Exploration_Ford_GoBike

March 1, 2021

1 Project : Communicate-Data-Findings (Ford GoBike System Data)

1.1 Table of Contents

- Section **??**
- Section **??**
- Section **??**
- Section **??**
- Section **??**
- Section **??**

1.1.1 Introduction

Bay Wheels is a regional public bicycle sharing system in California's San Francisco Bay Area. It is operated by Motivate in a partnership with the Metropolitan Transportation Commission and the Bay Area Air Quality Management District. Bay Wheels is the first regional and large-scale bicycle sharing system deployed in California and on the West Coast of the United States. It was established as Bay Area Bike Share in August 2013. As of January 2018, the Bay Wheels system had over 2,600 bicycles in 262 stations across San Francisco, East Bay and San Jose.

2 Preliminary Wrangling

```
In [1]: # import all packages and set plots to be embedded inline
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import random
        import seaborn as sns
        import seaborn as sb
        import pickle
        import os
        import glob
        %matplotlib inline
        random.seed()
```

In [2]:
```python
# load in the dataset into a pandas dataframe and clean up field dtypes
df = pd.read_csv('201902-fordgobike-tripdata.csv')
```

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

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              -122.400811            13.0
1               37.791464              -122.391034            81.0
2               37.769305              -122.426826             3.0
3               37.774836              -122.446546            70.0
4               37.804562              -122.271738           222.0

                              end_station_name  end_station_latitude  \
0               Commercial St at Montgomery St             37.794231
1                           Berry St at 4th St             37.775880
2  Powell St BART Station (Market St at 4th St)             37.786375
3                      Central Ave at Fell St             37.773311
4                       10th Ave at E 15th St             37.792714

   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]:
```python
# Let's take a peak into the data's basic information
df.info(null_counts = True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29225 entries, 0 to 29224
Data columns (total 16 columns):
duration_sec               29225 non-null int64
start_time                 29225 non-null object
end_time                   29225 non-null object
start_station_id           29191 non-null float64
start_station_name         29191 non-null object
start_station_latitude     29225 non-null float64
start_station_longitude    29225 non-null float64
end_station_id             29190 non-null float64
end_station_name           29190 non-null object
end_station_latitude       29224 non-null float64
end_station_longitude      29224 non-null float64
bike_id                    29224 non-null float64
user_type                  29224 non-null object
member_birth_year          28171 non-null float64
member_gender              28171 non-null object
bike_share_for_all_trip    29224 non-null object
dtypes: float64(8), int64(1), object(7)
memory usage: 3.6+ MB
```

In [5]:
```
#show the number of unique user

df.shape[0]
```

Out[5]: 29225

In [6]:
```
#show the number of unique user

df.nunique()
```

Out[6]:
```
duration_sec                2262
start_time                 29224
end_time                   29224
start_station_id             326
start_station_name           326
start_station_latitude       329
start_station_longitude      331
end_station_id               324
end_station_name             324
end_station_latitude         328
end_station_longitude        329
bike_id                     3400
user_type                      2
member_birth_year             65
member_gender                  3
```

```
bike_share_for_all_trip        2
dtype: int64
```

In [7]:
```
# Let's also get some additional description for stats figures
df.describe()
```

Out[7]:

	duration_sec	start_station_id	start_station_latitude
count	29225.000000	29191.000000	29225.000000
mean	675.335261	134.742215	37.768929
std	1633.914613	111.417506	0.102024
min	61.000000	3.000000	37.317298
25%	320.000000	44.000000	37.770407
50%	502.000000	95.000000	37.780526
75%	762.000000	232.000000	37.795392
max	83195.000000	398.000000	37.880222

	start_station_longitude	end_station_id	end_station_latitude
count	29225.000000	29190.000000	29224.000000
mean	-122.352717	132.422816	37.769280
std	0.119240	111.231060	0.101947
min	-122.453704	3.000000	37.317298
25%	-122.411738	41.000000	37.771058
50%	-122.397437	93.000000	37.780760
75%	-122.293400	223.000000	37.795392
max	-121.874119	398.000000	37.880222

	end_station_longitude	bike_id	member_birth_year
count	29224.000000	29224.000000	28171.000000
mean	-122.352093	4929.272139	1984.774271
std	0.118776	1547.813928	9.991789
min	-122.453704	11.000000	1878.000000
25%	-122.410807	4589.000000	1980.000000
50%	-122.397086	5315.000000	1987.000000
75%	-122.293528	6051.000000	1992.000000
max	-121.874119	6644.000000	2001.000000

In [8]:
```
df.dropna()
```

Out[8]:

	duration_sec	start_time	end_time
0	52185	2019-02-28 17:32:10.1450	2019-03-01 08:01:55.9750
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
5	1793	2019-02-28 23:49:58.6320	2019-03-01 00:19:51.7600
6	1147	2019-02-28 23:55:35.1040	2019-03-01 00:14:42.5880
7	1615	2019-02-28 23:41:06.7660	2019-03-01 00:08:02.7560
8	1570	2019-02-28 23:41:48.7900	2019-03-01 00:07:59.7150
9	1049	2019-02-28 23:49:47.6990	2019-03-01 00:07:17.0250
10	458	2019-02-28 23:57:57.2110	2019-03-01 00:05:35.4350

