Slidedeck_Exploration_Ford_GoBike

March 1, 2021

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

1.1 Table of Contents

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.

```
In [1]: from IPython.display import HTML

        HTML('''<script>
        code_show=true;
        function code_toggle() {
         if (code_show){
         $('div.input').hide();
         } else {
         $('div.input').show();
         }
         code_show = !code_show
        }
        $( document ).ready(code_toggle);
        </script>
        <form action="javascript:code_toggle()"><input type="submit" value="Click here to toggle
```

```
Out[1]: <IPython.core.display.HTML object>
```

2 Preliminary Wrangling

```
In [2]: # 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 [3]: # load in the dataset into a pandas dataframe and clean up field dtypes
        df = pd.read_csv('201902-fordgobike-tripdata.csv')
```

```
In [4]: df.head()
```

```
Out[4]:    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 [5]:
```
# 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 [6]:
```
#show the number of unique user

df.shape[0]
```

Out[6]: 29225

In [7]:
```
#show the number of unique user

df.nunique()
```

Out[7]:
```
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 [8]:
```
# Let's also get some additional description for stats figures
df.describe()
```

Out[8]:
```
       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 [9]:
```
df.dropna()
```

Out[9]:
```
       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 [10]:
```
# 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 [11]:
```
#show the number of unique user

df.shape[0]
```

Out[11]:
```
29225
```

In [12]:
```
#show the number of unique user

df.nunique()
```

Out[12]:
```
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 [13]:
```
# Let's also get some additional description for stats figures
df.describe()
```

Out[13]:
```
        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 [14]:
```
# Any duplicates?
df.duplicated().sum()
```

Out[14]: 0

In [15]:
```
# What about NaN values?
df.isnull().sum()
```

Out[15]:
```
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 [16]:
```
df.isnull().mean()
```

Out[16]:
```
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.

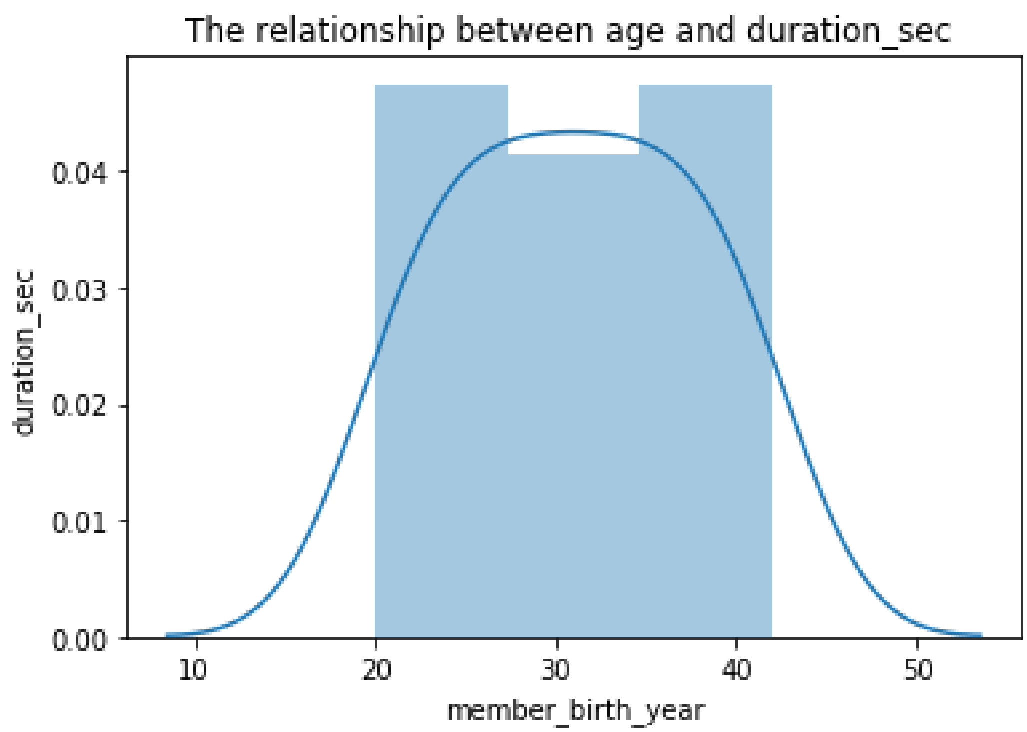
What features in the dataset do you think will help support your investigation into your feature(s) of interest?

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 [17]: df.member_birth_year.mean()

Out[17]: 1984.7742714138653

In [18]: df.isnull().mean().member_birth_year

Out[18]: 0.036065012831479899

In [19]: df.member_birth_year.sum()

Out[19]: 55913076.0

In [20]: df.dropna().member_birth_year.describe()

Out[20]: 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 [21]: df.dropna().duration_sec.describe()/60

Out[21]: 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 [22]: df.dropna().duration_sec.describe()/3600

Out[22]: 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 [23]: # 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

