non-null object
start_station_name         179592 non-null object
end_station_name           179592 non-null object
user_type                  179592 non-null object
member_birth_year          179592 non-null float64
member_gender              179592 non-null object
bike_share_for_all_trip    179592 non-null object
duration_min               179592 non-null float64
start_date                 179592 non-null datetime64[ns]
end_date                   179592 non-null datetime64[ns]
start_day                  179592 non-null int64
```

```
end_day                     179592 non-null int64
start_day_of_trip           179592 non-null object
end_day_of_trip             179592 non-null object
age                         179592 non-null float64
dtypes: datetime64[ns](2), float64(3), int64(2), object(9)
memory usage: 23.3+ MB
```

In [34]:
```
df_copy.head()
```

Out[34]:
```
        start_time         end_time  \
0  17:32:10.145000  08:01:55.975000
2  12:13:13.218000  05:24:08.146000
3  17:54:26.010000  04:02:36.842000
4  23:54:18.549000  00:20:44.074000
5  23:49:58.632000  00:19:51.760000

                              start_station_name  \
0  Montgomery St BART Station (Market St at 2nd St)
2                           Market St at Dolores St
3                           Grove St at Masonic Ave
4                               Frank H Ogawa Plaza
5                         4th St at Mission Bay Blvd S

                              end_station_name   user_type  \
0                   Commercial St at Montgomery St    Customer
2  Powell St BART Station (Market St at 4th St)    Customer
3                         Central Ave at Fell St  Subscriber
4                          10th Ave at E 15th St  Subscriber
5                             Broadway at Kearny  Subscriber

   member_birth_year member_gender bike_share_for_all_trip  duration_min  \
0             1984.0          Male                      No    869.750000
2             1972.0          Male                      No   1030.900000
3             1989.0         Other                      No    608.166667
4             1974.0          Male                     Yes     26.416667
5             1959.0          Male                      No     29.883333

  start_date   end_date  start_day  end_day start_day_of_trip end_day_of_trip  \
0 2019-02-28 2019-03-01         28        1          Thursday          Friday
2 2019-02-28 2019-03-01         28        1          Thursday          Friday
3 2019-02-28 2019-03-01         28        1          Thursday          Friday
4 2019-02-28 2019-03-01         28        1          Thursday          Friday
5 2019-02-28 2019-03-01         28        1          Thursday          Friday

    age
0  35.0
2  47.0
```

```
3   30.0
4   45.0
5   60.0
```

0.6.2 The first step of data visualization, exploration and explanation by configuring the various types of columns.

In [35]:
```
df_copy['start_day_of_trip'].value_counts()
```

Out[35]:
```
Thursday     38020
Tuesday      30584
Wednesday    28426
Friday       27995
Monday       25641
Sunday       14512
Saturday     14414
Name: start_day_of_trip, dtype: int64
```

In [36]:
```
df_copy['end_day_of_trip'].value_counts()
```

Out[36]:
```
Thursday     38010
Tuesday      30591
Wednesday    28417
Friday       27992
Monday       25641
Sunday       14519
Saturday     14422
Name: end_day_of_trip, dtype: int64
```

In [37]:
```
df_copy['member_gender'].describe()
```

Out[37]:
```
count     179592
unique         3
top         Male
freq      133916
Name: member_gender, dtype: object
```

In [38]:
```
df_copy['end_day_of_trip'].describe()
```

Out[38]:
```
count       179592
unique           7
top       Thursday
freq         38010
Name: end_day_of_trip, dtype: object
```

In [39]:
```
df_copy['start_day_of_trip'].describe()
```

Out[39]:
```
count       179592
unique           7
top       Thursday
freq         38020
Name: start_day_of_trip, dtype: object
```

In [40]: df_copy['start_day'].describe()

```
Out[40]: count    179592.000000
         mean         15.461134
         std           7.982037
         min           1.000000
         25%           8.000000
         50%          16.000000
         75%          22.000000
         max          28.000000
         Name: start_day, dtype: float64
```

In [41]: df_copy['end_day'].describe()

```
Out[41]: count    179592.000000
         mean         15.460555
         std           7.982267
         min           1.000000
         25%           8.000000
         50%          16.000000
         75%          22.000000
         max          28.000000
         Name: end_day, dtype: float64
```

In [42]: df_copy['start_date'].describe()

```
Out[42]: count                  179592
         unique                     28
         top       2019-02-21 00:00:00
         freq                    13428
         first     2019-02-01 00:00:00
         last      2019-02-28 00:00:00
         Name: start_date, dtype: object
```

In [43]: df_copy['end_date'].describe()

```
Out[43]: count                  179592
         unique                     29
         top       2019-02-21 00:00:00
         freq                    13428
         first     2019-02-01 00:00:00
         last      2019-03-01 00:00:00
         Name: end_date, dtype: object
```

In [44]: df_copy['start_time'].describe()