11	506	2019-02-28 23:56:55.5400	2019-03-01 00:05:21.7330
12	1176	2019-02-28 23:45:12.6510	2019-03-01 00:04:49.1840
14	395	2019-02-28 23:56:26.8480	2019-03-01 00:03:01.9470
15	208	2019-02-28 23:59:18.5480	2019-03-01 00:02:47.2280
16	548	2019-02-28 23:50:41.6070	2019-02-28 23:59:49.9530
17	674	2019-02-28 23:48:25.0950	2019-02-28 23:59:40.0920
18	557	2019-02-28 23:49:01.8510	2019-02-28 23:58:19.8090
19	874	2019-02-28 23:43:05.1830	2019-02-28 23:57:39.7960
20	417	2019-02-28 23:50:38.2390	2019-02-28 23:57:35.8520
21	414	2019-02-28 23:50:26.8790	2019-02-28 23:57:21.1300
22	743	2019-02-28 23:44:56.4390	2019-02-28 23:57:20.2120
23	367	2019-02-28 23:51:06.0140	2019-02-28 23:57:13.3120
24	252	2019-02-28 23:52:51.1640	2019-02-28 23:57:03.9760
25	360	2019-02-28 23:50:31.4310	2019-02-28 23:56:31.8910
26	385	2019-02-28 23:49:24.3990	2019-02-28 23:55:50.2840
27	408	2019-02-28 23:48:08.2820	2019-02-28 23:54:56.9300
29	629	2019-02-28 23:43:48.6580	2019-02-28 23:54:18.2540
30	163	2019-02-28 23:50:45.6980	2019-02-28 23:53:29.5690
31	223	2019-02-28 23:49:27.0270	2019-02-28 23:53:10.5350
32	405	2019-02-28 23:45:39.2340	2019-02-28 23:52:24.8500
...	...	...	...
29194	1291	2019-02-25 07:32:24.0100	2019-02-25 07:53:55.6680
29195	449	2019-02-25 07:46:22.7500	2019-02-25 07:53:51.8170
29196	723	2019-02-25 07:41:37.9720	2019-02-25 07:53:41.2940
29197	434	2019-02-25 07:46:15.9290	2019-02-25 07:53:30.5640
29198	344	2019-02-25 07:47:39.8300	2019-02-25 07:53:24.4340
29199	1541	2019-02-25 07:27:41.1330	2019-02-25 07:53:22.9100
29200	586	2019-02-25 07:43:27.1660	2019-02-25 07:53:13.4380
29201	737	2019-02-25 07:40:51.0550	2019-02-25 07:53:08.8780
29202	887	2019-02-25 07:38:17.5000	2019-02-25 07:53:05.2420
29203	368	2019-02-25 07:46:56.4000	2019-02-25 07:53:05.2380
29204	253	2019-02-25 07:48:50.7810	2019-02-25 07:53:04.3710
29205	187	2019-02-25 07:49:54.7080	2019-02-25 07:53:02.6380
29206	74	2019-02-25 07:51:47.2760	2019-02-25 07:53:01.4030
29207	815	2019-02-25 07:39:24.5480	2019-02-25 07:53:00.4250
29208	574	2019-02-25 07:43:24.3030	2019-02-25 07:52:58.4040
29209	102	2019-02-25 07:51:13.4910	2019-02-25 07:52:56.0980
29210	310	2019-02-25 07:47:25.5130	2019-02-25 07:52:35.6790
29211	386	2019-02-25 07:46:09.5350	2019-02-25 07:52:35.6070
29212	228	2019-02-25 07:48:45.1930	2019-02-25 07:52:34.1190
29213	837	2019-02-25 07:38:36.2250	2019-02-25 07:52:33.3610
29214	1480	2019-02-25 07:27:51.6700	2019-02-25 07:52:32.3190
29215	300	2019-02-25 07:47:29.7910	2019-02-25 07:52:30.5660
29216	339	2019-02-25 07:46:43.3870	2019-02-25 07:52:22.7300
29217	779	2019-02-25 07:39:21.2700	2019-02-25 07:52:20.7510
29218	867	2019-02-25 07:37:52.3010	2019-02-25 07:52:19.4230
29219	536	2019-02-25 07:43:20.5220	2019-02-25 07:52:17.3450
29220	370	2019-02-25 07:45:52.8230	2019-02-25 07:52:03.7650

```
29221          964  2019-02-25 07:35:59.1490  2019-02-25 07:52:03.7630
29222          293  2019-02-25 07:47:08.0680  2019-02-25 07:52:01.7980
29223         1106  2019-02-25 07:33:35.4450  2019-02-25 07:52:01.5660

       start_station_id                                   start_station_name  \
0                  21.0   Montgomery St BART Station (Market St at 2nd St)
2                  86.0                            Market St at Dolores St
3                 375.0                            Grove St at Masonic Ave
4                   7.0                                Frank H Ogawa Plaza
5                  93.0                       4th St at Mission Bay Blvd S
6                 300.0                               Palm St at Willow St
7                  10.0                         Washington St at Kearny St
8                  10.0                         Washington St at Kearny St
9                  19.0                               Post St at Kearny St
10                370.0                                Jones St at Post St
11                 44.0  Civic Center/UN Plaza BART Station (Market St ...
12                127.0                             Valencia St at 21st St
14                243.0                          Bancroft Way at College Ave
15                349.0                               Howard St at Mary St
16                131.0                             22nd St at Dolores St
17                 74.0                             Laguna St at Hayes St
18                321.0                                   5th St at Folsom
19                180.0                           Telegraph Ave at 23rd St
20                 72.0                                Page St at Scott St
21                163.0                            Lake Merritt BART Station
22                370.0                                Jones St at Post St
23                243.0                          Bancroft Way at College Ave
24                190.0                                West St at 40th St
25                163.0                            Lake Merritt BART Station
26                  6.0                      The Embarcadero at Sansome St
27                 78.0                                Folsom St at 9th St
29                258.0                        University Ave at Oxford St
30                238.0                       MLK Jr Way at University Ave
31                 28.0                       The Embarcadero at Bryant St
32                109.0                             17th St at Valencia St
...                 ...                                                ...
29194             371.0                         Lombard St at Columbus Ave
29195               6.0                      The Embarcadero at Sansome St
29196             168.0                        Alcatraz Ave at Shattuck Ave
29197              60.0                               8th St at Ringold St
29198             197.0                        El Embarcadero at Grand Ave
29199             130.0                           22nd St Caltrain Station
29200               4.0                        Cyril Magnin St at Ellis St
29201              56.0                                      Koshland Park
29202              16.0                            Steuart St at Market St
29203             323.0                                 Broadway at Kearny
29204              50.0                              2nd St at Townsend St
29205             205.0                             Miles Ave at Cavour St
```

```
29206            30.0    San Francisco Caltrain (Townsend St at 4th St)
29207            15.0  San Francisco Ferry Building (Harry Bridges Pl...
29208            75.0                          Market St at Franklin St
29209            64.0                              5th St at Brannan St
29210           315.0                              Market St at 45th St
29211           134.0                            Valencia St at 24th St
29212            89.0                        Division St at Potrero Ave
29213           257.0                           Fifth St at Delaware St
29214           141.0                    Valencia St at Cesar Chavez St
29215           315.0                              Market St at 45th St
29216            15.0  San Francisco Ferry Building (Harry Bridges Pl...
29217           263.0                     Channing Way at San Pablo Ave
29218           145.0                              29th St at Church St
29219            89.0                        Division St at Potrero Ave
29220            16.0                           Steuart St at Market St
29221            66.0                            3rd St at Townsend St
29222           245.0                            Downtown Berkeley BART
29223           285.0                        Webster St at O'Farrell St

       start_station_latitude  start_station_longitude  end_station_id  \
0                   37.789625              -122.400811            13.0
2                   37.769305              -122.426826             3.0
3                   37.774836              -122.446546            70.0
4                   37.804562              -122.271738           222.0
5                   37.770407              -122.391198           323.0
6                   37.317298              -121.884995           312.0
7                   37.795393              -122.404770           127.0
8                   37.795393              -122.404770           127.0
9                   37.788975              -122.403452           121.0
10                  37.787327              -122.413278            43.0
11                  37.781074              -122.411738           343.0
12                  37.756708              -122.421025           323.0
14                  37.869360              -122.254337           252.0
15                  37.781010              -122.405666            60.0
16                  37.755000              -122.425728            71.0
17                  37.776435              -122.426244           336.0
18                  37.780146              -122.403071            75.0
19                  37.812678              -122.268773           180.0
20                  37.772406              -122.435650           107.0
21                  37.797320              -122.265320           221.0
22                  37.787327              -122.413278            52.0
23                  37.869360              -122.254337           269.0
24                  37.830223              -122.270950           189.0
25                  37.797320              -122.265320           196.0
26                  37.804770              -122.403234            15.0
27                  37.773717              -122.411647            78.0
29                  37.872355              -122.266447           263.0
30                  37.871719              -122.273068           244.0
```

```
31          37.787168      -122.388098       50.0
32          37.763316      -122.421904       73.0
...               ...              ...        ...
29194       37.802746      -122.413579       50.0
29195       37.804770      -122.403234       22.0
29196       37.849595      -122.265569      258.0
29197       37.774520      -122.409449       30.0
29198       37.808848      -122.249680      181.0
29199       37.757288      -122.392051       17.0
29200       37.785881      -122.408915       58.0
29201       37.773414      -122.427317       30.0
29202       37.794130      -122.394430       42.0
29203       37.798014      -122.405950       23.0
29204       37.780526      -122.390288       27.0
29205       37.838800      -122.258732      171.0
29206       37.776598      -122.395282       80.0
29207       37.795392      -122.394203       66.0
29208       37.773793      -122.421239       21.0
29209       37.776754      -122.399018       30.0
29210       37.834174      -122.272968      176.0
29211       37.752428      -122.420628      356.0
29212       37.769218      -122.407646       67.0
29213       37.870407      -122.299676      256.0
29214       37.747998      -122.420219      364.0
29215       37.834174      -122.272968      176.0
29216       37.795392      -122.394203        6.0
29217       37.862827      -122.290230      241.0
29218       37.743684      -122.426806       53.0
29219       37.769218      -122.407646      122.0
29220       37.794130      -122.394430        6.0
29221       37.778742      -122.392741       15.0
29222       37.870139      -122.268422      254.0
29223       37.783521      -122.431158       67.0

                                      end_station_name  \
0                       Commercial St at Montgomery St
2          Powell St BART Station (Market St at 4th St)
3                                 Central Ave at Fell St
4                                  10th Ave at E 15th St
5                                     Broadway at Kearny
6                                San Jose Diridon Station
7                                 Valencia St at 21st St
8                                 Valencia St at 21st St
9                                     Mission Playground
10    San Francisco Public Library (Grove St at Hyde...
11                                  Bryant St at 2nd St
12                                    Broadway at Kearny
14                           Channing Way at Shattuck Ave
```

```
15                                    8th St at Ringold St
16                                  Broderick St at Oak St
17                             Potrero Ave and Mariposa St
18                               Market St at Franklin St
19                               Telegraph Ave at 23rd St
20                                  17th St at Dolores St
21              6th Ave at E 12th St (Temporary Location)
22                               McAllister St at Baker St
23                            Telegraph Ave at Carleton St
24                                    Genoa St at 55th St
25                                 Grand Ave at Perkins St
26       San Francisco Ferry Building (Harry Bridges Pl...
27                                    Folsom St at 9th St
29                          Channing Way at San Pablo Ave
30                               Shattuck Ave at Hearst Ave
31                                  2nd St at Townsend St
32                                  Pierce St at Haight St
...                                                    ...
29194                               2nd St at Townsend St
29195                                Howard St at Beale St
29196                           University Ave at Oxford St
29197      San Francisco Caltrain (Townsend St at 4th St)
29198                              Grand Ave at Webster St
29199    Embarcadero BART Station (Beale St at Market St)
29200                                  Market St at 10th St
29201      San Francisco Caltrain (Townsend St at 4th St)
29202       San Francisco City Hall (Polk St at Grove St)
29203                        The Embarcadero at Steuart St
29204                              Beale St at Harrison St
29205                                Rockridge BART Station
29206                                 Townsend St at 5th St
29207                                 3rd St at Townsend St
29208    Montgomery St BART Station (Market St at 2nd St)
29209      San Francisco Caltrain (Townsend St at 4th St)
29210                                MacArthur BART Station
29211                           Valencia St at Clinton Park
29212    San Francisco Caltrain Station 2  (Townsend St...
29213                              Hearst Ave at Euclid Ave
29214                               China Basin St at 3rd St
29215                                MacArthur BART Station
29216                        The Embarcadero at Sansome St
29217                                    Ashby BART Station
29218                                Grove St at Divisadero
29219                                 19th St at Mission St
29220                        The Embarcadero at Sansome St
29221    San Francisco Ferry Building (Harry Bridges Pl...
29222                               Vine St at Shattuck Ave
29223    San Francisco Caltrain Station 2  (Townsend St...
```