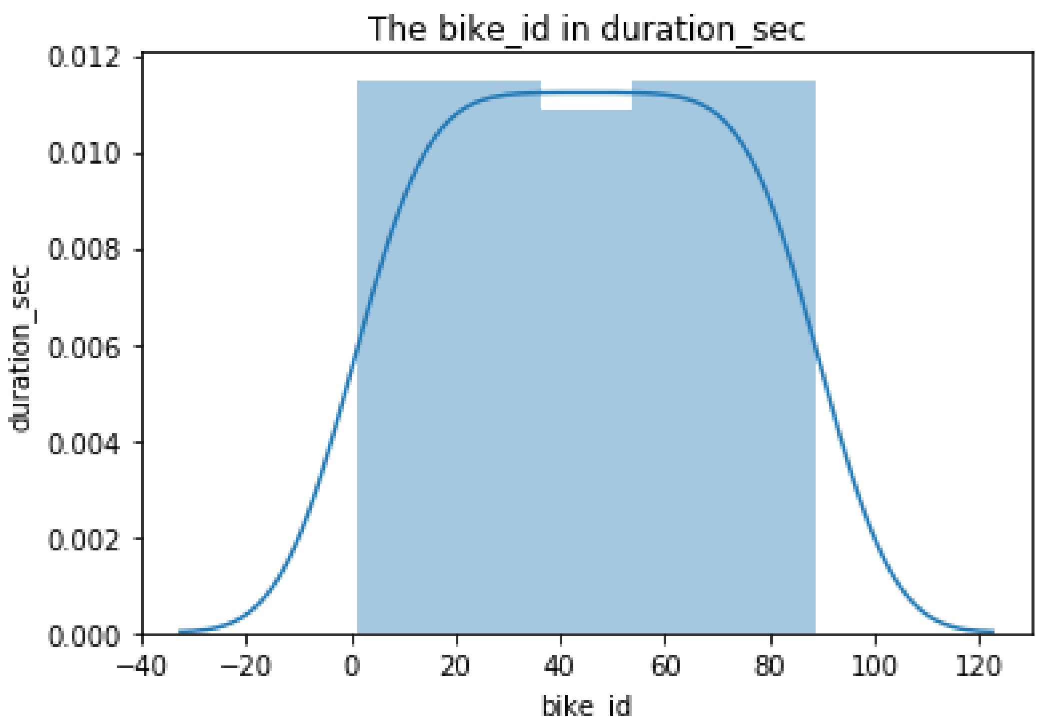
The age of users from 20 to 43. So, the age between 20 to 25 and 35 to 43 they are slower to arrive in duration unlike the age from 25 to 35 they are faster to arrive

```
In [24]: df.dropna().bike_id.describe()
```

```
Out[24]: 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 [25]: # 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()
```

