Part_I_Ford_GoBike_service

January 23, 2022

1 Part I - Ford GoBike Data Visualization

1.1 by (Olga Kurguzova)

1.2 Introduction

Ford GoBike shares anonymized data about their users' trips. This data set includes information about individual rides made in a bike-sharing system covering the greater San Francisco Bay area

1.3 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 seaborn as sb
        from datetime import datetime as dt
        import datetime
        %matplotlib inline
```

```
In [2]: #load csv file and
        go_bikes = pd.read_csv('201902-fordgobike-tripdata.csv')
```

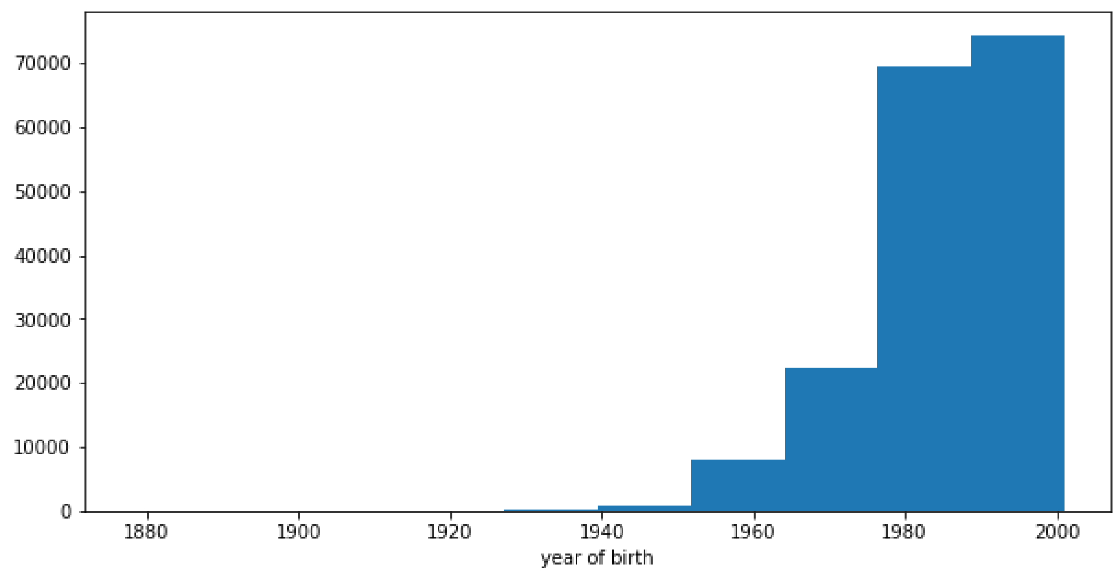
```
In [3]: #check go_bikes for visual assessment
        go_bikes
```

```
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
        ...              ...                       ...                       ...
        183407           480  2019-02-01 00:04:49.7240  2019-02-01 00:12:50.0340
        183408           313  2019-02-01 00:05:34.7440  2019-02-01 00:10:48.5020
        183409           141  2019-02-01 00:06:05.5490  2019-02-01 00:08:27.2200
        183410           139  2019-02-01 00:05:34.3600  2019-02-01 00:07:54.2870
        183411           271  2019-02-01 00:00:20.6360  2019-02-01 00:04:52.0580
```

```
       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
...                 ...                                              ...
183407             27.0                           Beale St at Harrison St
183408             21.0  Montgomery St BART Station (Market St at 2nd St)
183409            278.0                          The Alameda at Bush St
183410            220.0                      San Pablo Ave at MLK Jr Way
183411             24.0                            Spear St at Folsom St

       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
...                       ...                      ...             ...
183407              37.788059              -122.391865           324.0
183408              37.789625              -122.400811            66.0
183409              37.331932              -121.904888           277.0
183410              37.811351              -122.273422           216.0
183411              37.789677              -122.390428            37.0