	end_station_latitude	end_station_longitude	bike_id	user_type	\
0	37.794231	-122.402923	4902.0	Customer	
2	37.786375	-122.404904	5905.0	Customer	
3	37.773311	-122.444293	6638.0	Subscriber	
4	37.792714	-122.248780	4898.0	Subscriber	
5	37.798014	-122.405950	5200.0	Subscriber	
6	37.329732	-121.901782	3803.0	Subscriber	
7	37.756708	-122.421025	6329.0	Subscriber	
8	37.756708	-122.421025	6548.0	Subscriber	
9	37.759210	-122.421339	6488.0	Subscriber	
10	37.778768	-122.415929	5318.0	Subscriber	
11	37.783172	-122.393572	5848.0	Subscriber	
12	37.798014	-122.405950	5328.0	Customer	
14	37.865847	-122.267443	4786.0	Subscriber	
15	37.774520	-122.409449	6361.0	Subscriber	
16	37.773063	-122.439078	6572.0	Subscriber	
17	37.763281	-122.407377	5343.0	Subscriber	
18	37.773793	-122.421239	5854.0	Subscriber	
19	37.812678	-122.268773	5629.0	Customer	
20	37.763015	-122.426497	4999.0	Subscriber	
21	37.794396	-122.253842	6007.0	Subscriber	
22	37.777416	-122.441838	5479.0	Subscriber	
23	37.862320	-122.258801	1804.0	Subscriber	
24	37.839649	-122.271756	5678.0	Subscriber	
25	37.808894	-122.256460	6240.0	Subscriber	
26	37.795392	-122.394203	6531.0	Customer	
27	37.773717	-122.411647	5410.0	Subscriber	
29	37.862827	-122.290230	363.0	Subscriber	
30	37.873676	-122.268487	5669.0	Subscriber	
31	37.780526	-122.390288	6267.0	Customer	
32	37.771793	-122.433708	5130.0	Subscriber	
...	...	...	...	...	
29194	37.780526	-122.390288	1226.0	Customer	
29195	37.789756	-122.394643	6318.0	Subscriber	
29196	37.872355	-122.266447	1266.0	Subscriber	
29197	37.776598	-122.395282	6087.0	Subscriber	
29198	37.811377	-122.265192	4872.0	Subscriber	
29199	37.792251	-122.397086	6543.0	Subscriber	
29200	37.776619	-122.417385	102.0	Subscriber	
29201	37.776598	-122.395282	4715.0	Subscriber	
29202	37.778650	-122.418230	6303.0	Customer	
29203	37.791464	-122.391034	4450.0	Subscriber	
29204	37.788059	-122.391865	6232.0	Subscriber	
29205	37.844279	-122.251900	4628.0	Subscriber	
29206	37.775235	-122.397437	5948.0	Subscriber	
29207	37.778742	-122.392741	5857.0	Subscriber	
29208	37.789625	-122.400811	5875.0	Subscriber	

```
29209              37.776598          -122.395282   6072.0  Subscriber
29210              37.828410          -122.266315   5894.0  Subscriber
29211              37.769188          -122.422285   4767.0  Subscriber
29212              37.776639          -122.395526   4728.0  Subscriber
29213              37.875112          -122.260553   6239.0  Subscriber
29214              37.772000          -122.389970   5937.0  Subscriber
29215              37.828410          -122.266315   5690.0  Subscriber
29216              37.804770          -122.403234   5518.0  Subscriber
29217              37.852477          -122.270213   3028.0  Subscriber
29218              37.775946          -122.437777   5051.0  Subscriber
29219              37.760299          -122.418892   4772.0  Subscriber
29220              37.804770          -122.403234   4747.0  Subscriber
29221              37.795392          -122.394203   1517.0  Subscriber
29222              37.880222          -122.269592   5123.0    Customer
29223              37.776639          -122.395526   6325.0  Subscriber

       member_birth_year member_gender bike_share_for_all_trip
0                 1984.0          Male                      No
2                 1972.0          Male                      No
3                 1989.0         Other                      No
4                 1974.0          Male                     Yes
5                 1959.0          Male                      No
6                 1983.0        Female                      No
7                 1989.0          Male                      No
8                 1988.0         Other                      No
9                 1992.0          Male                      No
10                1996.0        Female                     Yes
11                1993.0          Male                      No
12                1990.0          Male                      No
14                1988.0          Male                      No
15                1993.0          Male                     Yes
16                1981.0          Male                      No
17                1975.0          Male                      No
18                1990.0          Male                      No
19                1978.0          Male                      No
20                1983.0          Male                      No
21                1984.0          Male                     Yes
22                1991.0        Female                      No
23                1997.0        Female                      No
24                1975.0          Male                      No
25                1986.0          Male                      No
26                2000.0          Male                      No
27                1982.0          Male                      No
29                1995.0          Male                      No
30                1996.0          Male                     Yes
31                1993.0          Male                      No
32                1980.0        Female                      No
...                  ...           ...                     ...
```

```
29194            1991.0     Male              No
29195            1979.0     Male              No
29196            1976.0   Female              No
29197            1983.0   Female              No
29198            1985.0   Female              No
29199            1961.0     Male              No
29200            1967.0     Male              No
29201            1987.0     Male              No
29202            1984.0     Male              No
29203            1976.0    Other              No
29204            1984.0     Male              No
29205            1982.0   Female              No
29206            1984.0     Male              No
29207            1984.0     Male              No
29208            1994.0     Male              No
29209            1990.0     Male              No
29210            1964.0    Other              No
29211            1980.0   Female              No
29212            1986.0     Male              No
29213            1994.0   Female              No
29214            1990.0     Male              No
29215            1991.0     Male              No
29216            1980.0     Male              No
29217            1978.0     Male              No
29218            1967.0     Male             Yes
29219            1979.0     Male              No
29220            1974.0     Male              No
29221            1964.0     Male              No
29222            1980.0   Female              No
29223            1990.0     Male              No

[28137 rows x 16 columns]
```

In [9]:
```
# Let's take a peak into the data's basic information
df.info(null_counts = True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29225 entries, 0 to 29224
Data columns (total 16 columns):
duration_sec               29225 non-null int64
start_time                 29225 non-null object
end_time                   29225 non-null object
start_station_id           29191 non-null float64
start_station_name         29191 non-null object
start_station_latitude     29225 non-null float64
start_station_longitude    29225 non-null float64
end_station_id             29190 non-null float64
end_station_name           29190 non-null object
```

```
end_station_latitude       29224 non-null float64
end_station_longitude      29224 non-null float64
bike_id                    29224 non-null float64
user_type                  29224 non-null object
member_birth_year          28171 non-null float64
member_gender              28171 non-null object
bike_share_for_all_trip    29224 non-null object
dtypes: float64(8), int64(1), object(7)
memory usage: 3.6+ MB
```

In [10]:
```
#show the number of unique user

df.shape[0]
```

Out[10]: 29225

In [11]:
```
#show the number of unique user

df.nunique()
```

Out[11]:
```
duration_sec                2262
start_time                 29224
end_time                   29224
start_station_id             326
start_station_name           326
start_station_latitude       329
start_station_longitude      331
end_station_id               324
end_station_name             324
end_station_latitude         328
end_station_longitude        329
bike_id                     3400
user_type                      2
member_birth_year             65
member_gender                  3
bike_share_for_all_trip        2
dtype: int64
```

In [12]:
```
# Let's also get some additional description for stats figures
df.describe()
```

Out[12]:
```
       duration_sec  start_station_id  start_station_latitude  \
count  29225.000000      29191.000000            29225.000000
mean     675.335261        134.742215               37.768929
std     1633.914613        111.417506                0.102024
min       61.000000          3.000000               37.317298
25%      320.000000         44.000000               37.770407
50%      502.000000         95.000000               37.780526
```

```
75%      762.000000        232.000000                 37.795392
max    83195.000000        398.000000                 37.880222

       start_station_longitude  end_station_id  end_station_latitude  \
count             29225.000000    29190.000000          29224.000000
mean               -122.352717      132.422816             37.769280
std                   0.119240      111.231060              0.101947
min                -122.453704        3.000000             37.317298
25%                -122.411738       41.000000             37.771058
50%                -122.397437       93.000000             37.780760
75%                -122.293400      223.000000             37.795392
max                -121.874119      398.000000             37.880222

       end_station_longitude       bike_id  member_birth_year
count           29224.000000  29224.000000       28171.000000
mean             -122.352093   4929.272139        1984.774271
std                 0.118776   1547.813928           9.991789
min              -122.453704     11.000000        1878.000000
25%              -122.410807   4589.000000        1980.000000
50%              -122.397086   5315.000000        1987.000000
75%              -122.293528   6051.000000        1992.000000
max              -121.874119   6644.000000        2001.000000
```

In [13]:
```
# Any duplicates?
df.duplicated().sum()
```

Out[13]:
```
0
```

In [14]:
```
# What about NaN values?
df.isnull().sum()
```

Out[14]:
```
duration_sec                  0
start_time                    0
end_time                      0
start_station_id             34
start_station_name           34
start_station_latitude        0
start_station_longitude       0
end_station_id               35
end_station_name             35
end_station_latitude          1
end_station_longitude         1
bike_id                       1
user_type                     1
member_birth_year          1054
member_gender              1054
bike_share_for_all_trip       1
dtype: int64
```

In [15]: df.isnull().mean()

```
Out[15]: duration_sec               0.000000
         start_time                 0.000000
         end_time                   0.000000
         start_station_id           0.001163
         start_station_name         0.001163
         start_station_latitude     0.000000
         start_station_longitude    0.000000
         end_station_id             0.001198
         end_station_name           0.001198
         end_station_latitude       0.000034
         end_station_longitude      0.000034
         bike_id                    0.000034
         user_type                  0.000034
         member_birth_year          0.036065
         member_gender              0.036065
         bike_share_for_all_trip    0.000034
         dtype: float64
```

What is the structure of your dataset?

it contains 16 columns and 29225 rows.

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

member birthyear, member gender, start and end station id and start and end stations name from the dataset.

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

Start and end stations name and member birtyear because it show the relationship berween the age and the distastance of the start and end stations

2.1 Univariae Exploration

```
In [16]: df.member_birth_year.mean()

Out[16]: 1984.7742714138653

In [17]: df.isnull().mean().member_birth_year

Out[17]: 0.036065012831479899

In [18]: df.member_birth_year.sum()

Out[18]: 55913076.0

In [19]: df.dropna().member_birth_year.describe()

Out[19]: count    28137.00000
         mean      1984.76984
         std          9.99456
```

```
min        1878.00000
25%        1980.00000
50%        1987.00000
75%        1992.00000
max        2001.00000
Name: member_birth_year, dtype: float64
```

In [20]:
```
df.dropna().duration_sec.describe()/60
```

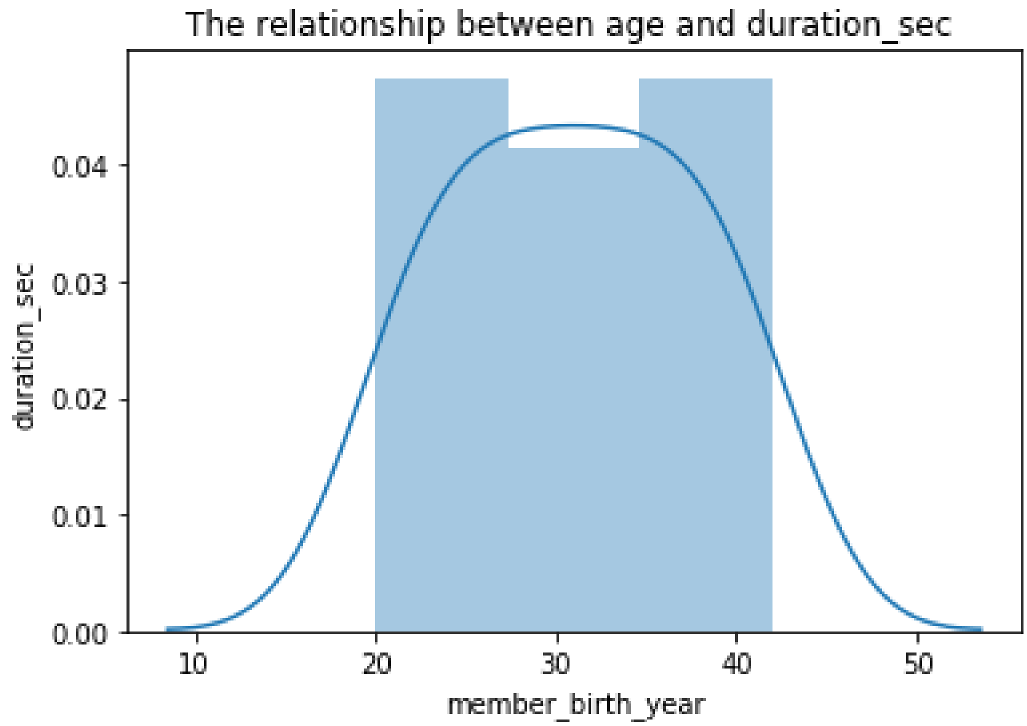
Out[20]:
```
count     468.950000
mean       11.134962
std        26.398406
min         1.016667
25%         5.316667
50%         8.333333
75%        12.650000
max      1386.583333
Name: duration_sec, dtype: float64
```