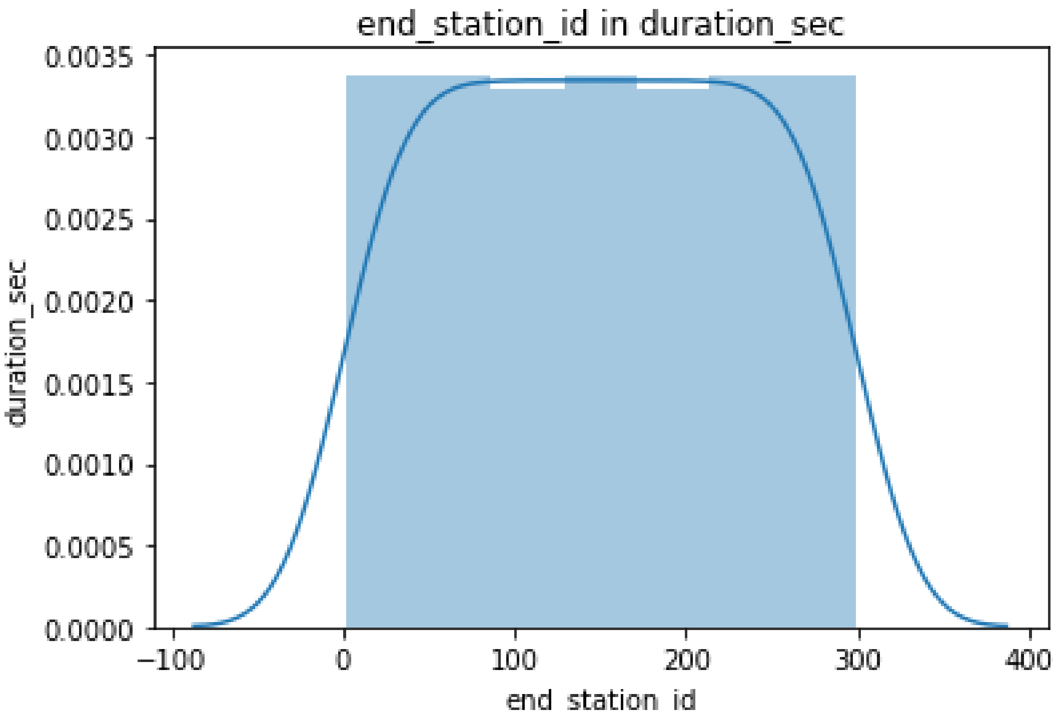


Duration vs. bike_id

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 [26]: import matplotlib.pyplot as plt
         import seaborn as sns
         x=range(1 , 300)
         plt.xlabel("end_station_id")
```

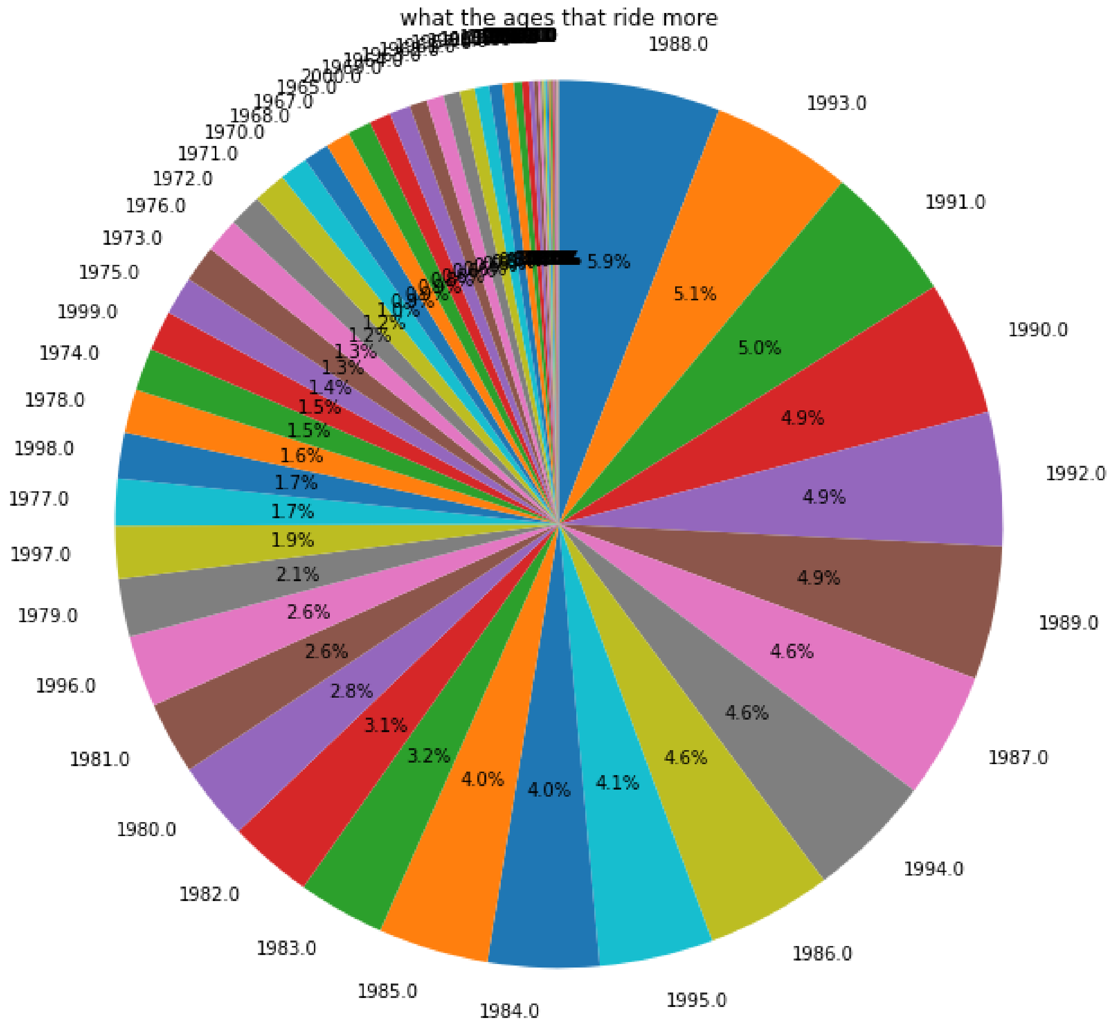
```
plt.ylabel("duration_sec")
plt.title("end_station_id in duration_sec")
sns.distplot(x)
plt.show()
```



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

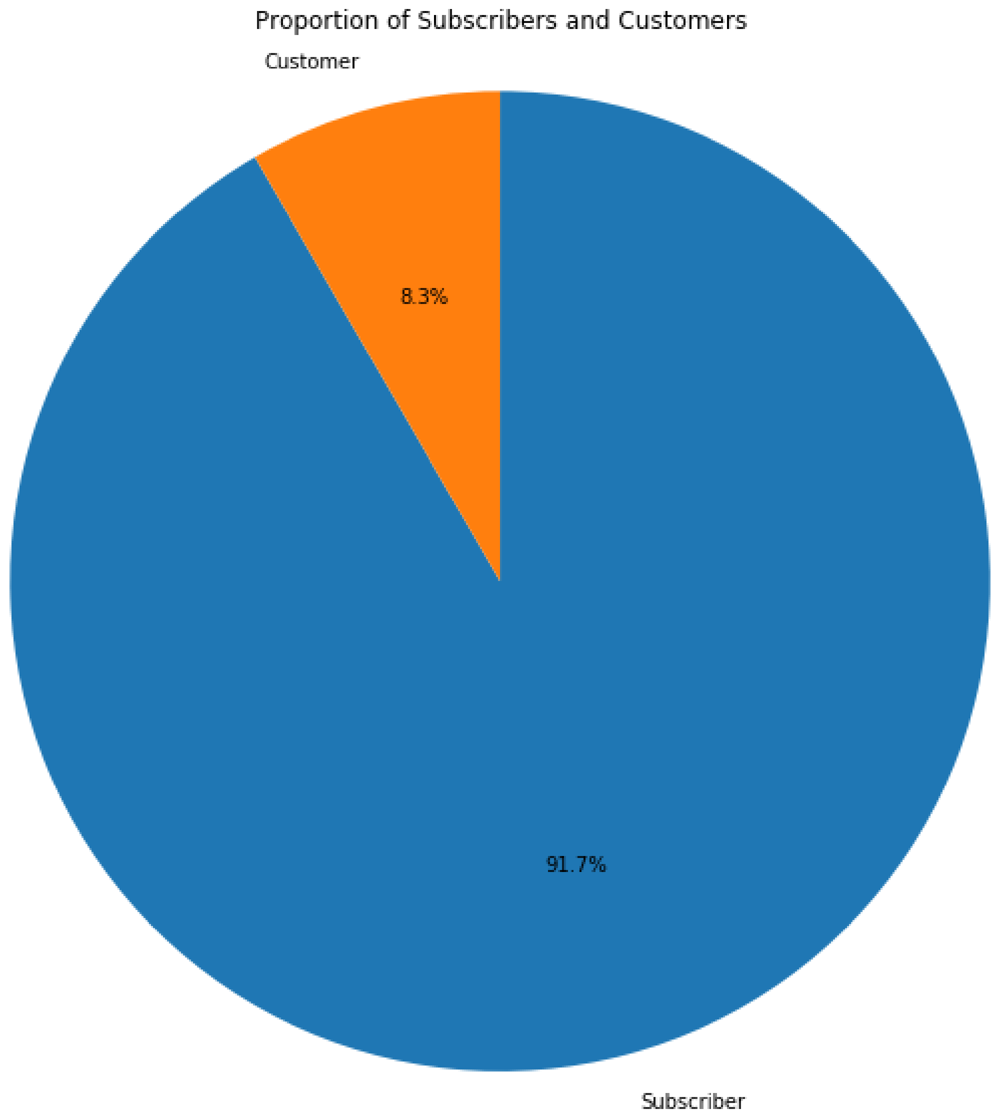
```
In [27]: plt.figure(figsize = [10, 10])
         sorted_counts = df['member_birth_year'].value_counts()
         plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90, counterclock = Fa
         plt.axis('square');
         plt.title('what the ages that ride more');
```