                                     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
...                                               ...                   ...
183407           Union Square (Powell St at Post St)             37.788300
183408                         3rd St at Townsend St             37.778742
183409                      Morrison Ave at Julian St             37.333658
183410                       San Pablo Ave at 27th St             37.817827
183411                           2nd St at Folsom St             37.785000

       end_station_longitude  bike_id   user_type  member_birth_year  \
0                -122.402923     4902    Customer             1984.0
1                -122.393170     2535    Customer                NaN
2                -122.404904     5905    Customer             1972.0
3                -122.444293     6638  Subscriber             1989.0
4                -122.248780     4898  Subscriber             1974.0
...                      ...      ...         ...                ...
183407           -122.408531     4832  Subscriber             1996.0
183408           -122.392741     4960  Subscriber             1984.0
```

```
183409          -121.908586     3824  Subscriber              1990.0
183410          -122.275698     5095  Subscriber              1988.0
183411          -122.395936     1057  Subscriber              1989.0

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

[183412 rows x 16 columns]
```

In [4]:
```python
#plot member year of bith distibution
plt.figure(figsize = [10, 5])
plt.hist(data = go_bikes, x = 'member_birth_year')
plt.xlabel('year of birth');
```



In [5]:
```python
#data info
go_bikes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
```

```
Data columns (total 16 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             183412 non-null  int64
 1   start_time               183412 non-null  object
 2   end_time                 183412 non-null  object
 3   start_station_id         183215 non-null  float64
 4   start_station_name       183215 non-null  object
 5   start_station_latitude   183412 non-null  float64
 6   start_station_longitude  183412 non-null  float64
 7   end_station_id           183215 non-null  float64
 8   end_station_name         183215 non-null  object
 9   end_station_latitude     183412 non-null  float64
 10  end_station_longitude    183412 non-null  float64
 11  bike_id                  183412 non-null  int64
 12  user_type                183412 non-null  object
 13  member_birth_year        175147 non-null  float64
 14  member_gender            175147 non-null  object
 15  bike_share_for_all_trip  183412 non-null  object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

In [6]:
```
#check the Null values
go_bikes.isnull().sum()
```

Out[6]:
```
duration_sec                  0
start_time                    0
end_time                      0
start_station_id            197
start_station_name          197
start_station_latitude        0
start_station_longitude       0
end_station_id              197
end_station_name            197
end_station_latitude          0
end_station_longitude         0
bike_id                       0
user_type                     0
member_birth_year          8265
member_gender              8265
bike_share_for_all_trip       0
dtype: int64
```