In [21]:
```
df.dropna().duration_sec.describe()/3600
```

Out[21]:
```
count     7.815833
mean      0.185583
std       0.439973
min       0.016944
25%       0.088611
50%       0.138889
75%       0.210833
max      23.109722
Name: duration_sec, dtype: float64
```

In [22]:
```
# library
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
x=range(20, 43)

plt.xlabel("member_birth_year")
plt.ylabel("duration_sec")
plt.title("The relationship between age and duration_sec ")
sns.distplot(x)
plt.show()
```



Duration vs. Age

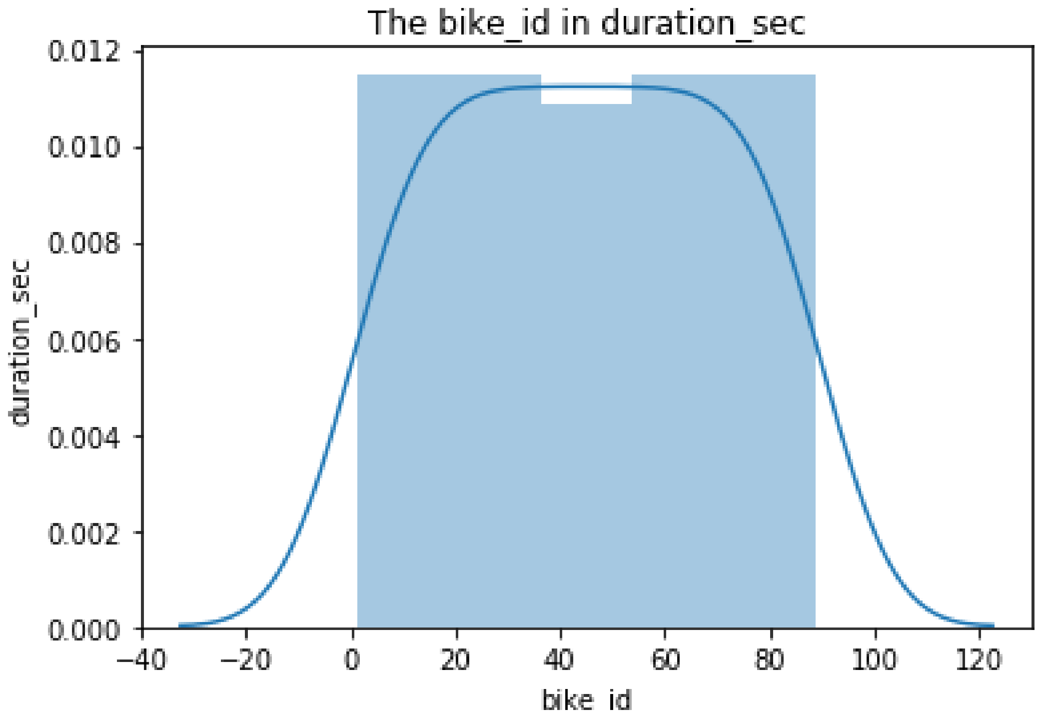
The age of users from 20 to 43. So, the age between 20 to 25 and 35 to 43 they are slower to arrive in duration unlike the age from 25 to 35 they are faster to arrive

In [23]:
```
df.dropna().bike_id.describe()
```

Out[23]:
```
count    28137.000000
mean      4933.576394
std       1545.730184
min         11.000000
25%       4600.000000
50%       5318.000000
75%       6051.000000
max       6644.000000
Name: bike_id, dtype: float64
```

In [24]:
```
# library
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
x=range(1,90)
plt.xlabel("bike_id")
plt.ylabel("duration_sec")
plt.title("The bike_id in duration_sec")
```

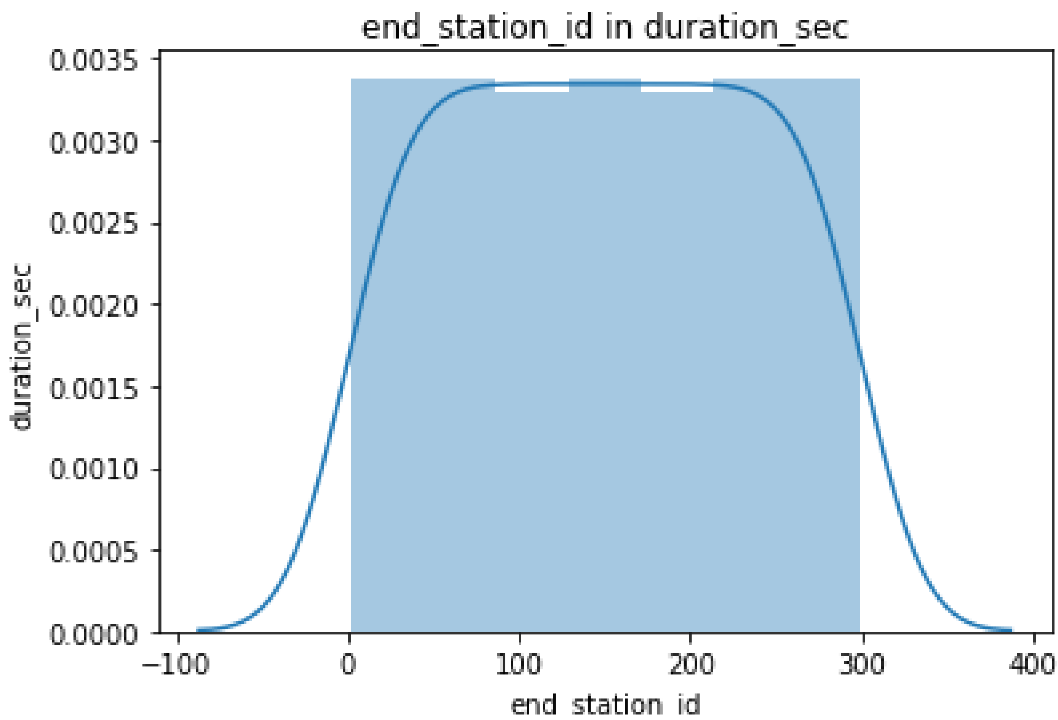
```
sns.distplot(x)
plt.show()
```



Duration vs. bike_id

The bike_id from -40 to 120 bike id doesn't have much affect on the duration very much. Because, bike id is equall in all but fom 40 to 60 is less time to arrive by 0.001 to arrive unlike the rest of the bike_id. So, the bike_id from 1 to 40 and 60 to 88 they are slower to arrive in duration unlike the bike_id from 40 to 60 they are faster to arrive

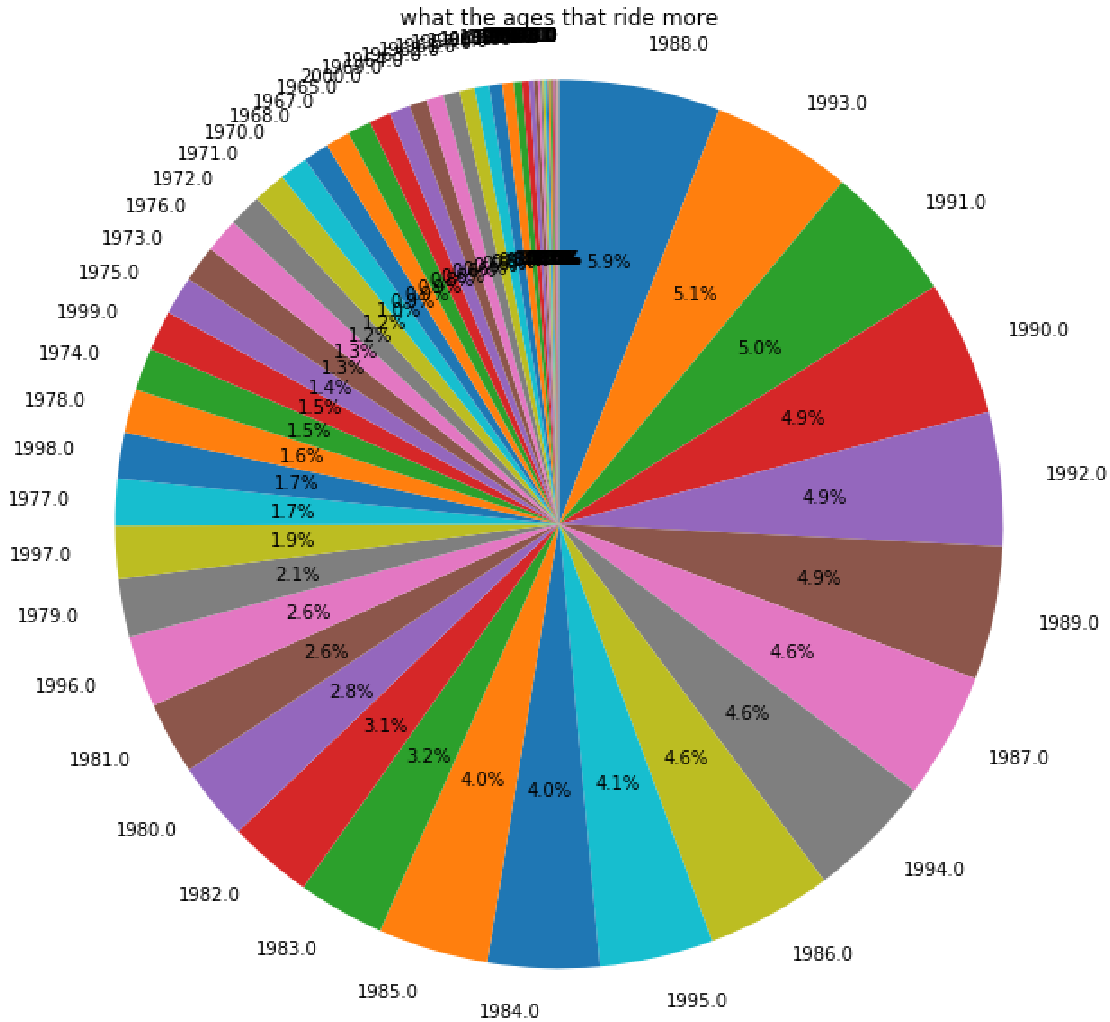
```
In [25]: import matplotlib.pyplot as plt
         import seaborn as sns
         x=range(1 , 300)
         plt.xlabel("end_station_id")
         plt.ylabel("duration_sec")
         plt.title("end_station_id in duration_sec")
         sns.distplot(x)
         plt.show()
```