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

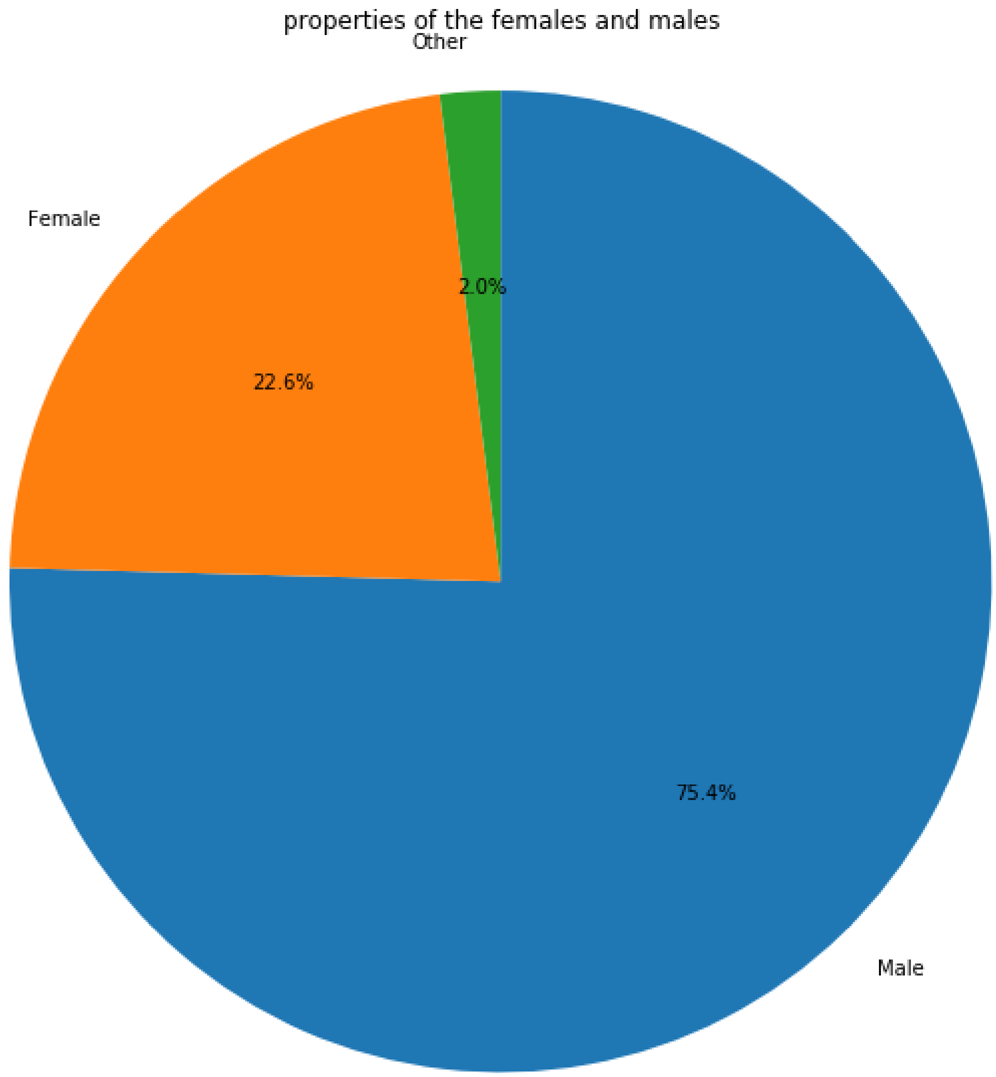
```
In [28]: plt.figure(figsize = [10, 10])
         sorted_counts = df['user_type'].value_counts()
         plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90, counterclock = Fa
         plt.axis('square');
         plt.title('Proportion of Subscribers and Customers');
```



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 [29]: 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 [30]: df.dropna().end_time.describe()

Out[30]: count                      28137
         unique                     28136
         top        2019-02-28 17:40:37.3280
         freq                           2
         Name: end_time, dtype: object

In [31]: df.dropna().start_time.describe()
```