```
Out[44]: count              179592
         unique             174648
         top       16:58:28.525000
         freq                    3
         Name: start_time, dtype: object
```

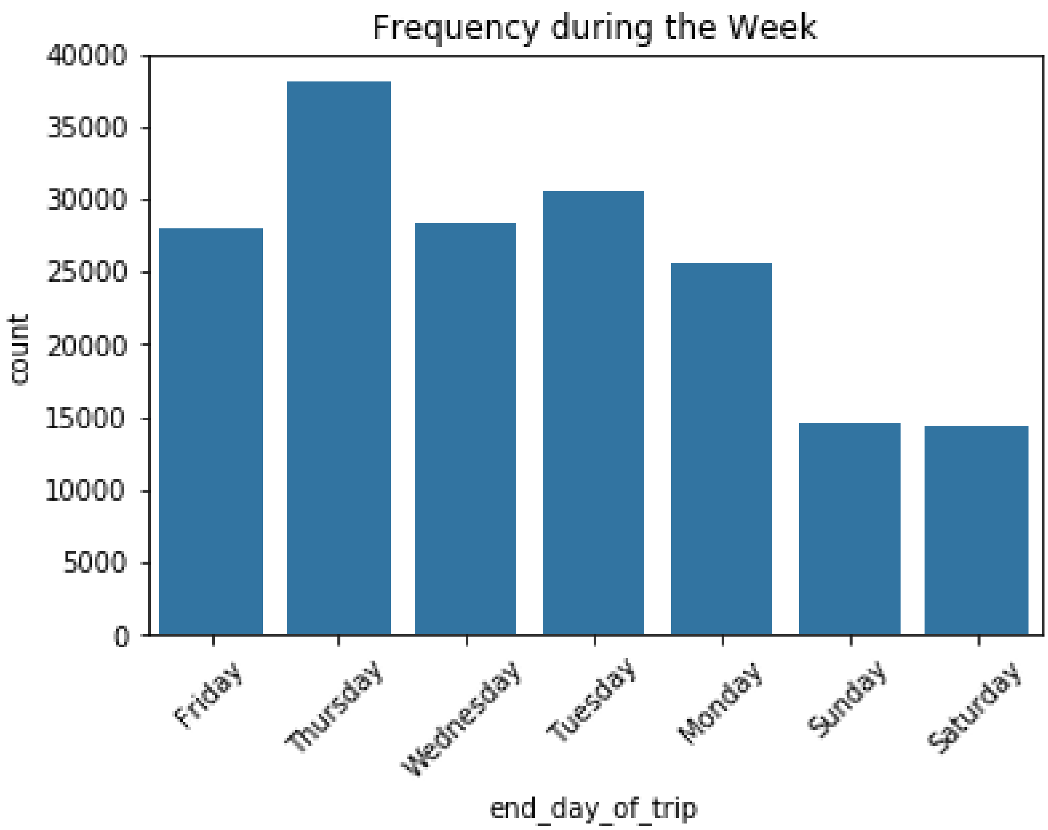
```
In [45]: df_copy['end_time'].describe()

Out[45]: count               179592
         unique              174622
         top        22:16:04.478000
         freq                     4
         Name: end_time, dtype: object

In [46]: df_copy['duration_min'].describe()

Out[46]: count    179592.000000
         mean         11.722707
         std          27.265254
         min           1.016667
         25%           5.383333
         50%           8.500000
         75%          13.150000
         max        1409.133333
         Name: duration_min, dtype: float64

In [47]: np.log10(df_copy['duration_min']).describe()

Out[47]: count    179592.000000
         mean          0.929580
         std           0.304996
         min           0.007179
         25%           0.731051
         50%           0.929419
         75%           1.118926
         max           3.148952
         Name: duration_min, dtype: float64

In [48]: df_copy['user_type'].describe()

Out[48]: count         179592
         unique             2
         top       Subscriber
         freq          162610
         Name: user_type, dtype: object

In [49]: df_copy['member_birth_year'].describe()

Out[49]: count    179592.000000
         mean       1984.806205
         std          10.113561
         min        1878.000000
         25%        1980.000000
         50%        1987.000000
         75%        1992.000000
         max        2001.000000
         Name: member_birth_year, dtype: float64
```

0.6.3 Univariant exploration

0.6.4 In this step i will explore the various items or column in the data set to find out the desied elements for me.

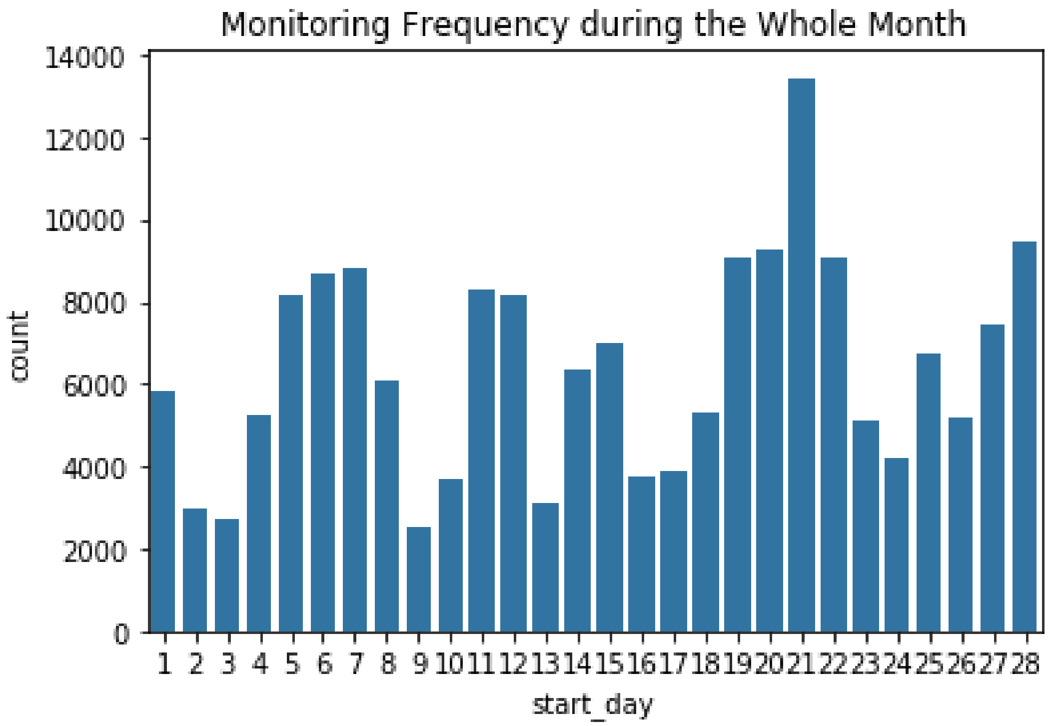
```
In [50]: sb.countplot(data = df_copy, x = 'end_day_of_trip', color=sb.color_palette()[0]);
         plt.xlabel('end_day_of_trip')
         plt.xticks(rotation = 45)
         plt.title('Frequency during the Week')
```

```
Out[50]: Text(0.5,1,'Frequency during the Week')
```




```
In [51]: sb.countplot(data=df_copy,x='start_day', color=sb.color_palette()[0])
         plt.title('Monitoring Frequency during the Whole Month')
```

