

# The Exploration Visualization Project

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## 0.1 The visualization Project:

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## 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 addition to the explanatory work concerning the previous data of ford go bike.

0.2.2 First about this project i enjoyed 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 gave me 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 achieve 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 representative so need to be in minutes.

After transformation 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 libraries.
```

```
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: Columns (1) have dtype object, which may not be convertible to int. If you have a column of dtype object, please use pd.to_numeric to convert it to dtype float or int, depending on whether you have NaNs or not.
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.shape
```

```
Out[6]: (188280, 16)
```

```
In [7]: df.dtypes
```

```
Out[7]: 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 tididy and clean dataset.**

```
In [8]: # Mking a copy of the dataframe.
```

```
df_copy = df
```

```
In [9]: df_copy.shape
```

```
Out[9]: (188280, 16)
```

```
In [10]: # 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 [11]: # transferring the seconds into minutes.
```

```
df_copy['duration_min']=df_copy['duration_sec']/60
```

```
In [12]: # Dropping the duration _sec column.
```

```
df_copy.drop(['duration_sec'], inplace=True, axis = 1)
```

```
In [13]: # 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 [14]: df_copy.shape
```

```
Out[14]: (188280, 9)
```

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

```
In [15]: df_copy.isnull().sum()
```

```
Out[15]: 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 [16]: 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 [17]: df_copy.dropna(inplace=True)
```

```
In [18]: # Dropping Nan confirmation
df_copy.isnull().sum()
```

```
Out[18]: 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 [19]: # 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 [20]: df_copy.head(5)
```

```
Out[20]:
```

		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 [21]: 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 [22]: 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 [23]: 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[23]:
```

	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 [24]: 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 [25]: df_copy['start_date'] = pd.to_datetime(df_copy['start_date'])
         df_copy['end_date'] = pd.to_datetime(df_copy['end_date'])

```

```

In [26]: df_copy.dtypes

```

```

Out[26]: 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 [27]: 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

```

```
In [28]: df_copy['start_day_of_trip'] = df_copy[['start_date']].apply(lambda x: dt.datetime.strptime(x, '%Y-%m-%d').weekday())
```

```
In [29]: df_copy['end_day_of_trip'] = df_copy[['end_date']].apply(lambda x: dt.datetime.strptime(x, '%Y-%m-%d').weekday())
```

```
In [30]: df_copy.head()
```

```

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

```
In [32]: df['member_birth_year'].astype(int)
```

```
Out[32]: 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 [33]: df_copy['age'] = 2019 - df_copy['member_birth_year']
```

```
In [34]: 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 [35]: df_copy.head()
```

```

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

```
Out[36]: Thursday      38020
         Tuesday       30584
         Wednesday     28426
         Friday        27995
         Monday        25641
         Sunday        14512
         Saturday      14414
         Name: start_day_of_trip, dtype: int64
```

```
In [37]: df_copy['end_day_of_trip'].value_counts()
```

```
Out[37]: Thursday      38010
         Tuesday       30591
         Wednesday     28417
         Friday        27992
         Monday        25641
         Sunday        14519
         Saturday      14422
         Name: end_day_of_trip, dtype: int64
```

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

```
Out[38]: count      179592
         unique        3
         top          Male
         freq      133916
         Name: member_gender, dtype: object
```