Duration vs. end_station_id

The end_station_id is also equal from -100 to 400 end_station_id doesn't have much affect on the duration very much. Because, end_station_id is equall in all but fom 40 to 100 and 200 to 220 is less time to arrive by 0.011 to arrive unlike the rest of end_station_id. So, the end_station_id from 1 to 40 and 100 to 200 and 220 to 300 they are slower to arrive in duration

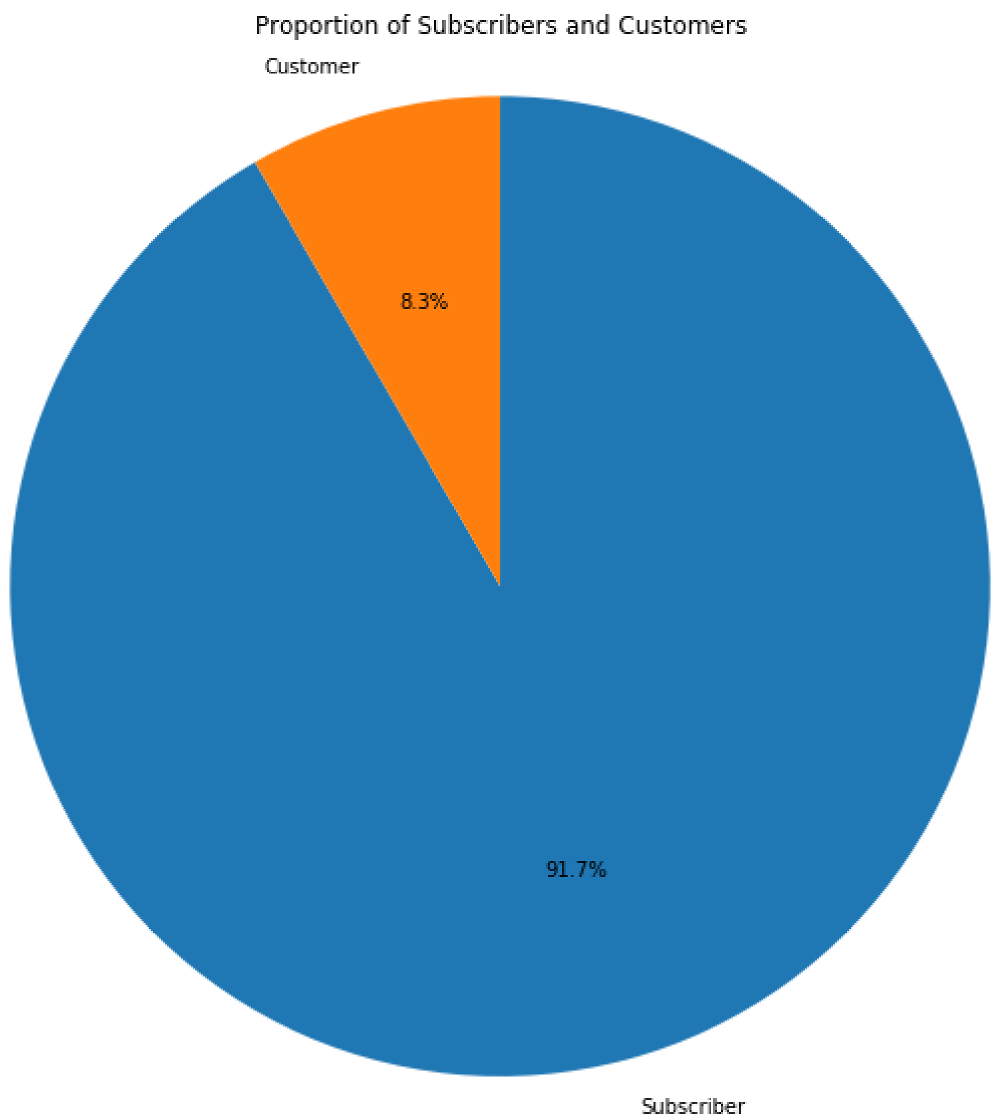
```
In [26]: plt.figure(figsize = [10, 10])
         sorted_counts = df['member_birth_year'].value_counts()
         plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90, counterclock = Fa
         plt.axis('square');
         plt.title('what the ages that ride more');
```



member birth year of the system users

The member birth year of the members users are from 1878 to 2001 but the categories that use the system more are born 1988

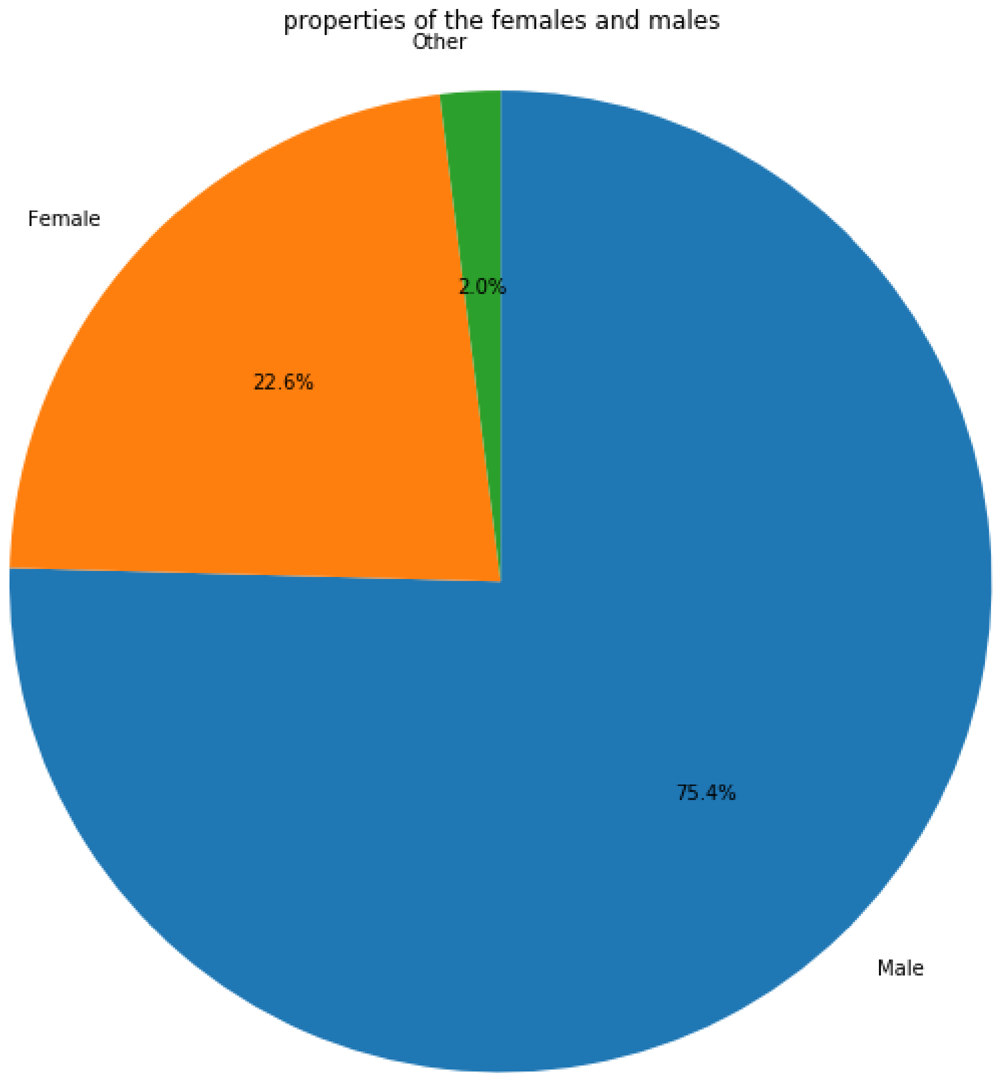
```
In [27]: plt.figure(figsize = [10, 10])
         sorted_counts = df['user_type'].value_counts()
         plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90, counterclock = Fa
         plt.axis('square');
         plt.title('Proportion of Subscribers and Customers');
```



the types of users that use the system more

the user that use the system more is the subscribers especially in the summer seasons more than the customer.

```
In [28]: plt.figure(figsize = [10, 10])
         sorted_counts = df['member_gender'].value_counts()
         plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90, counterclock = Fa
         plt.axis('square');
         plt.title('properties of the females and males');
```



the types of genders that use the system more

the gender that more use the system is the male not female. the subscribers use the system more than the customers especially in the summer seasons

```
In [29]: df.dropna().end_time.describe()
```

```
Out[29]: count                          28137
         unique                         28136
         top       2019-02-28 17:40:37.3280
         freq                               2
         Name: end_time, dtype: object
```

```
In [30]: df.dropna().start_time.describe()
```

Out[30]:
```
count                          28137
unique                         28136
top         2019-02-25 08:52:07.5820
freq                               2
Name: start_time, dtype: object
```