```
Out[51]: Text(0.5,1,'Monitoring Frequency during the Whole Month')
```

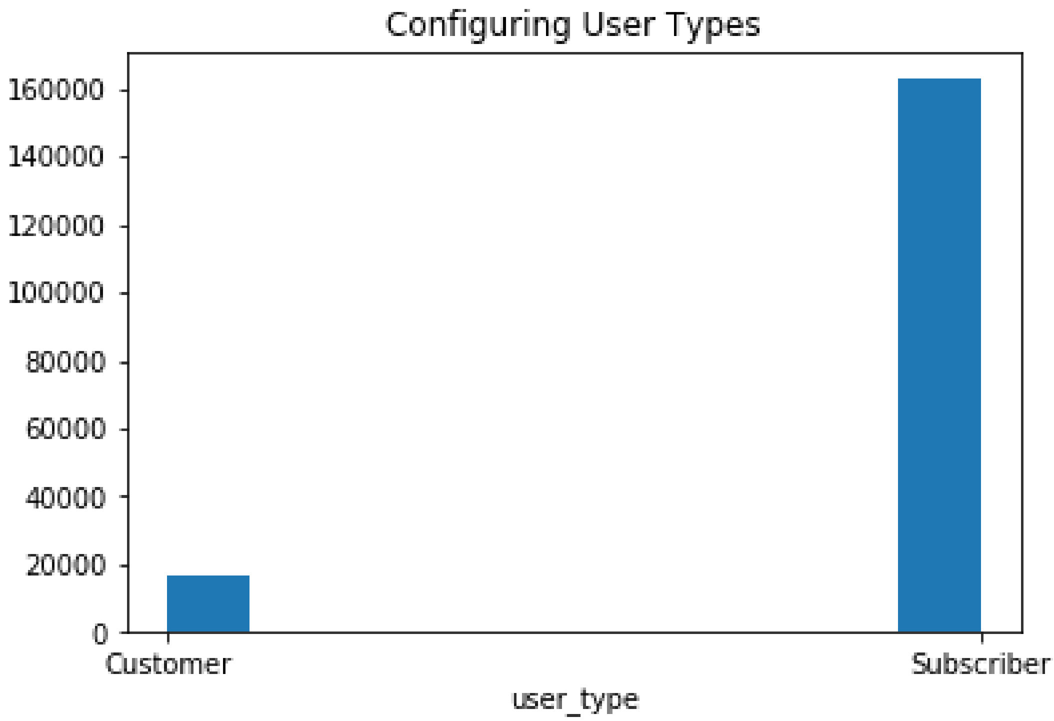


As for the days of the week, the result was relatively amazing to me. It seems that the weekends have witnessed a significant decrease in the ridding of cycling. It seems that it is a real holiday, and it seems that a significant percentage of the population uses bicycles in their daily routine

In addition the idea dealing with how about the frequency during the month of concern showed a variation in count of ridding but supported the weekly conclusion related to the low rate in the weekends

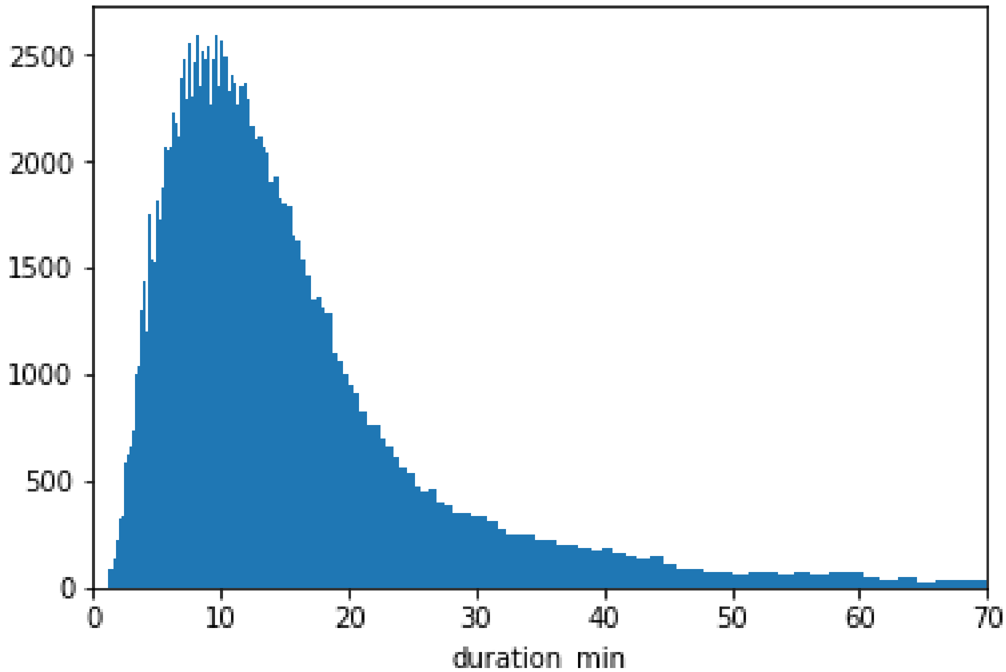
In [52]:
```
plt.hist(data = df_copy, x = 'user_type');
plt.xlabel('user_type')
plt.title('Configuring User Types')
```

Out[52]:
```
Text(0.5,1,'Configuring User Types')
```



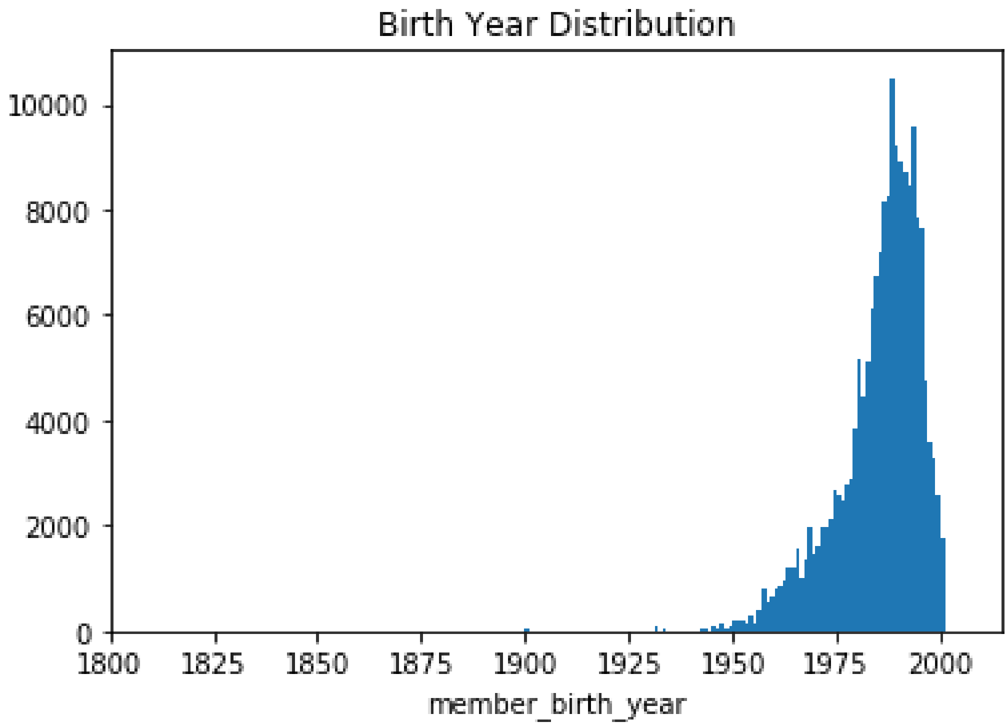
For the user type it is traditional the subscriber is huge against customers it seems that the loyality programs is good but it is just a guess from the results.