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

```
Out[39]: count      179592
         unique        7
         top      Thursday
         freq      38010
         Name: end_day_of_trip, dtype: object
```

```
In [40]: df_copy['start_day_of_trip'].describe()
```

```
Out[40]: count      179592
         unique        7
         top      Thursday
         freq      38020
         Name: start_day_of_trip, dtype: object
```

```
In [41]: df_copy['start_day'].describe()
```

```
Out[41]: 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 [42]: df_copy['end_day'].describe()
```

```
Out[42]: 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 [43]: df_copy['start_date'].describe()
```

```
Out[43]: 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 [44]: df_copy['end_date'].describe()
```

```
Out[44]: 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 [45]: df_copy['start_time'].describe()
```

```
Out[45]: count              179592
         unique            174648
         top    17:08:39.140000
         freq                3
         Name: start_time, dtype: object
```

```

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

Out[46]: count          179592
         unique          174622
         top      22:16:04.478000
         freq              4
         Name: end_time, dtype: object

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

Out[47]: 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 [48]: np.log10(df_copy['duration_min']).describe()

Out[48]: 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 [49]: df_copy['user_type'].describe()

Out[49]: count          179592
         unique           2
         top      Subscriber
         freq          162610
         Name: user_type, dtype: object

In [50]: df_copy['member_birth_year'].describe()

Out[50]: 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

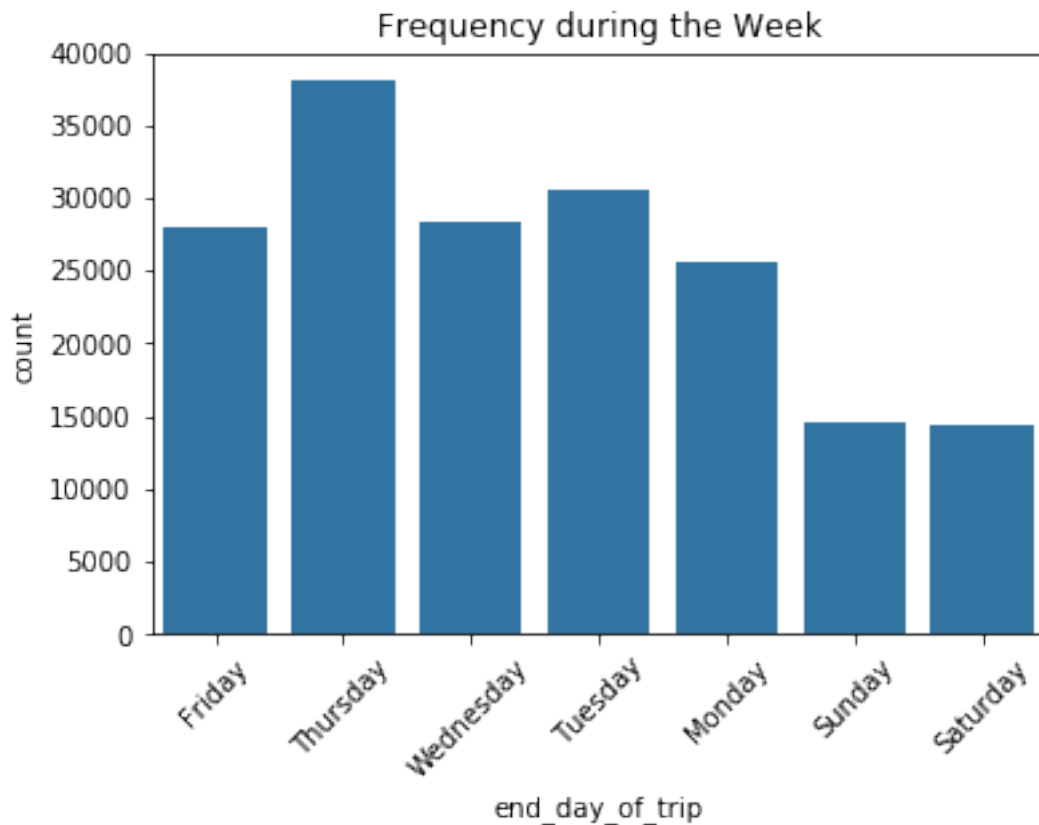
```

### 0.6.3 Univariate 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.

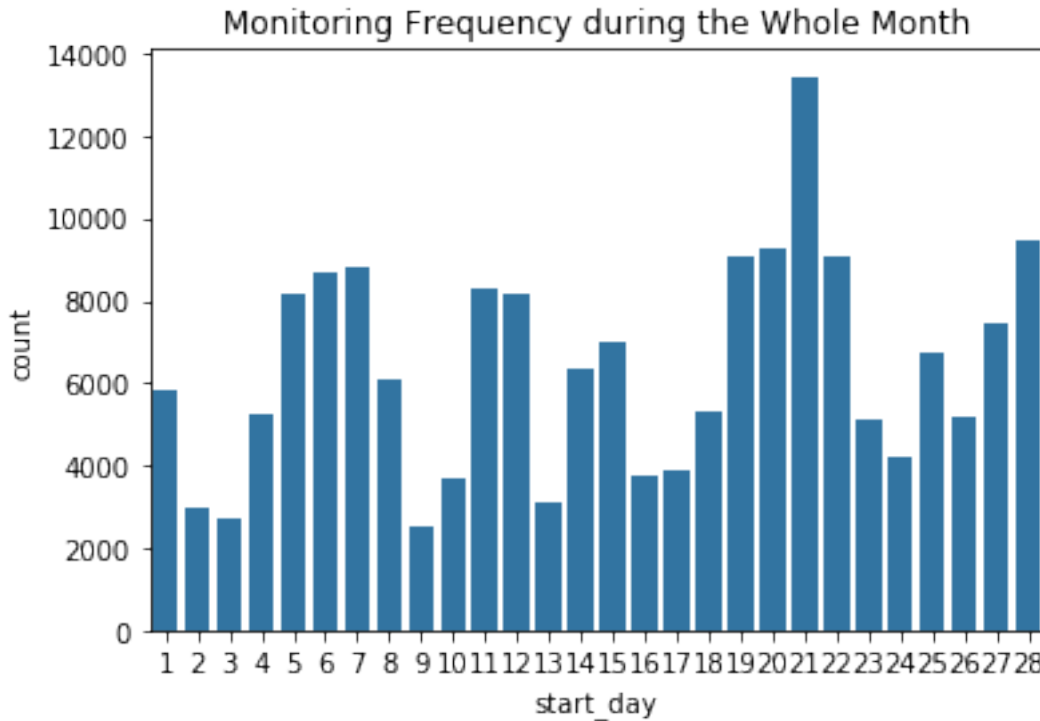
```
In [51]: sb.countplot(data = df_copy, x = 'end_day_of_trip', color=sb.color_palette()[0]);  
         plt.xlabel('end_day_of_trip')  
         plt.xticks(rotation = 45)  
         plt.title('Frequency during the Week')
```

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



```
In [52]: sb.countplot(data=df_copy,x='start_day', color=sb.color_palette()[0])  
         plt.title('Monitoring Frequency during the Whole Month')
```

```
Out[52]: Text(0.5,1,'Monitoring Frequency during the Whole Month')
```