In [7]:
```
go_bikes[go_bikes.isnull().any(1)]
```

Out[7]:
```
        duration_sec                start_time                  end_time  \
1              42521  2019-02-28 18:53:21.7890  2019-03-01 06:42:03.0560
13               915  2019-02-28 23:49:06.0620  2019-03-01 00:04:21.8670
```

```
28              650  2019-02-28 23:43:27.5030  2019-02-28 23:54:18.4510
53             3418  2019-02-28 22:41:16.3620  2019-02-28 23:38:14.3630
65              926  2019-02-28 23:17:05.8530  2019-02-28 23:32:32.6820
...             ...                       ...                       ...
183354          449  2019-02-01 01:35:07.6630  2019-02-01 01:42:36.8780
183356          795  2019-02-01 01:25:50.3660  2019-02-01 01:39:05.9500
183363          673  2019-02-01 01:12:24.4200  2019-02-01 01:23:37.6450
183371          196  2019-02-01 01:08:38.6410  2019-02-01 01:11:54.9490
183402          122  2019-02-01 00:17:32.2580  2019-02-01 00:19:34.9380

        start_station_id              start_station_name  \
1                   23.0   The Embarcadero at Steuart St
13                 252.0    Channing Way at Shattuck Ave
28                 258.0     University Ave at Oxford St
53                  11.0          Davis St at Jackson St
65                  13.0  Commercial St at Montgomery St
...                  ...                             ...
183354             244.0      Shattuck Ave at Hearst Ave
183356             368.0            Myrtle St at Polk St
183363              75.0        Market St at Franklin St
183371              58.0            Market St at 10th St
183402             119.0               18th St at Noe St

        start_station_latitude  start_station_longitude  end_station_id  \
1                    37.791464              -122.391034            81.0
13                   37.865847              -122.267443           244.0
28                   37.872355              -122.266447           263.0
53                   37.797280              -122.398436            11.0
65                   37.794231              -122.402923            81.0
...                        ...                      ...             ...
183354               37.873676              -122.268487           253.0
183356               37.785434              -122.419622           125.0
183363               37.773793              -122.421239           133.0
183371               37.776619              -122.417385            75.0
183402               37.761047              -122.432642           120.0

                     end_station_name  end_station_latitude  \
1                   Berry St at 4th St             37.775880
13         Shattuck Ave at Hearst Ave             37.873676
28        Channing Way at San Pablo Ave             37.862827
53             Davis St at Jackson St             37.797280
65                  Berry St at 4th St             37.775880
...                               ...                   ...
183354         Haste St at College Ave             37.866418
183356            20th St at Bryant St             37.759200
183363          Valencia St at 22nd St             37.755213
183371        Market St at Franklin St             37.773793
183402            Mission Dolores Park             37.761420
```

```
        end_station_longitude  bike_id   user_type  member_birth_year  \
1                 -122.393170     2535    Customer                NaN
13                -122.268487     5101  Subscriber                NaN
28                -122.290231     4784    Customer                NaN
53                -122.398436      319    Customer                NaN
65                -122.393170     2951  Subscriber                NaN
...                       ...      ...         ...                ...
183354            -122.253799     5430    Customer                NaN
183356            -122.409851     5400  Subscriber                NaN
183363            -122.420975     5166    Customer                NaN
183371            -122.421239     2395    Customer                NaN
183402            -122.426435     4326  Subscriber                NaN

       member_gender bike_share_for_all_trip
1                NaN                      No
13               NaN                      No
28               NaN                      No
53               NaN                      No
65               NaN                      No
...              ...                     ...
183354           NaN                      No
183356           NaN                      No
183363           NaN                      No
183371           NaN                      No
183402           NaN                      No

[8460 rows x 16 columns]
```

In [8]:
```
#Check duplicates
go_bikes.duplicated().sum()
```

Out[8]: 0

In [9]:
```
#statistic description
go_bikes.describe()
```

Out[9]:
```
         duration_sec  start_station_id  start_station_latitude  \
count  183412.000000     183215.000000           183412.000000
mean      726.078435        138.590427               37.771223
std      1794.389780        111.778864                0.099581
min        61.000000          3.000000               37.317298
25%       325.000000         47.000000               37.770083
50%       514.000000        104.000000               37.780760
75%       796.000000        239.000000               37.797280
max     85444.000000        398.000000               37.880222

       start_station_longitude  end_station_id  end_station_latitude  \
count            183412.000000   183215.000000         183412.000000
```

```
mean                -122.352664      136.249123              37.771427
std                    0.117097      111.515131               0.099490
min                 -122.453704        3.000000              37.317298
25%                 -122.412408       44.000000              37.770407
50%                 -122.398285      100.000000              37.781010
75%                 -122.286533      235.000000              37.797320
max                 -121.874119      398.000000              37.880222

       end_station_longitude        bike_id  member_birth_year
count          183412.000000  183412.000000      175147.000000
mean             -122.352250    4472.906375        1984.806437
std                 0.116673    1664.383394          10.116689
min              -122.453704      11.000000        1878.000000
25%              -122.411726    3777.000000        1980.000000
50%              -122.398279    4958.000000        1987.000000
75%              -122.288045    5502.000000        1992.000000
max              -121.874119    6645.000000        2001.000000
```

```
In [10]: go_bikes[go_bikes.duration_sec == 85444]
```

```
Out[10]:         duration_sec                start_time                  end_time  \
        101361         85444  2019-02-13 17:59:55.1240  2019-02-14 17:43:59.9540

                start_station_id                           start_station_name  \
        101361               5.0  Powell St BART Station (Market St at 5th St)

                start_station_latitude  start_station_longitude  end_station_id  \
        101361               37.783899              -122.408445            98.0

                      end_station_name  end_station_latitude  end_station_longitude  \
        101361  Valencia St at 16th St             37.765052            -122.421866

                bike_id   user_type  member_birth_year member_gender  \
        101361     6168  Subscriber                NaN           NaN

               bike_share_for_all_trip
        101361                      No
```