Out[31]:
```
count                         28137
unique                        28136
top       2019-02-25 08:52:07.5820
freq                              2
Name: start_time, dtype: object
```

In [32]:
```
import datetime

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

Out[32]:
```
3
```

In [33]:
```
df.dropna().duration_sec.describe()
```

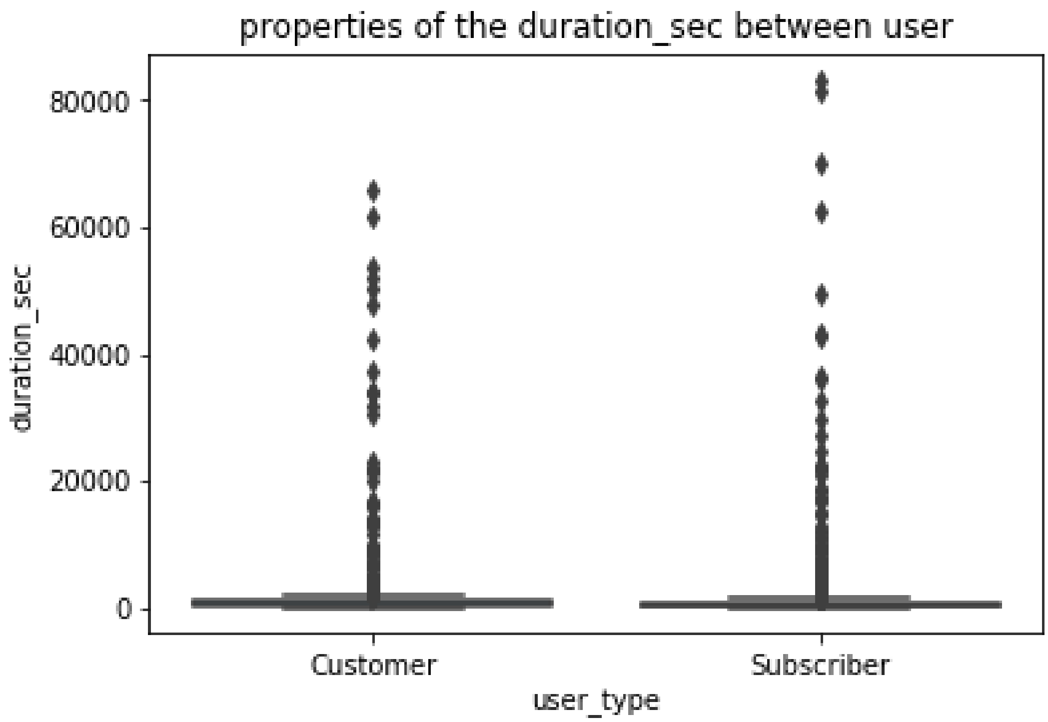
Out[33]:
```
count    28137.000000
mean       668.097701
std       1583.904334
min         61.000000
25%        319.000000
50%        500.000000
75%        759.000000
max      83195.000000
Name: duration_sec, dtype: float64
```

In [34]:
```
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 [35]:
```
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

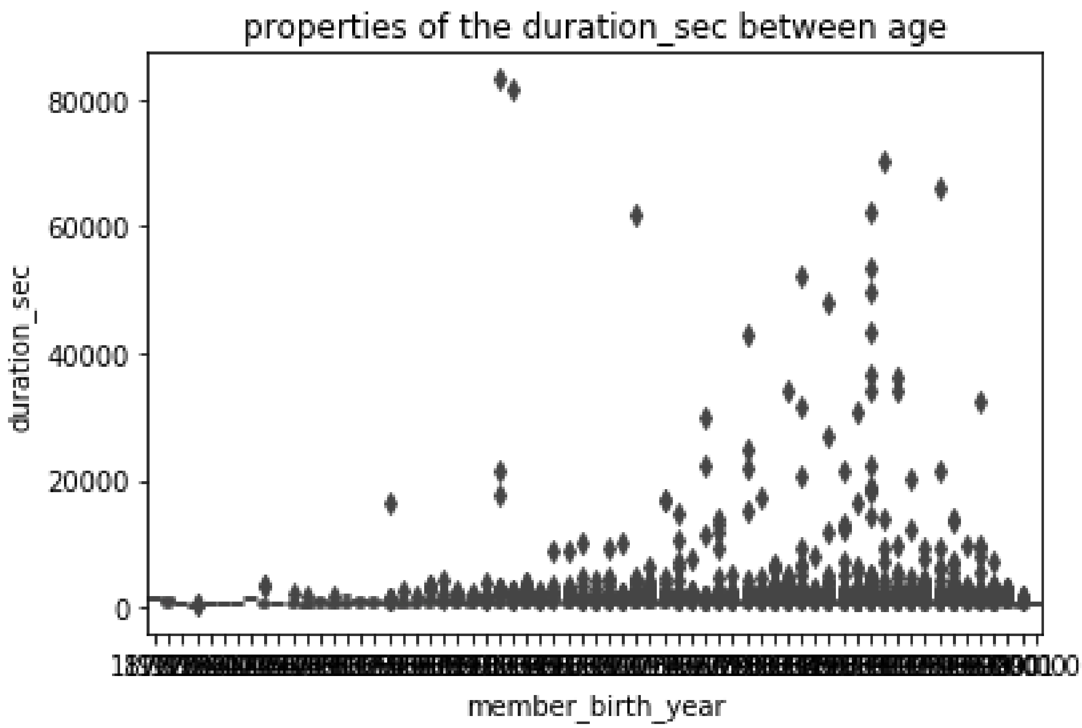
the subscribers is using the system more than the customers but the subscribe are take more time to arrive unlike the customers

In [36]:
```
df.dropna().duration_sec.describe()
```

Out[36]:
```
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 [37]:
```python
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 [38]:
```python
df.dropna().start_station_id.describe()
```

Out[38]:
```
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 [39]:
```
df.dropna().duration_sec.describe()
```