In [31]:
```
import datetime

datetime.datetime.now().month
```

Out[31]:
```
2
```

In [32]:
```
df.dropna().duration_sec.describe()
```

Out[32]:
```
count    28137.000000
mean       668.097701
std       1583.904334
min         61.000000
25%        319.000000
50%        500.000000
75%        759.000000
max      83195.000000
Name: duration_sec, dtype: float64
```

In [33]:
```
sns.boxplot( x=df["member_gender"], y=df["duration_sec"] )

plt.title('properties of the duration_sec between gender');

#sns.plt.show()
```

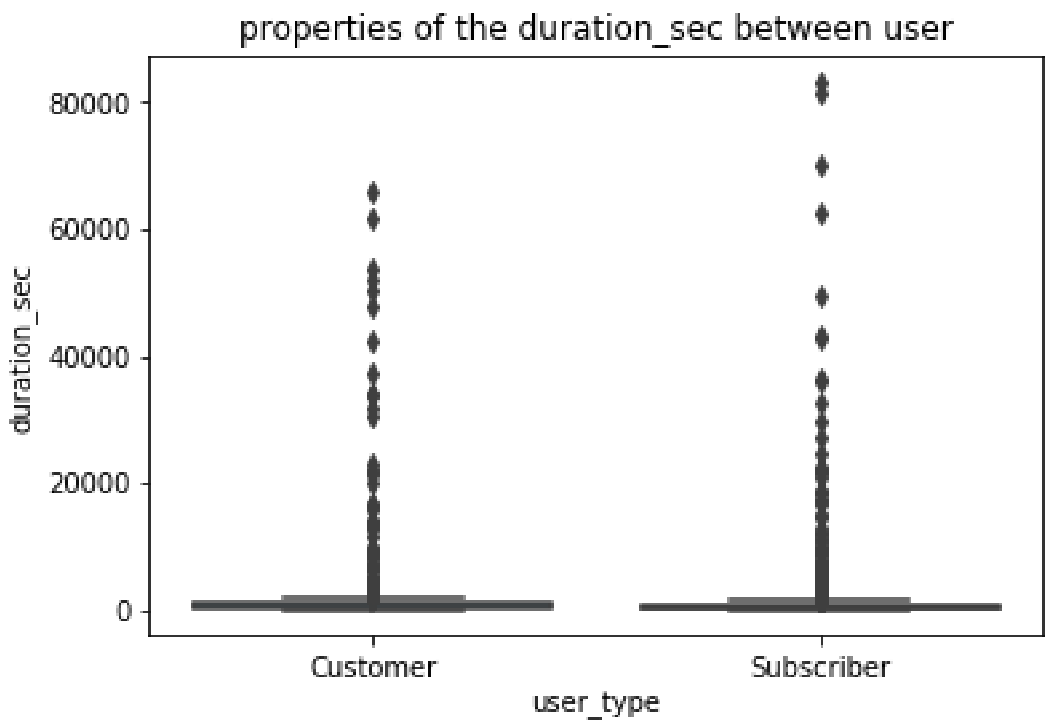
members gender VS duration

the males is using the system more than the females but the females are take more time to arrive unlike the man

In [34]:
```
sns.boxplot( x=df["user_type"], y=df["duration_sec"] )

plt.title('properties of the duration_sec between user');

#sns.plt.show()
```



type users VS duration

the subscribers is using the system more than the customers but the subscribe are take more time to arrive unlike the customers

In [35]:
```
df.dropna().duration_sec.describe()
```

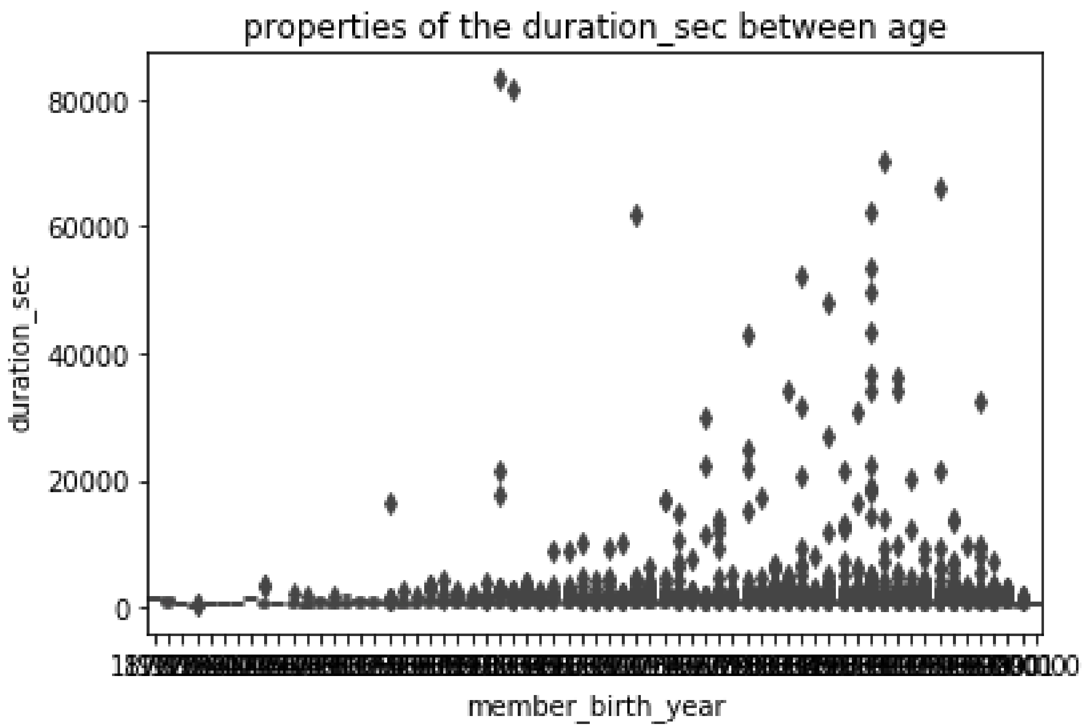
Out[35]:
```
count    28137.000000
mean       668.097701
std       1583.904334
min         61.000000
25%        319.000000
50%        500.000000
75%        759.000000
```

```
max      83195.000000
Name: duration_sec, dtype: float64
```

```
In [36]: sns.boxplot( x=df["member_birth_year"], y=df["duration_sec"] )

         plt.title('properties of the duration_sec between age');

         #sns.plt.show()
```



members birth year VS duration

age of users from 20 to 43. So, the age between 20 to 25 and 35 to 43 they are slower to arrive in duration unlike the age from 25 to 35 they are faster to arrive

```
In [37]: df.dropna().start_station_id.describe()
```

```
Out[37]: count    28137.000000
         mean       135.069055
         std        111.416510
         min          3.000000
         25%         44.000000
         50%         96.000000
         75%        233.000000
         max        398.000000
         Name: start_station_id, dtype: float64
```

3 Bivariate Exploration

In [38]:
```
df.dropna().duration_sec.describe()
```

Out[38]:
```
count    28137.000000
mean       668.097701
std       1583.904334
min         61.000000
25%        319.000000
50%        500.000000
75%        759.000000
max      83195.000000
Name: duration_sec, dtype: float64
```

In [39]:
```
df.dropna().member_birth_year.describe()
```

Out[39]:
```
count    28137.00000
mean      1984.76984
std          9.99456
min       1878.00000
25%       1980.00000
50%       1987.00000
75%       1992.00000
max       2001.00000
Name: member_birth_year, dtype: float64
```

In [41]:
```
df.dropna().duration_sec.describe()
```

Out[41]:
```
count    28137.000000
mean       668.097701
std       1583.904334
min         61.000000
25%        319.000000
50%        500.000000
75%        759.000000
max      83195.000000
Name: duration_sec, dtype: float64
```

In [42]:
```
df.dropna().start_station_longitude.describe()
```

Out[42]:
```
count    28137.000000
mean      -122.352031
std          0.119796
min       -122.453704
25%       -122.411726
50%       -122.397405
75%       -122.291360
max       -121.874119
Name: start_station_longitude, dtype: float64
```

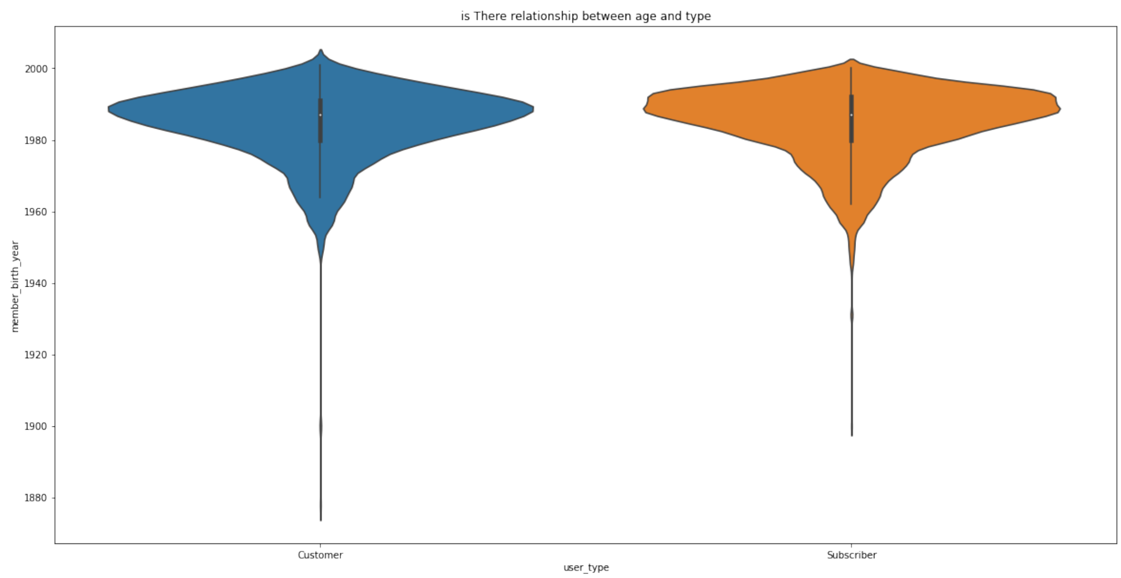
In [45]: # plot
```
plt.figure(figsize=(20,10))

sns.violinplot( x=df["user_type"], y=df["member_birth_year"] )

plt.title("is There relationship between age and type")


#sns.plt.show()
```

Out[45]: Text(0.5,1,'is There relationship between age and type')



members birth year VS users_type

type of users is customers and subscribers . So, the the subscribers using the system more than the customers but the customer age is older than the subscribers.