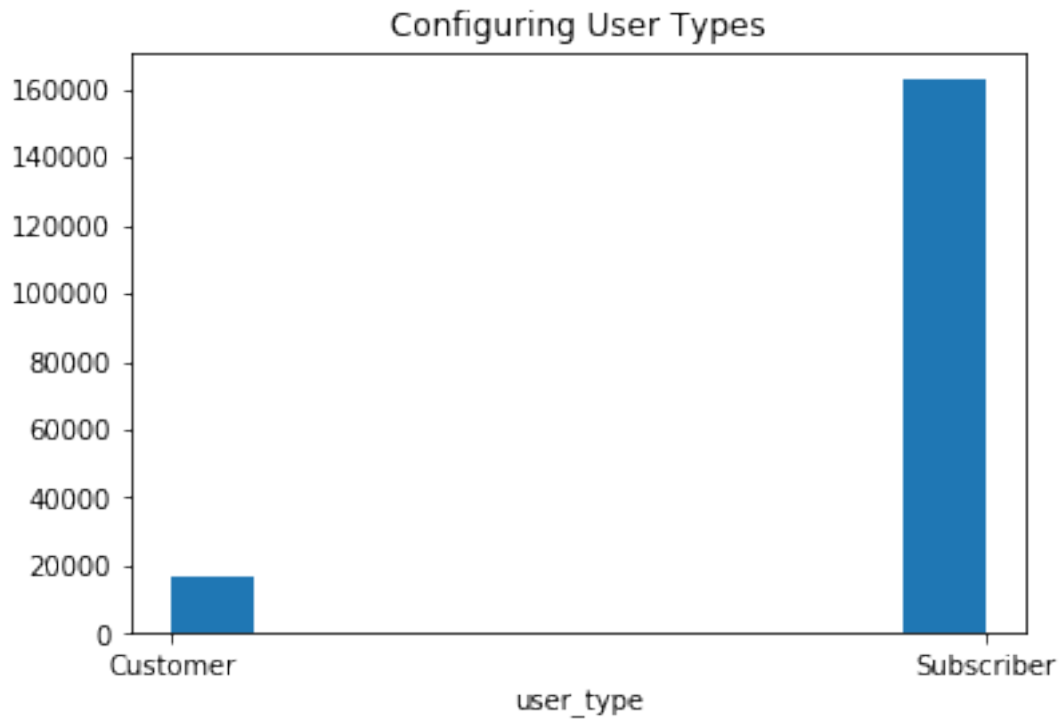


As for the days of the week, the result was relatively amazing to me. It seems that the weekends have witnessed a significant decrease in the ridding of cycling. It seems that it is a real holiday, and it seems that a significant percentage of the population uses bicycles in their daily routine

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

```
Out[53]: Text(0.5,1,'Configuring User Types')
```

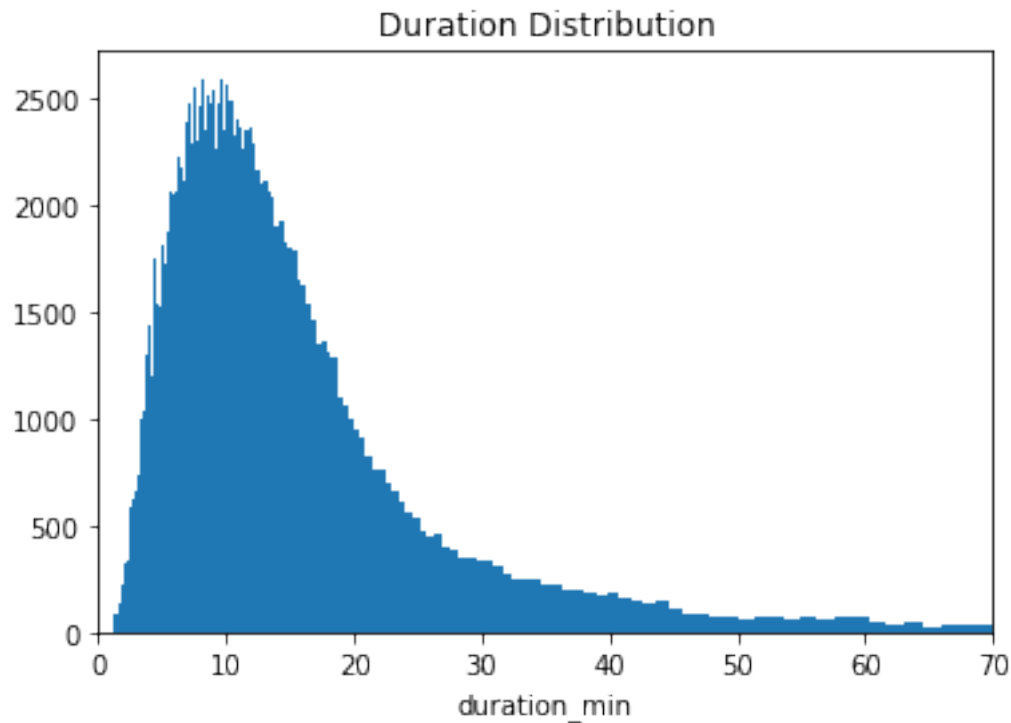


For the user type it is traditional the subscriber is huge against customers it seems that the loyalty programs is good but it is just a guess from the results.

```
In [54]: 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')
plt.title('Duration Distribution')
```