```
In [53]: bins = 10 ** np.arange(0.1, 3.14+0.01, 0.01)
         plt.hist(data = df_copy, x = 'duration_min', bins = bins);
         plt.xlim([0,70])
         plt.xlabel('duration_min')

Out[53]: Text(0.5,0,'duration_min')
```



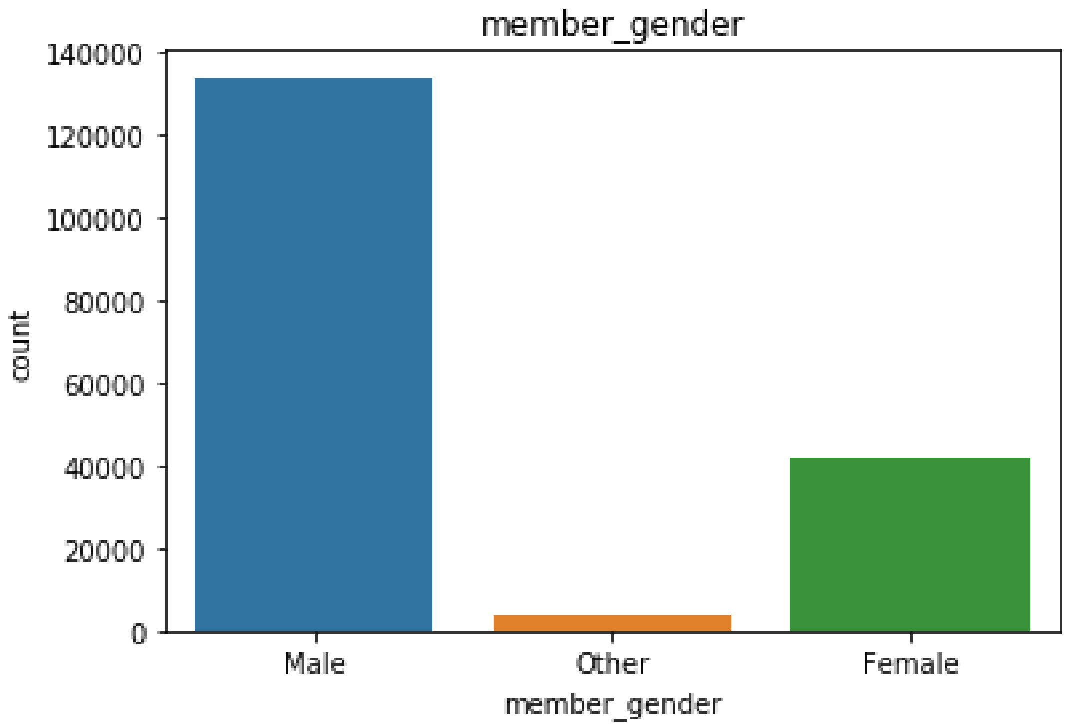
At this point i had to transfer the original data to (log) to figure out the shape of data and as it seems it is highly skewed to the right so the majority of the riders tends to use the ride for may be fro (10-20 minutes) per day while others for many more time.

```
In [54]: bins = np.arange(1878, 2001+1, 1)
         plt.hist(data = df_copy, x = 'member_birth_year', bins = bins);
         plt.xlim([1800,2015])
         plt.xlabel('member_birth_year')
         plt.title('Birth Year Distribution')

Out[54]: Text(0.5,1,'Birth Year Distribution')
```



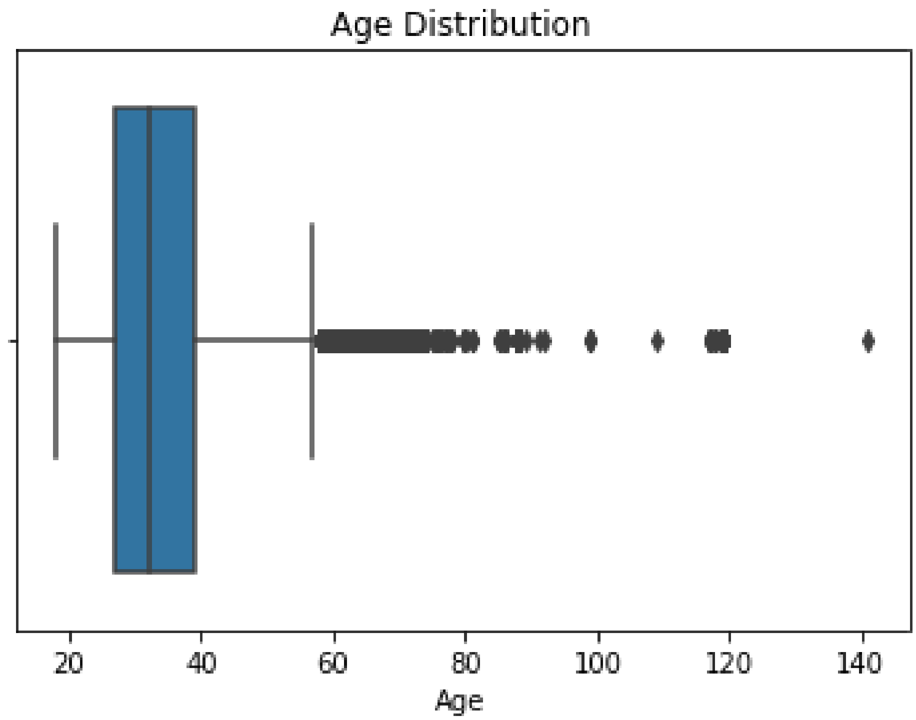
The birth year is another amazing factor it seems that in that city there are ridders exceded in age 100 years which needs more investigations about the validity of the data is it true or not and if true we need to standout the reasons about that fact which is appearing in the left skewenes.

In [55]:
```
sb.countplot(data = df_copy, x = 'member_gender')
plt.title('member_gender');
```



I am sorry men competing hardly it is a big deference in favor to men.