Out[39]:
```
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 [40]:
```
df.dropna().member_birth_year.describe()
```

Out[40]:
```
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()
```

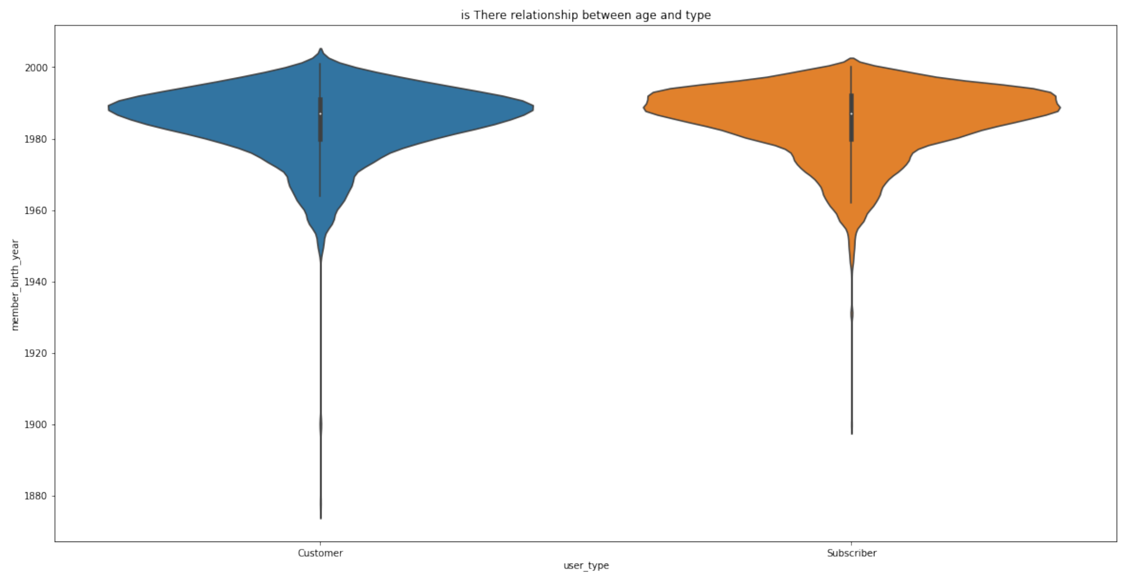
Out[41]:
```
count    28137.000000
mean       668.097701
std       1583.904334
min         61.000000
25%        319.000000
50%        500.000000
75%        759.000000
max      83195.000000
Name: duration_sec, dtype: float64
```

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 [43]:
```
# 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[43]:
```
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.

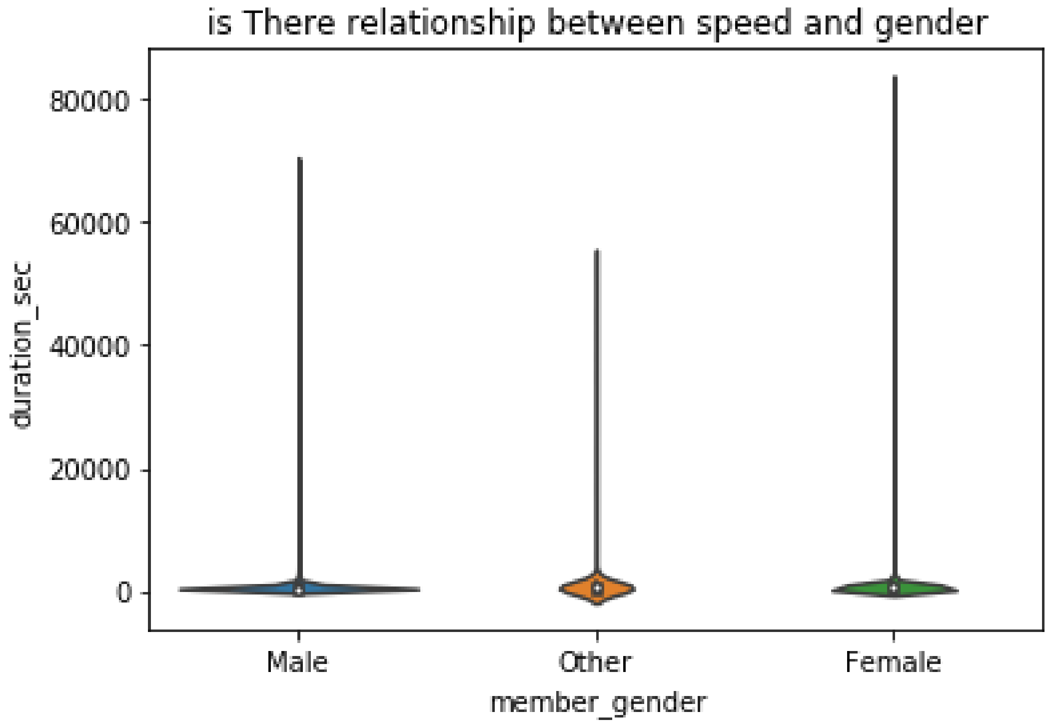
In [ ]:

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 [44]:
```
# plot

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

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

#sns.plt.show()
```

Out[44]: Text(0.5,1,'is There relationship between speed and gender')

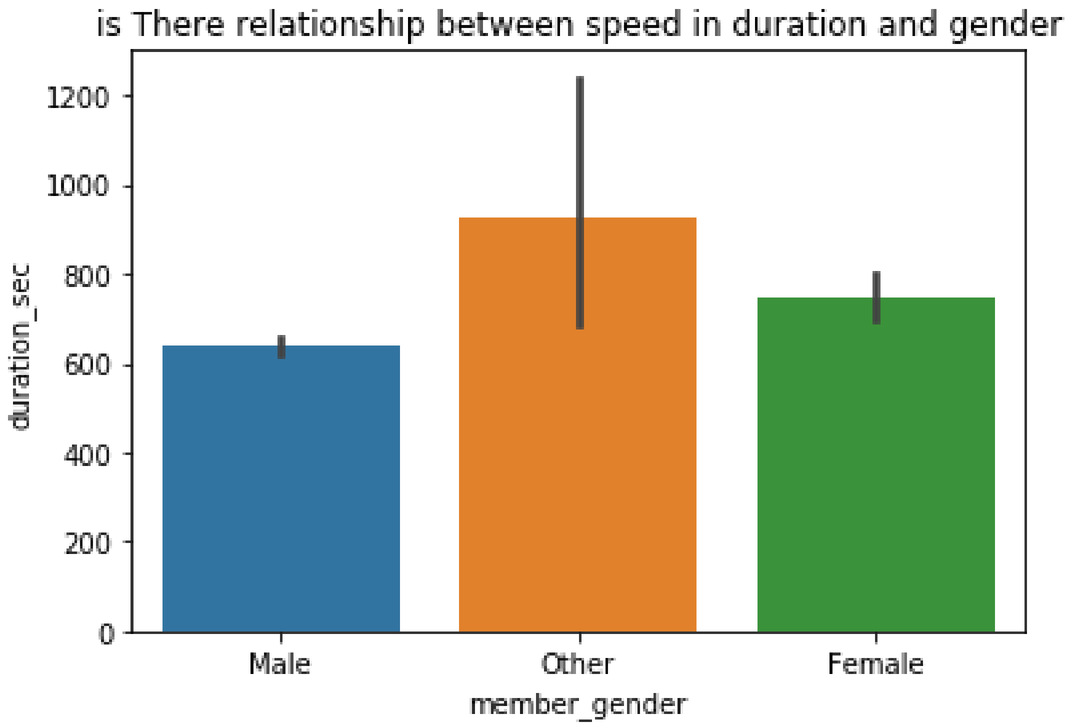


members gender VS duration

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

In [45]:
```
sb.barplot( x=df["member_gender"], y=df["duration_sec"] )