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

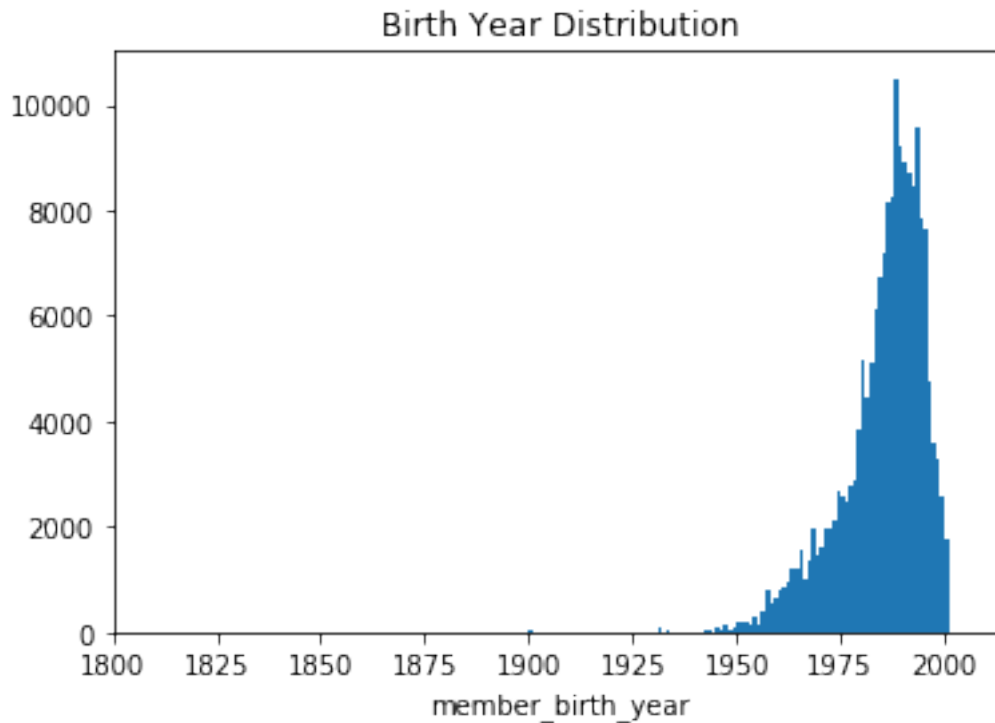




At this point i had to transfer the original data to (log) to figure out the shape of data and as it seems it is highly skewed to the right so the majority of the riders tends to use the ride for may be fro (10-20 minutes) per day while others for many more time.

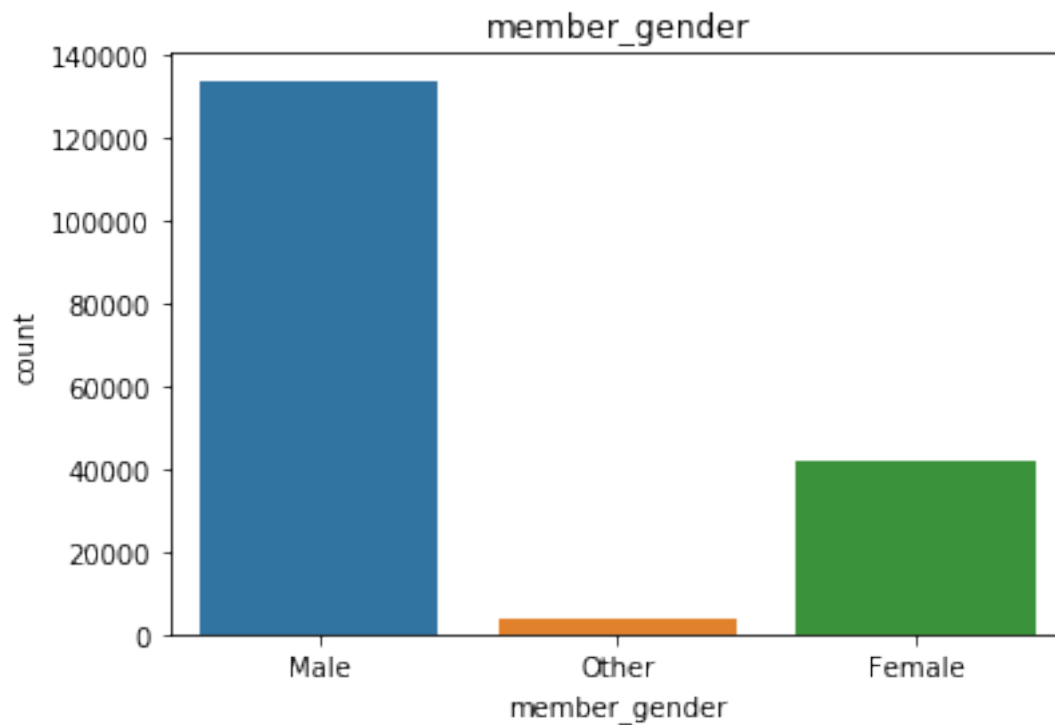
```
In [55]: bins = np.arange(1878, 2001+1, 1)
plt.hist(data = df_copy, x = 'member_birth_year', bins = bins);
plt.xlim([1800,2015])
plt.xlabel('member_birth_year')
plt.title('Birth Year Distribution')
```

```
Out[55]: 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.

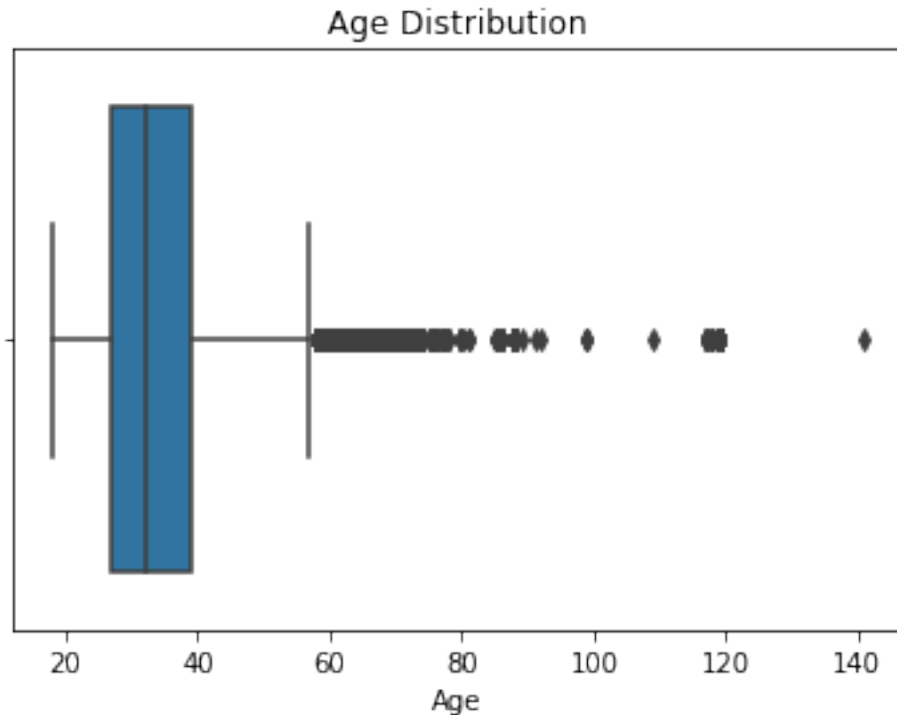
```
In [56]: sb.countplot(data = df_copy, x = 'member_gender')  
         plt.title('member_gender');
```



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