```
In [56]: sb.boxplot(data=df_copy, x='age', color=sb.color_palette()[0]);
         plt.xlabel('Age');
         plt.title('Age Distribution')

Out[56]: Text(0.5,1,'Age Distribution')
```



Just for the records the extreme outliers in age highlighting the fact that many are ridding who exceded the 90 years

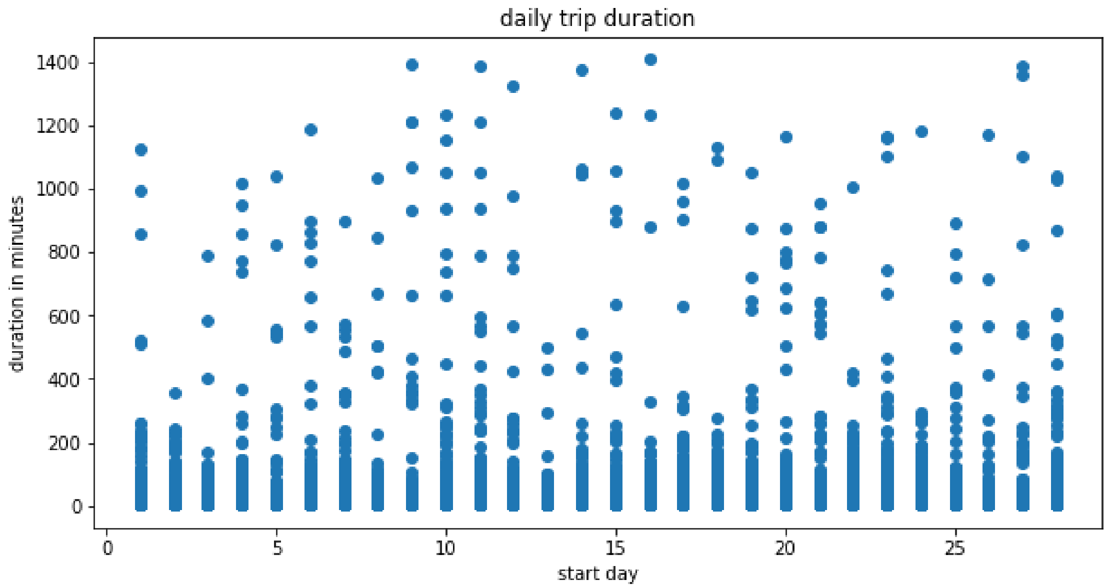
0.6.5 The univariant explanation:

After exploring many items in the dataset i found out many interesting things as follows;

It is worth noting that on Thursday of every week there is a noticeable activity for riding the stairs, unlike the weekend which is witnessing a remarkable decline and also balanced activity for the rest of the days of the week. The number of subscribers is much greater than the tenants, which at the same time represents an economic activity with more opportunities Taking into account that in terms of marketing, attention should be given to females more than that due to the variation in interest indicated by the difference in the ratio between males and females

0.6.6 Bivariant exploration

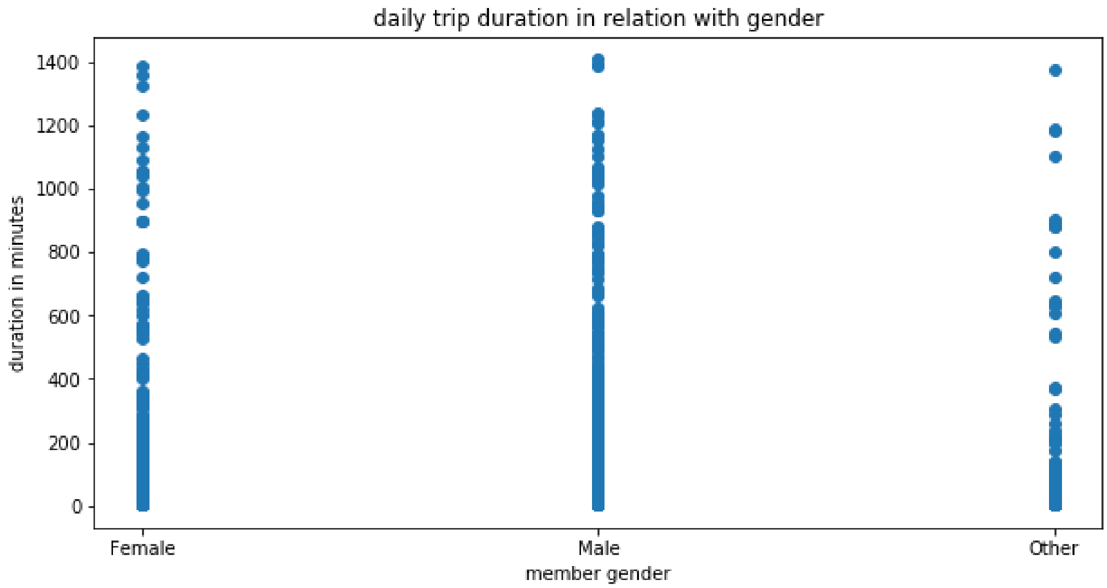
```
In [57]: plt.figure(figsize = [10,5])
         plt.scatter(data = df_copy , x = 'start_day' , y = 'duration_min' , alpha = 1 )
         plt.title('daily trip duration')
         plt.xlabel('start day')
         plt.ylabel('duration in minutes');
```



Here I will combin another factor to have a better vision and all moving around the relation between the duration (which represent the consumption here) and another factors to judge it better.

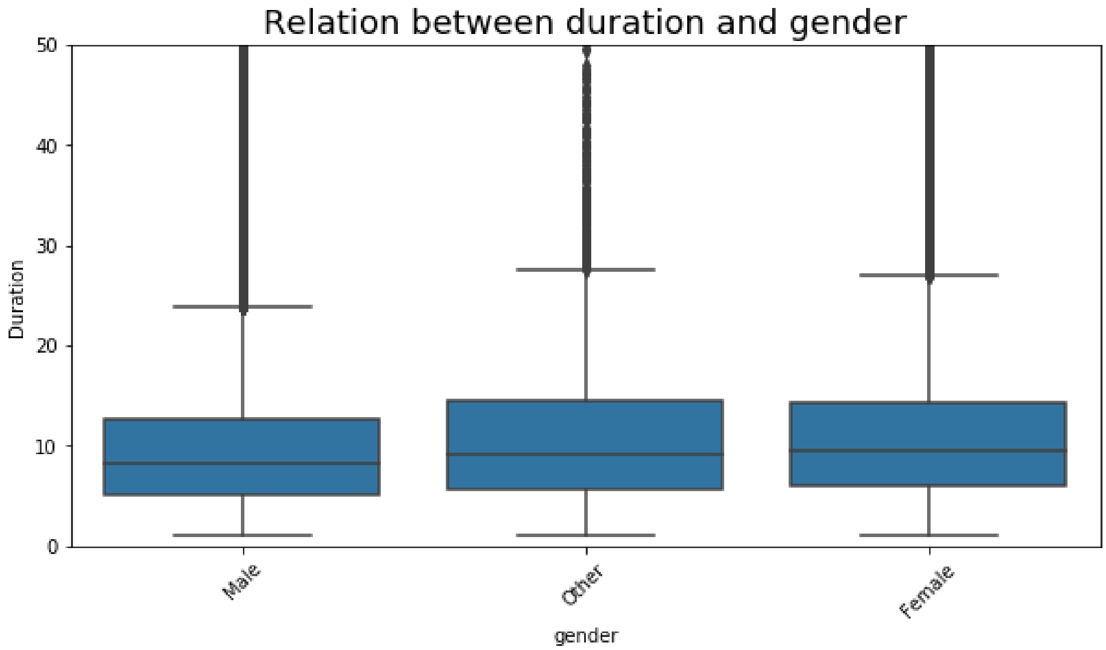
The relation between the start day of the week and duration in minutes the rate is maintained the work days is better in ridding and duration.