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



#sns.plt.show()
```

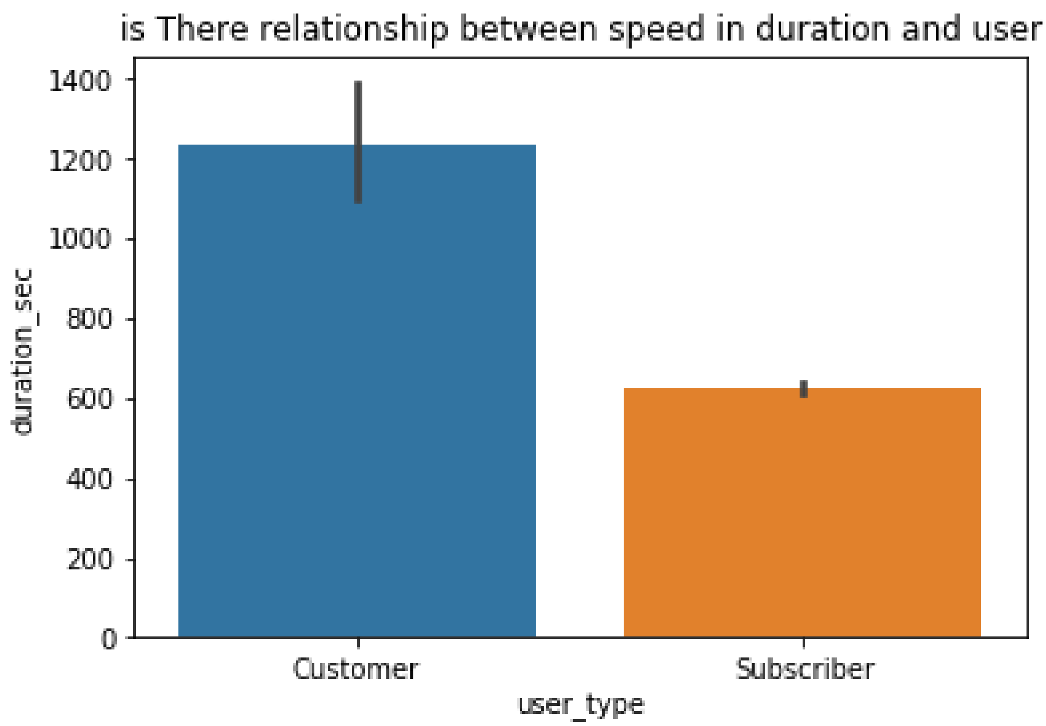
Out[45]: Text(0.5,1,'is There relationship between speed in duration and gender')



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 [46]: 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[46]: Text(0.5,1,'is There relationship between speed in duration and user')
```