```
In [57]: sb.boxplot(data=df_copy, x='age', color=sb.color_palette()[0]);  
         plt.xlabel('Age');  
         plt.title('Age Distribution')
```

```
Out[57]: 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

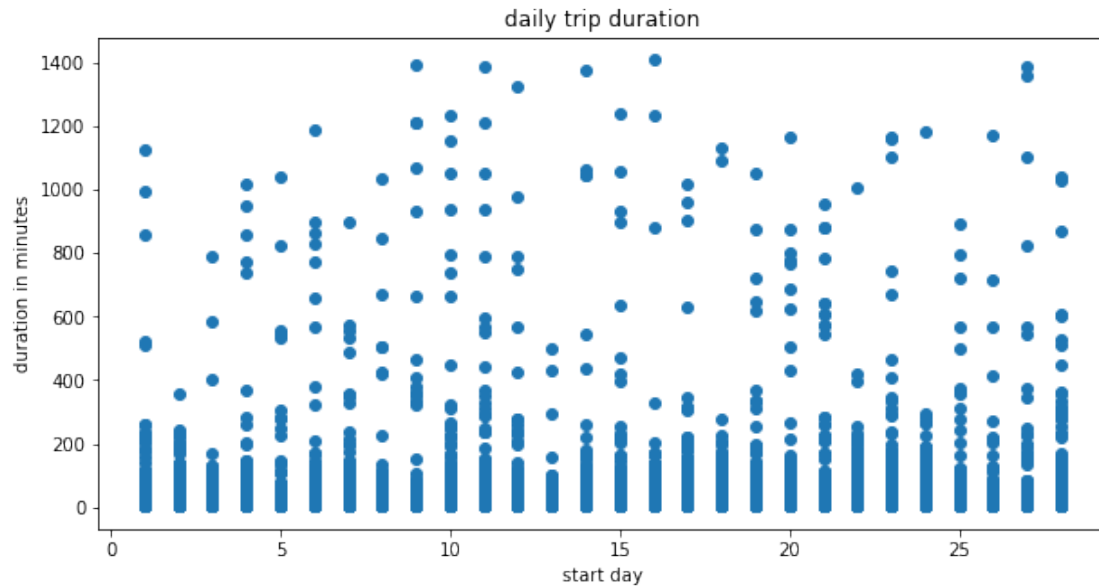
#### 0.6.5 The univariant explanation:

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

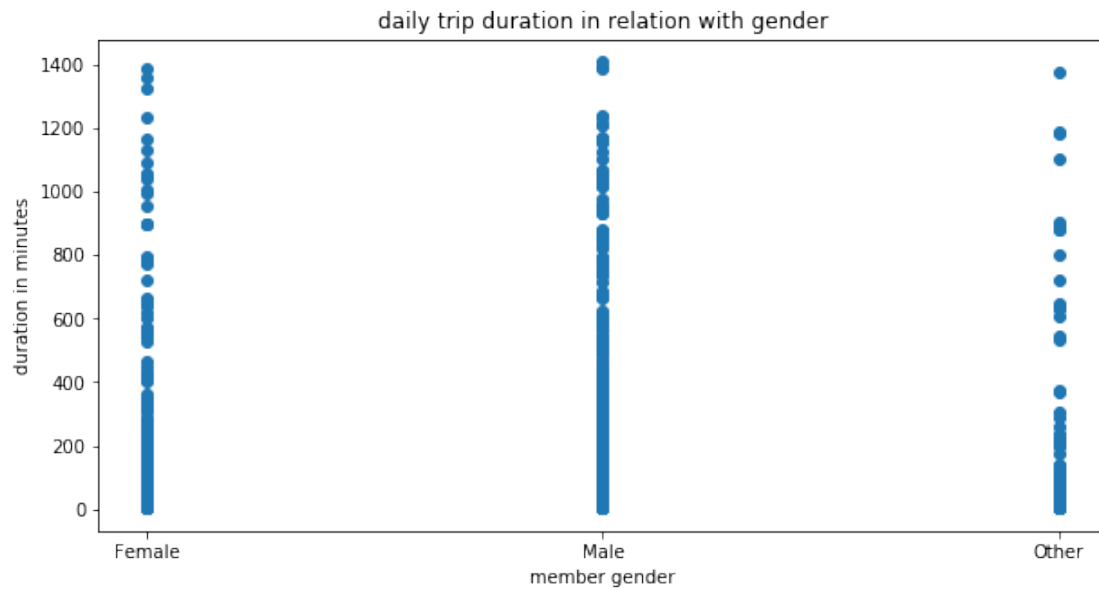
```
In [58]: plt.figure(figsize = [10,5])
plt.scatter(data = df_copy , x = 'start_day' , y = 'duration_min' , alpha = 1 )
plt.title('daily trip duration')
plt.xlabel('start day')
plt.ylabel('duration in minutes');
```



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.

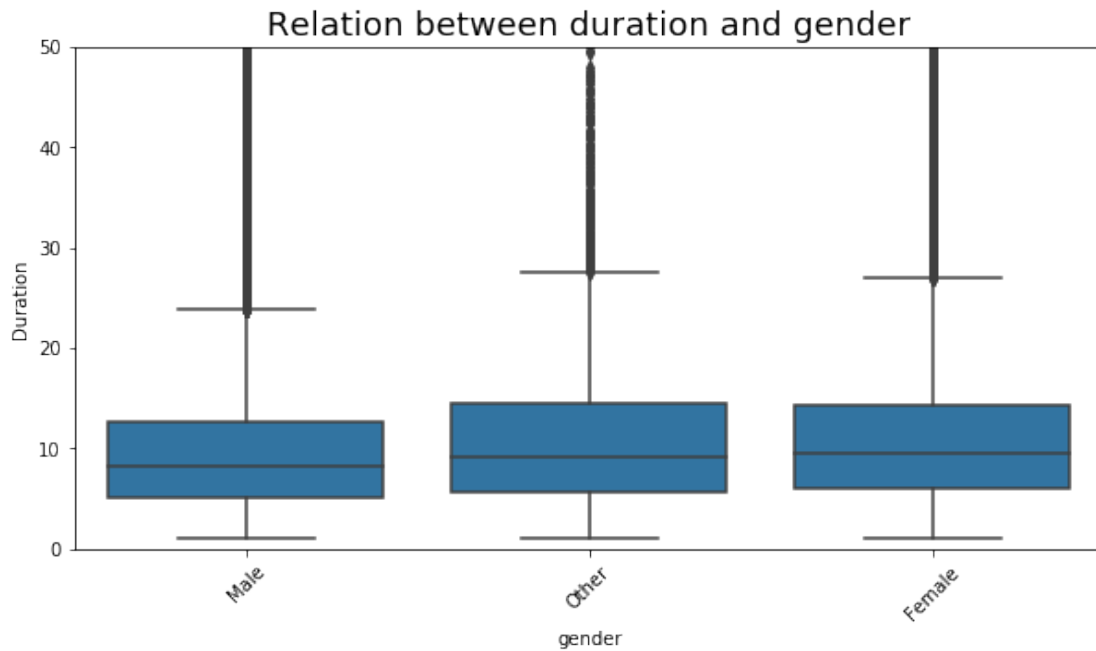
The relation between the start day of the week and duration in minutes the rate is maintained the work days is better in ridding and duration.

```
In [59]: 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');
```