```
In [58]: plt.figure(figsize = [10,5])
         plt.scatter(data = df_copy , x = 'member_gender' , y = 'duration_min' , alpha = 1 )
         plt.title('daily trip duration in relation with gender')
         plt.xlabel('member gender')
         plt.ylabel('duration in minutes');
```



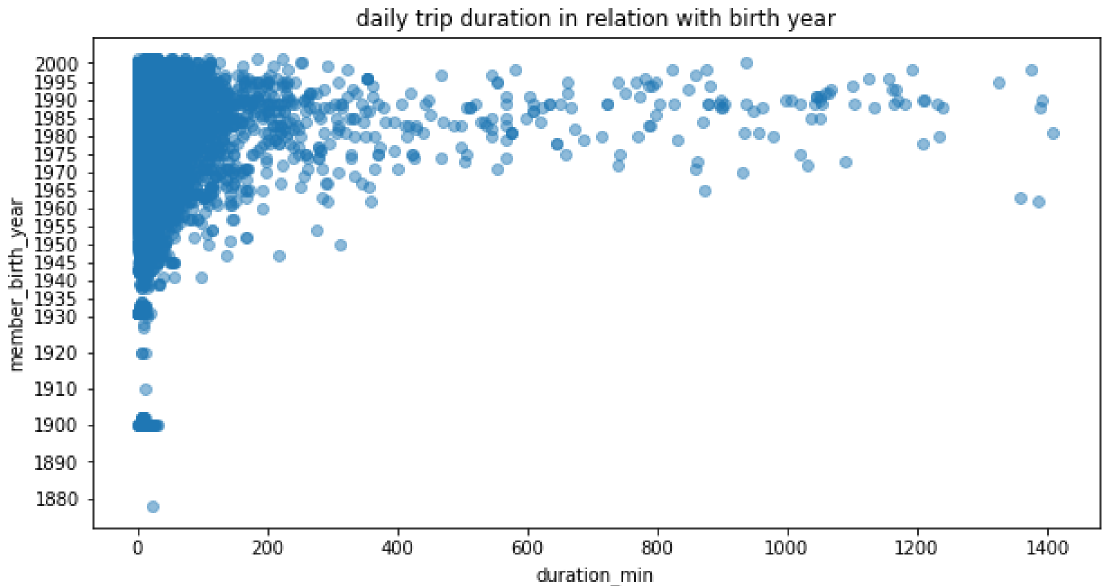
The men are the most ridder in the city and a segmented marketing targeting the women and other need to be done.

```
In [59]: base_color = sb.color_palette()[0]
         plt.figure(figsize = (10,5))
         yticks = [1, 5, 10, 50, 100, 500, 1000, 1500]
         sb.boxplot(data = df_copy, x = 'member_gender', y = 'duration_min', color = base_color)
         plt.xticks(rotation = 45);
         plt.ylim(0, 50);
         plt.title('Relation between duration and gender', fontsize = 18);
         plt.xlabel('gender');
         plt.ylabel('Duration')
         plt.yticks();
```



The box plot for the three listed genders showed a relative right skeweness in male distribution which become more in case of other and female.