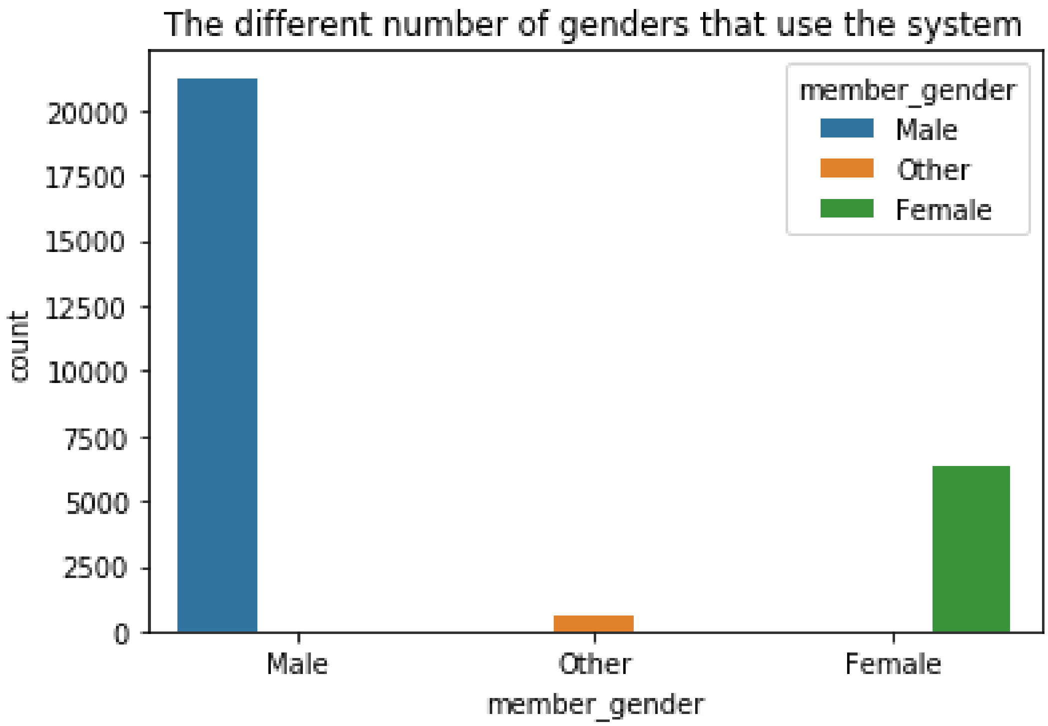


type users VS duration

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

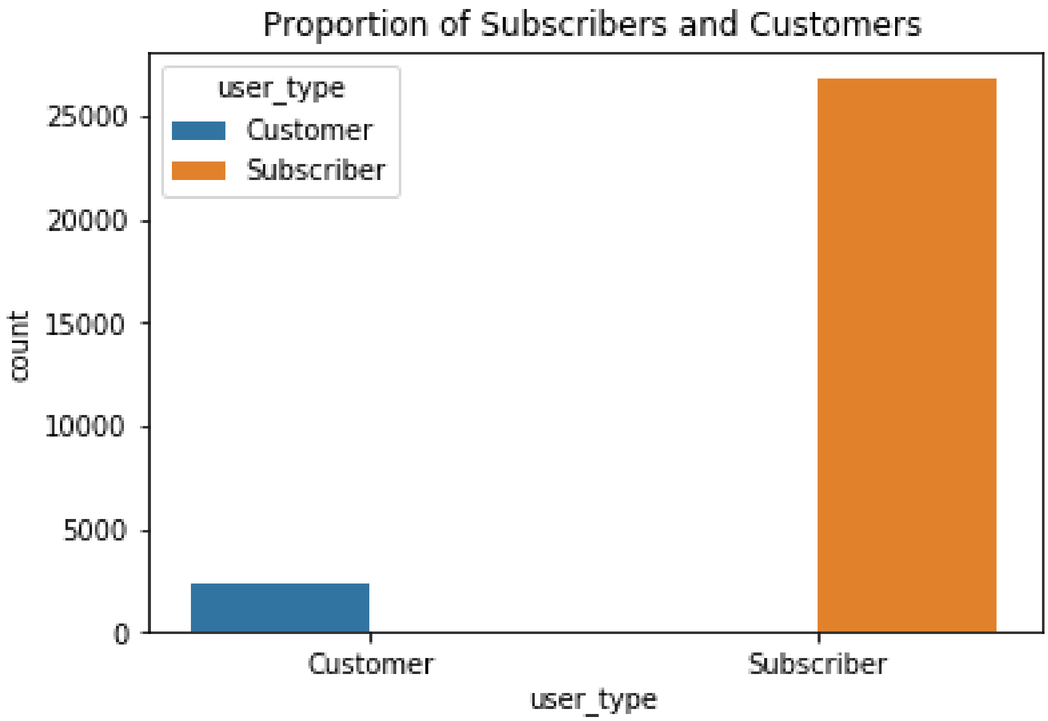
```
In [47]: ax = sns.countplot(data = df, x="member_gender", hue="member_gender")
         plt.title('The different number of genders that use the system');
```



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

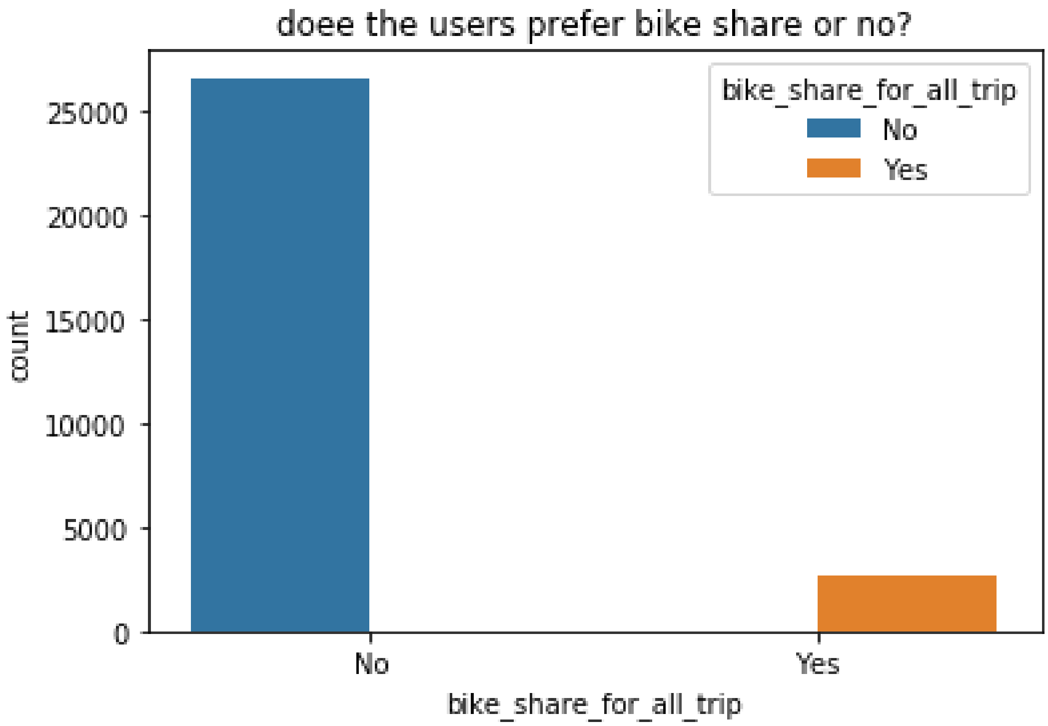
```
In [48]: ax = sns.countplot(data = df, x="user_type", hue="user_type")
         plt.title('Proportion of Subscribers and Customers');
```



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 [49]: 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.