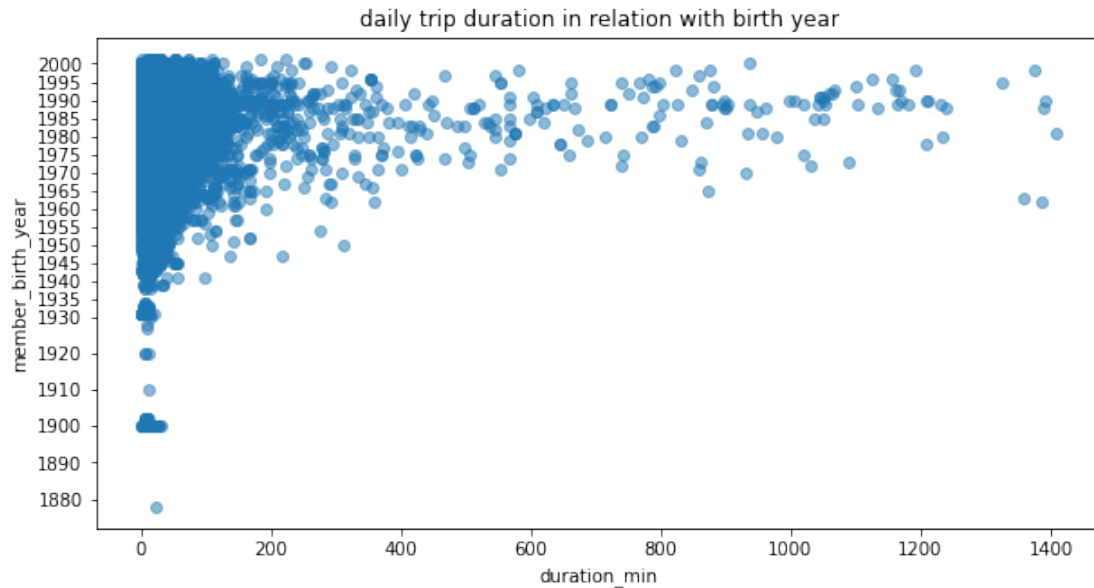
**The men are the most rider in the city and a segmented marketing targeting the women and other need to be done.**

```
In [60]: 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 [61]: 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 rider age and the duration and it showed the the relative increase in the segment between 1980 to 2000.

#### 0.6.7 The bivariate 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.

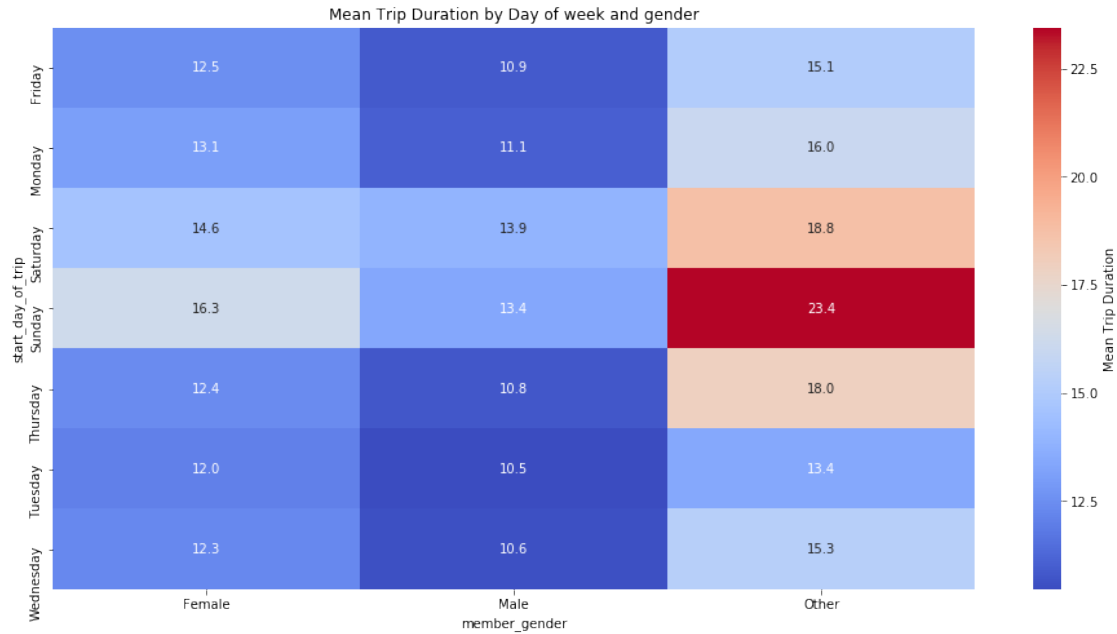
#### 0.6.8 The multivariate explanation

0.6.9 Let me see with you the whole picture by combining more than two elements together.

```
In [62]: pivot = df_copy.pivot_table(values='duration_min',index='start_day_of_trip',columns='member_gender')
plt.figure(figsize=(16,8))
sns.heatmap(pivot, annot=True, fmt='.1f', cbar_kws={'label' : 'Mean Trip Duration'}, cm='magma')
plt.title("Mean Trip Duration by Day of week and gender")
```

```
Out[62]: Text(0.5,1,'Mean Trip Duration by Day of week and gender')
```



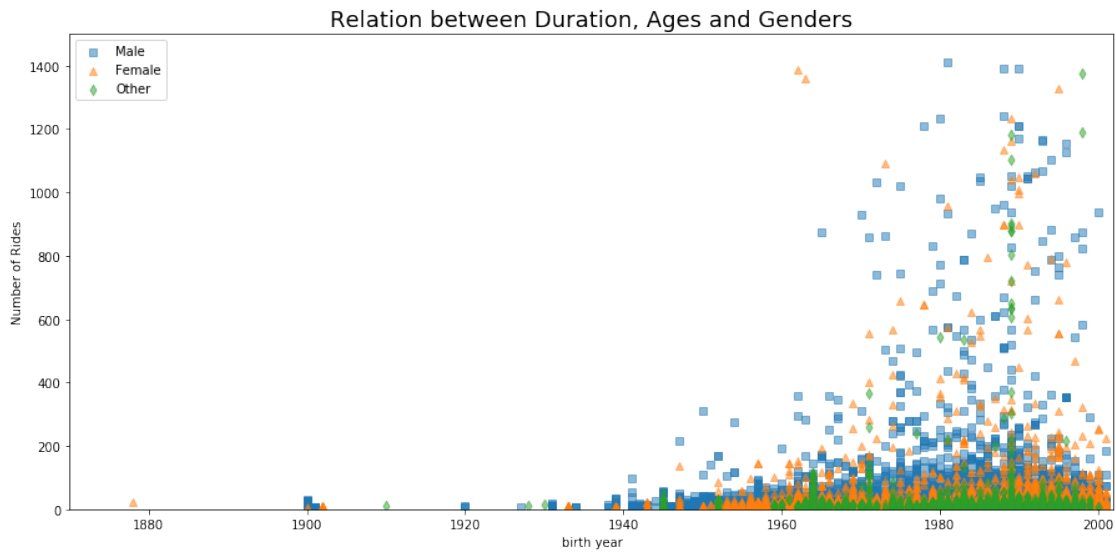


**0.6.10 Amazing fact it is not by the size or the type finally we found out that mean duration for female is greater than male and that of others is the highest.**