```
In [60]: plt.figure(figsize = [10,5])
         ticks = [1880, 1890, 1900, 1910, 1920, 1930, 1935, 1940, 1945, 1950, 1955, 1960, 1965,
         plt.scatter(data = df_copy , x = 'duration_min' , y = 'member_birth_year' , alpha = 0.5
         plt.title('daily trip duration in relation with birth year')
         plt.xlabel('duration_min')
         plt.ylabel('member_birth_year');
         plt.yticks(ticks);
```



Another point i wanted to explore is the relation between birth year or the ridder age and the duration and it showed the the relative increase in the segment between 1980 to 2000.

0.6.7 The bivariant explanation

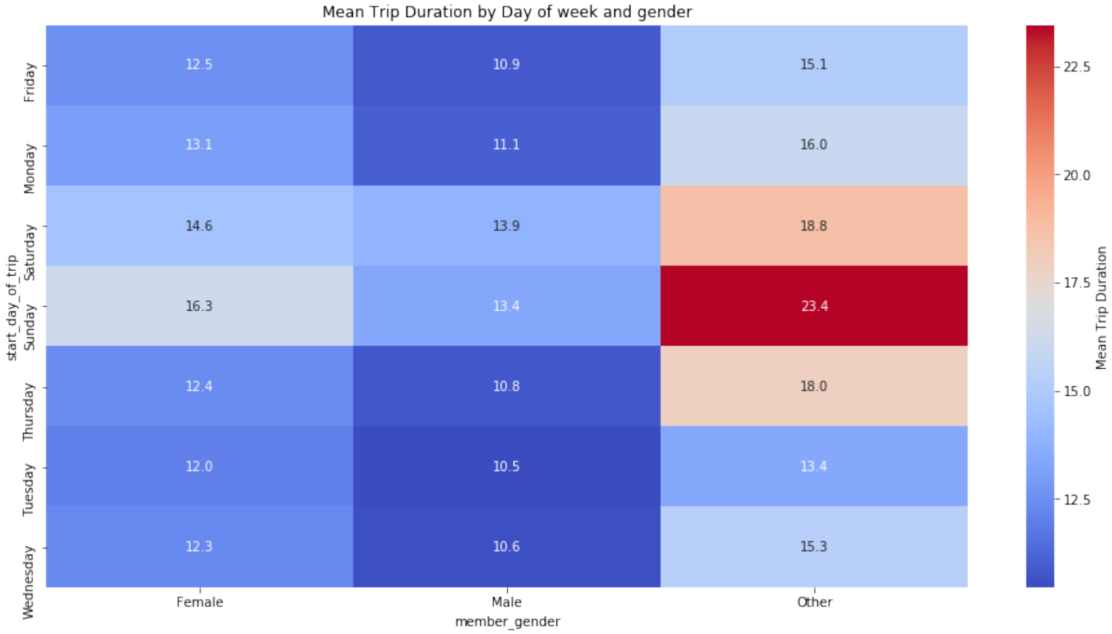
Adding an element to another element helps to clarify things or may lead to obliterating them, but in our case this adding a second element to the equation led to the consolidation of the discovered facts and proposals submitted to the decision-maker regarding the age or age, as well as the gender or type of interest in different age groups And also focus on the female.

0.6.8 The multivariante explanation

0.6.9 Lte me see with you the whole picture by combining mpre than two elements together.

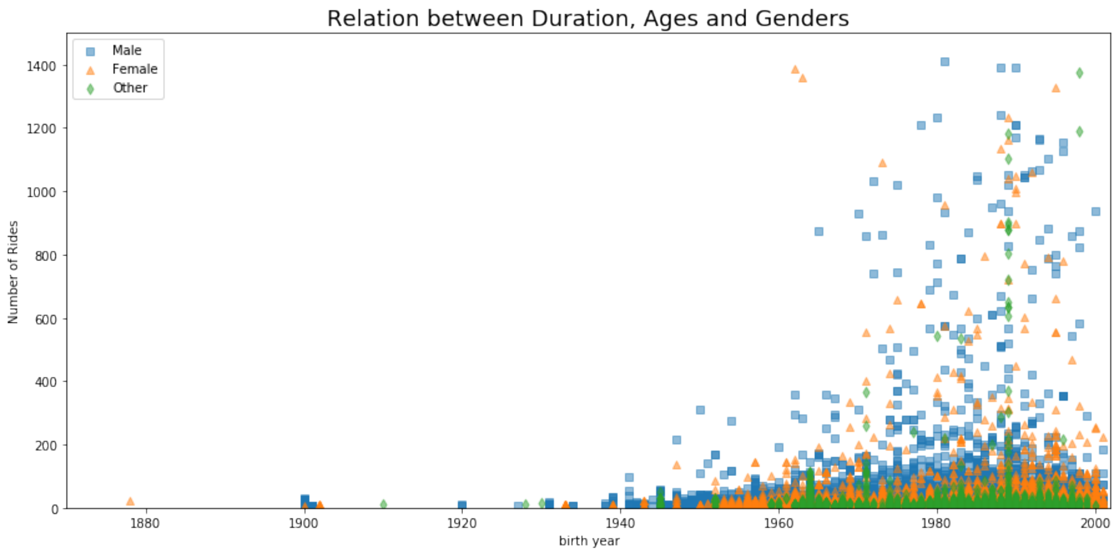
```
In [61]: pivot = df_copy.pivot_table(values='duration_min',index='start_day_of_trip',columns='me
         plt.figure(figsize=(16,8))
         sns.heatmap(pivot, annot=True, fmt='.1f', cbar_kws={'label' : 'Mean Trip Duration'}, cm
         plt.title("Mean Trip Duration by Day of week and gender")
```

```
Out[61]: Text(0.5,1,'Mean Trip Duration by Day of week and gender')
```



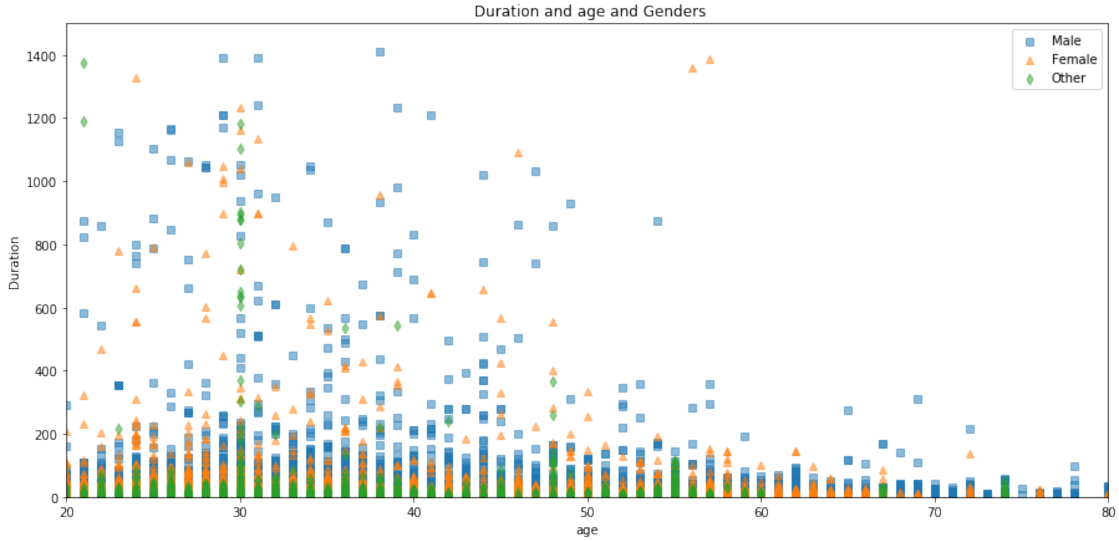
0.6.10 Amazing fact it is not by the size or the type finally we found out that mean duration for female is greater than male and that of others is the highest.

In [62]:
```
plt.figure(figsize = (15,7))