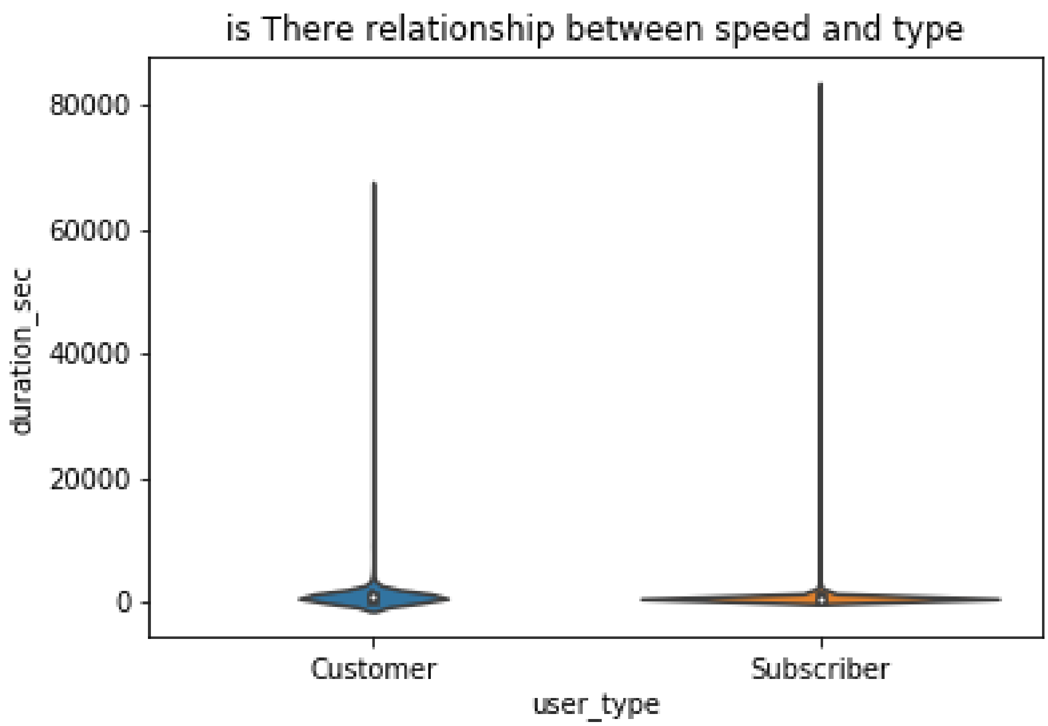
In [46]: # plot
```

sns.violinplot( x=df["user_type"], y=df["duration_sec"] )

plt.title("is There relationship between speed and type")


#sns.plt.show()


plt.show()
```



type users VS duration

the subscribers is using the system more than the customers but the subscribe are take more time to arrive unlike the customers

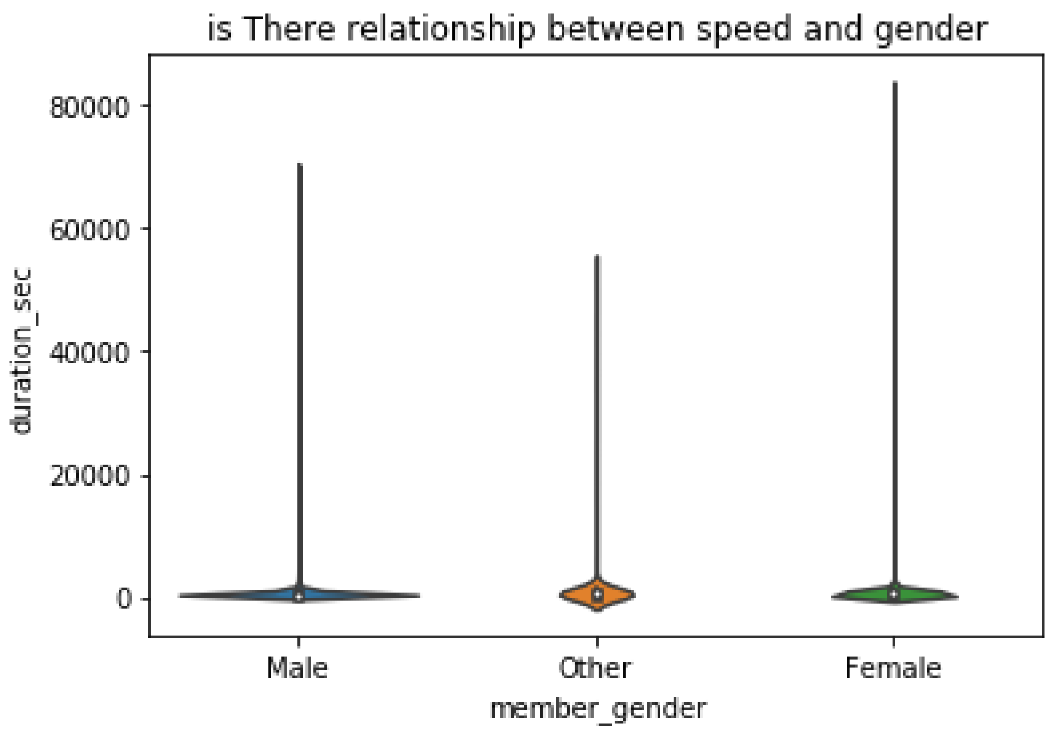
In [47]:
```
# plot

sns.violinplot( x=df["member_gender"], y=df["duration_sec"] )

plt.title("is There relationship between speed and gender")

#sns.plt.show()
```

Out[47]: Text(0.5,1,'is There relationship between speed and gender')



members gender VS duration

the males is using the system more than the females but the females are take more time to arrive unlike the man

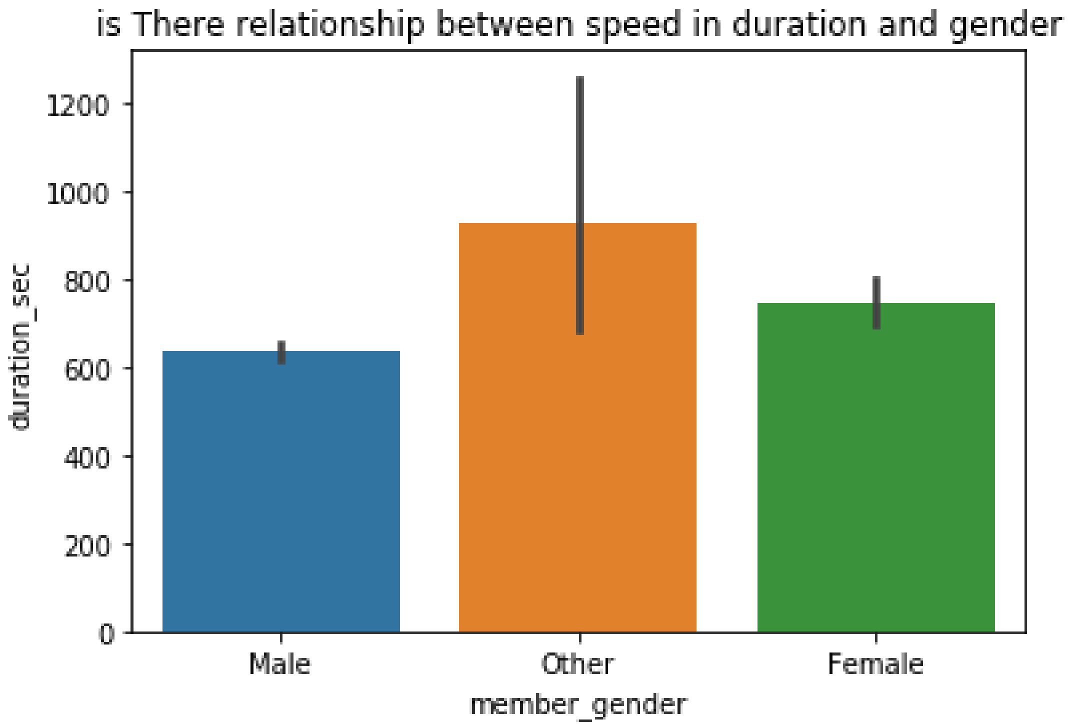
```
In [49]: sb.barplot( x=df["member_gender"], y=df["duration_sec"] )

         plt.title("is There relationship between speed in duration and gender")



         #sns.plt.show()

Out[49]: Text(0.5,1,'is There relationship between speed in duration and gender')
```



members gender VS duration

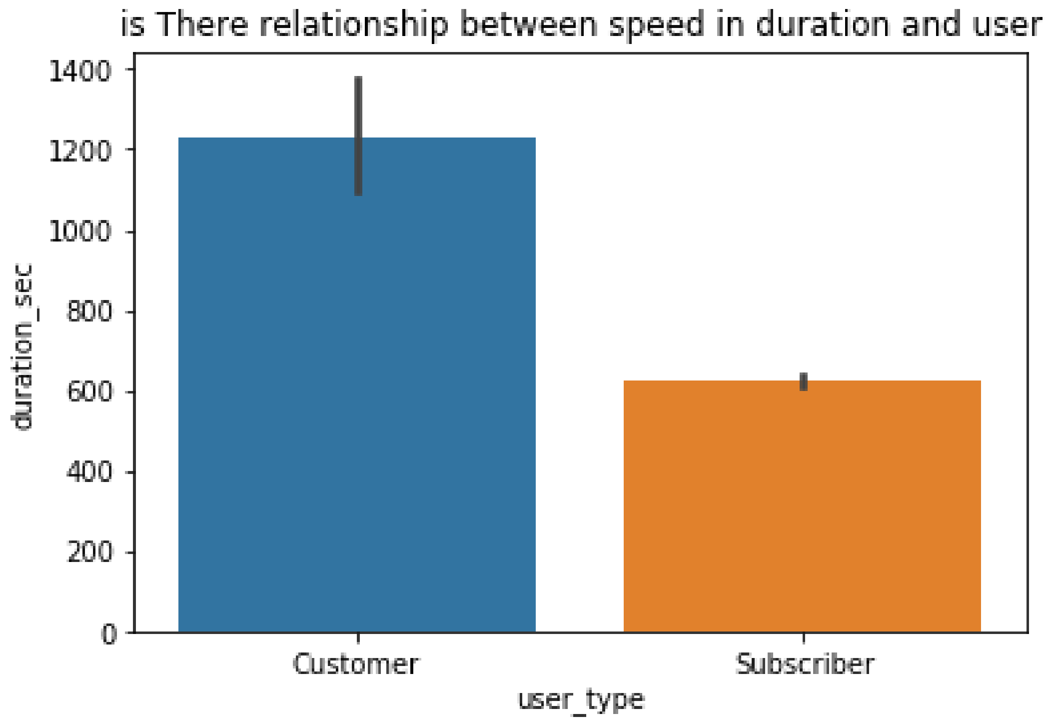
the males is using the system more than the females but the females are take more time to arrive unlike the man