```
In [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 = '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');
```

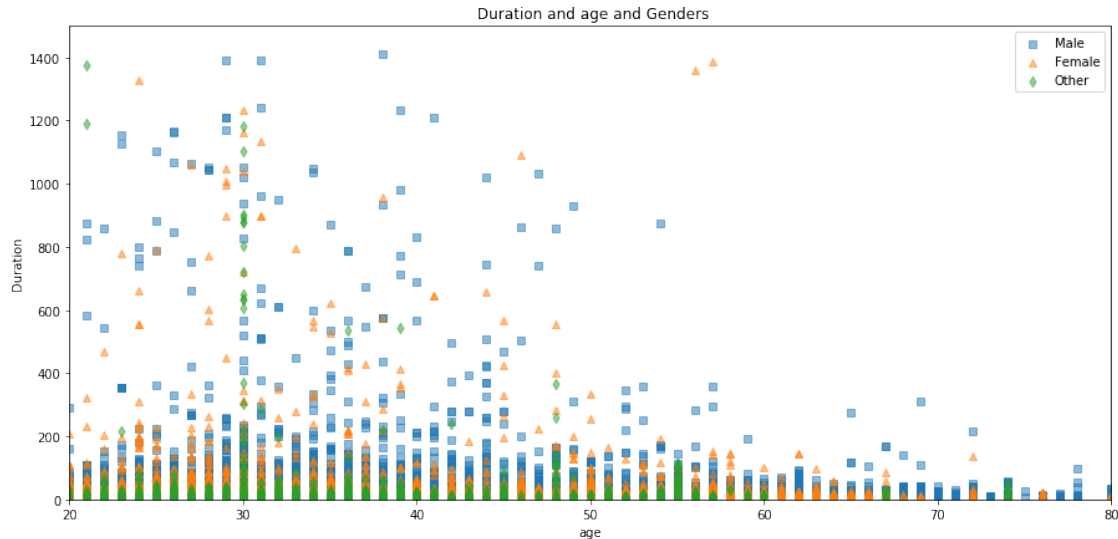


**Men in the birth year ranging 1980 - 2019 are most riders way the way not necessary the best but facts dealing with percents not skills**

```
In [64]: 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=0.5)
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');
```

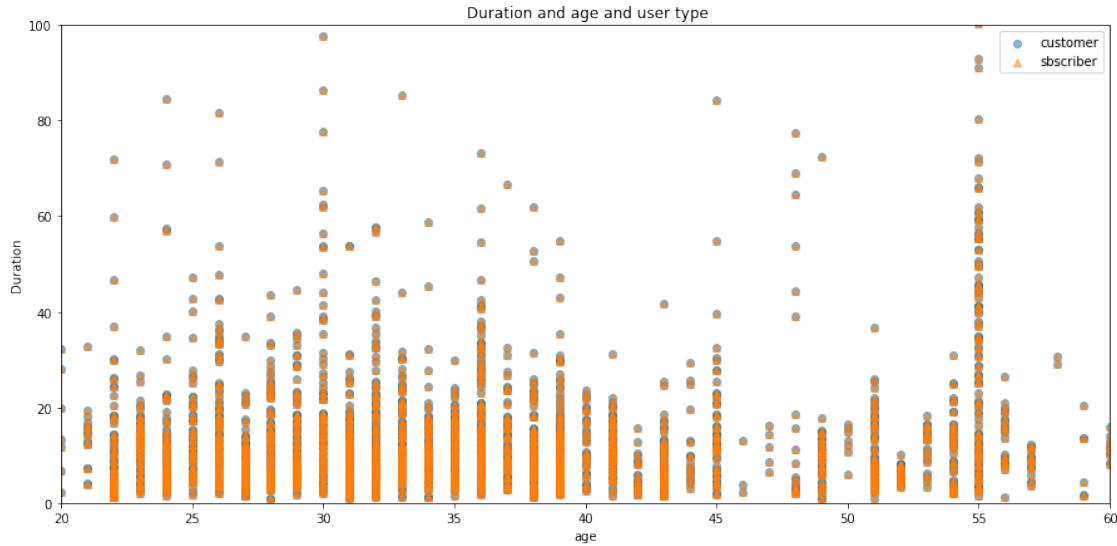


After extracting the age from the birth year yes it was right the most riders in the age zone of from 20 - 40 supporting the previous one of the birth year from 1980 - 2000

```
In [65]: 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=0.5)
plt.legend(['customer', 'subscriber']);
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.

```
In [ ]:
```