cat_markers = [['Male', 's'],
               ['Female', '^'],
               ['Other', 'd']]

for cat, marker in cat_markers:
    df_gender = df_copy[df_copy['member_gender'] == cat]
    plt.scatter(data = df_gender, x = 'member_birth_year', y = 'duration_min', marker =
plt.legend(['Male', 'Female', 'Other']);
plt.xlim(1870, 2002);
plt.ylim(0, 1500);
plt.title('Relation between Duration, Ages and Genders', fontsize = 18);
plt.xlabel('birth year');
plt.ylabel('Number of Rides');
```



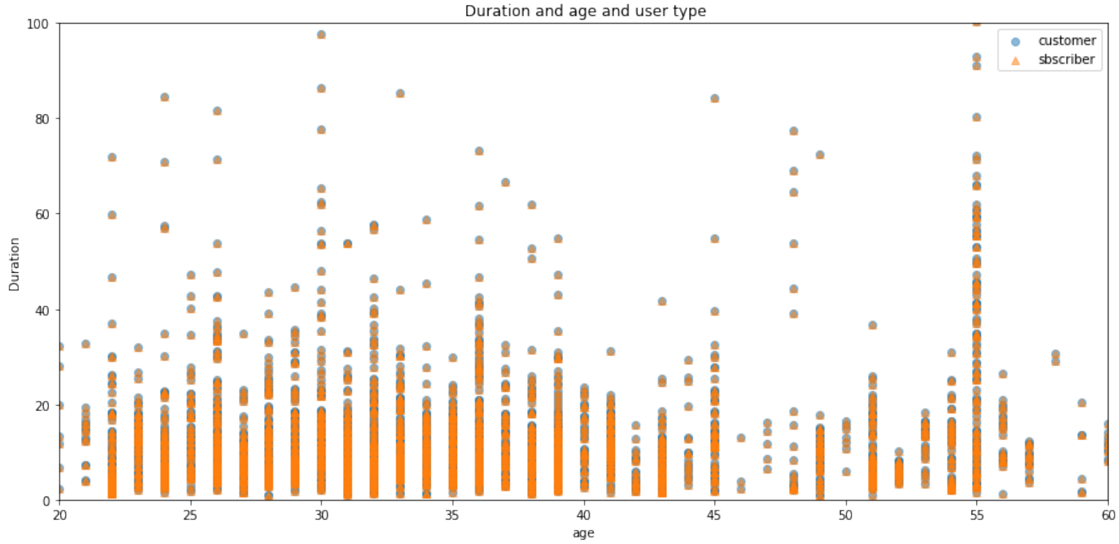
Men in the birth year ranging 1980 - 2000 are most ridders way the way not necessary the best but facts dealing with percents not skills

In [63]:
```
plt.figure(figsize = (15,7))

cat_markers = [['Male', 's'],
               ['Female', '^'],
               ['Other', 'd']]

for cat, marker in cat_markers:
    df_gender = df_copy[df_copy['member_gender'] == cat]
    plt.scatter(data = df_gender, x = 'age', y = 'duration_min', marker = marker, alpha
plt.legend(['Male', 'Female', 'Other']);
plt.xlim(20, 80);
plt.ylim(0, 1500);
plt.title(' Duration and age and Genders', fontsize = 12);
plt.xlabel('age');
plt.ylabel('Duration');
```



After extracting the age from the birth year yes it eas right the most ridders in the age zone of from 20 - 40 supporting the previous one of the birth year from 1980 - 2000

In [64]:
```
plt.figure(figsize = (15,7))

cat_markers = [['customer', 'o'],
               ['subscriber', '^']]

for cat, marker in cat_markers:
    df_user = df_copy[df_copy['user_type'] == cat]
    plt.scatter(data = df_gender, x = 'age', y = 'duration_min', marker = marker, alpha
plt.legend(['customer', 'sbscriber']);
plt.xlim(20, 60);
plt.ylim(0, 100);
plt.title(' Duration and age and user type', fontsize = 12);
plt.xlabel('age');
plt.ylabel('Duration');
```



The same point is tested between the age and user type in relation with duration give out that subscribers are competing during the age cycle.

0.6.11 Multivariant explanation

The addition of a new element to the equation supported the same course of speech and expectations regarding the relationship of each of the contestant's type, gender, and age, or more precisely, the year in which he was born, supported by the previous conclusions, which will be listed in the summary.

0.7 Conclusion

The focus of my attention was the first thing I examined the information available to me about renting bicycles from Ford and regarding February of 2019 to find the vital points that may affect the rate and amount of use. I focused my focus on the human factor in the main, because I believe it is the most important factor in Regarding gender, age, and from a commercial point of view, days of the week, and the type of passenger, is he a subscriber or a regular customer.

And it has become evident to me that the number of males is much greater than the number of females, and it seems that they want more attention, for example, by putting feminine touches on degrees or colors or even pictures of heroines on bicycles.

Also, the number of subscribers to regular customers indicates that subscription programs were available, which led to an increase in the number of subscribers, which is a good thing.

What astonished me while studying the available information was the age of the riders, which seems to have exceeded the ninety years at times and is a very good thing and can be used if it is correct in the propaganda and advertising.