In [50]:
```
sb.barplot( x=df["user_type"], y=df["duration_sec"] )

plt.title("is There relationship between speed in duration and user")


#sns.plt.show()
```

Out[50]:
```
Text(0.5,1,'is There relationship between speed in duration and user')
```

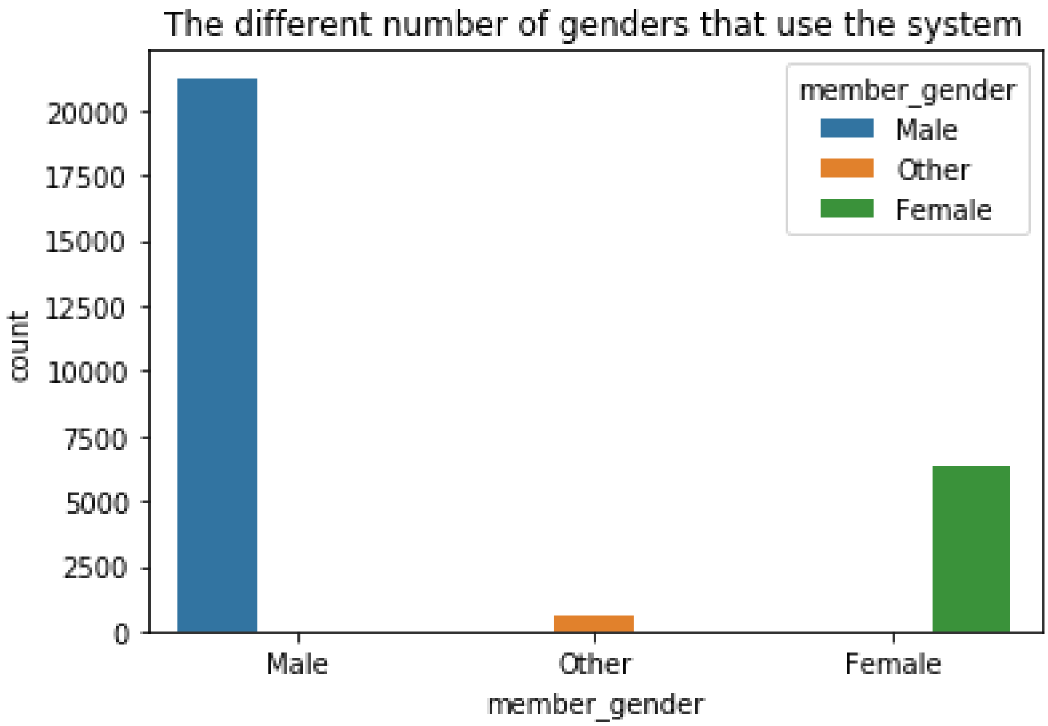


type users VS duration

the subscribers is using the system more than the customers but the subscribe are take more time to arrive unlike the customers

4 Multivariate Exploration

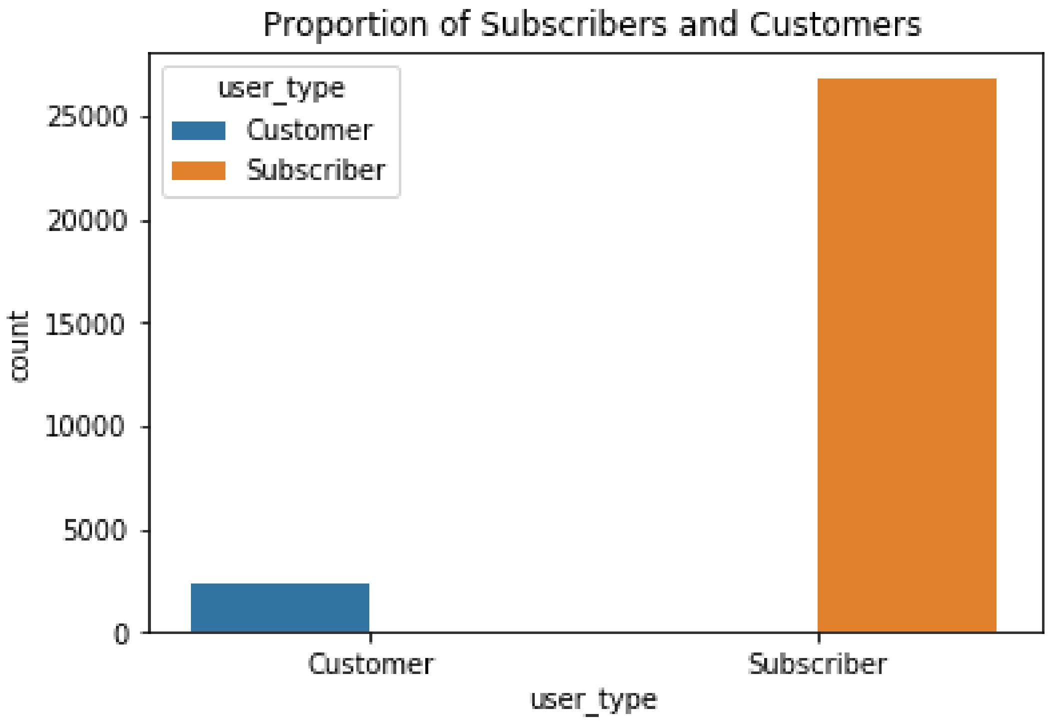
```
In [51]: ax = sns.countplot(data = df, x="member_gender", hue="member_gender")
         plt.title('The different number of genders that use the system');
```



members gender that using the system

the males is using the system more than the females but the females are take more time to arrive unlike the man

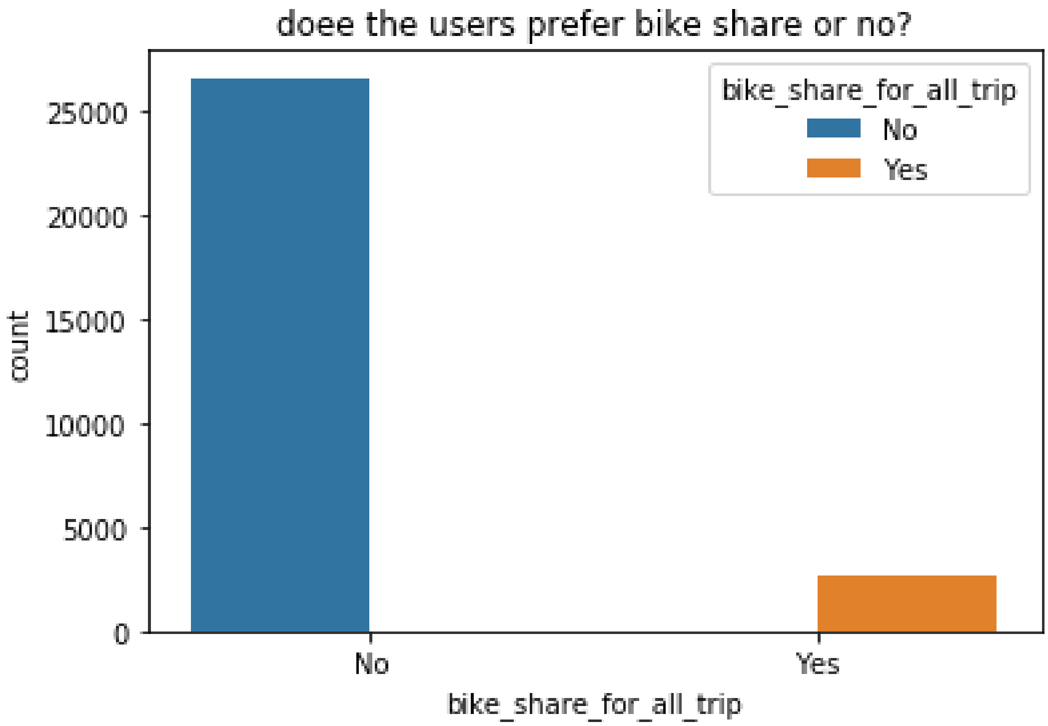
```
In [52]: ax = sns.countplot(data = df, x="user_type", hue="user_type")
         plt.title('Proportion of Subscribers and Customers');
```



type users that use the system

the subscribers is using the system more than the customers but the subscribe are take more time to arrive unlike the customers

```
In [53]: ax = sns.countplot(data = df, x="bike_share_for_all_trip", hue="bike_share_for_all_trip
         plt.title('doee the users prefer bike share or no?');
```



is users agree to the bike share

users doesn't prefer to bikes share, so the bike share system is useless to the system.

in Summary a lot more subscribers using the bike sharing system than casual customers overall,subscribers ride during the summer season the most and the least during the winter months. subscribers used the system heavily on work days concentrated around 7-9am and 17-18pm for work commute, whereas customers ride a lot over weekends and in the afternoon for leisure/touring purposes. Subscribers tended to have much shorter/quicker trips compared to customers which makes subscriber usage more efficient. both Customer and Subscriber are showing similar trends for age and trip duration, but for subscribers the trip duration is higher for older age.

```
In [ ]:
```