1.3.1 onclusion after the first checks

During assessing the data I found some quality and tidiness issues. So I decided to clean up the Dataset before I starting exploration process.
Quality and tidiness issues:

1. Unnecessary columns:`start_station_latitude`,`start_station_longitude`,`end_station_id`,`end_station_`
2. Drop null-values in columns `start_station_id`, `start_station_name`, `end_station_id`, `end__station_name`, `member_birth_year`;

3. Erroneous datatypes in columns: `start_time`, `end_time`, `start_station_id`, `end_station_id`, `member_birth_year`;
4. For the purposes of our analysis, we need to create columns with values of starting sharing bikes: weekday and time of the;
5. For the purposes of our analysis, we need the column with values of the member's age at the time of bike sharing;
6. There are a lot of people over 70 years old and even 118 years old. Most likely, these are outliers, and we need to delete the rows with them;

1.3.2 Cleaning Data

Issue 1 Drop unnecessary columns

```
In [11]: # Make a copy of an original data
         go_bikes_clean = go_bikes.copy()
```

```
In [12]: #drop unnecessary columns
         go_bikes_clean.drop(['start_station_latitude','start_station_longitude', 'end_station_l
```

```
In [13]: # check for the absence of unnecessary columns
         go_bikes_clean.columns
```

```
Out[13]: Index(['duration_sec', 'start_time', 'end_time', 'start_station_id',
                'start_station_name', 'end_station_id', 'end_station_name', 'bike_id',
                'user_type', 'member_birth_year', 'member_gender',
                'bike_share_for_all_trip'],
               dtype='object')
```

Issue 2 Drop null-values in columns start_station_id, start_station_name, end_station_id, end__station_name, member_birth_year

```
In [14]: #drop null-values
         go_bikes_clean = go_bikes_clean.dropna()
```

```
In [15]: #check for the absence of null-values
         go_bikes_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
Data columns (total 12 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             174952 non-null  int64
 1   start_time               174952 non-null  object
 2   end_time                 174952 non-null  object
 3   start_station_id         174952 non-null  float64
 4   start_station_name       174952 non-null  object
```

```
 5   end_station_id           174952 non-null  float64
 6   end_station_name         174952 non-null  object
 7   bike_id                  174952 non-null  int64
 8   user_type                174952 non-null  object
 9   member_birth_year        174952 non-null  float64
 10  member_gender            174952 non-null  object
 11  bike_share_for_all_trip  174952 non-null  object
dtypes: float64(3), int64(2), object(7)
memory usage: 17.4+ MB
```

Issue 3 Correct datatypes for `start_time`, `end_time`. This columns should have datetime type.

In [16]:
```
# create loop for corection datatypes and droping unnesery values
for c in ['start_time', 'end_time']:
    go_bikes_clean[c] = go_bikes_clean[c].apply(lambda x : x.split ('.')[0])
    go_bikes_clean[c] = pd.to_datetime(go_bikes_clean[c])
```

Issue 4 Correct datatypes for `start_station_id`, `end_station_id`, `member_birth_year`. Correct datatypes for `member_gender` into category type

In [17]:
```
#create def for convert into  int and category

def multi_astype(data, **column_types):
    for column, typ in column_types.items():
        data[column] = data[column].astype(typ)

multi_astype(go_bikes_clean, member_gender='category',
             start_station_id=int, end_station_id=int, member_birth_year=int)
```

In [18]:
```
# check data types
go_bikes_clean.dtypes
```

Out[18]:
```
duration_sec                        int64
start_time                 datetime64[ns]
end_time                   datetime64[ns]
start_station_id                    int64
start_station_name                 object
end_station_id                      int64
end_station_name                   object
bike_id                             int64
user_type                          object
member_birth_year                   int64
member_gender                    category
bike_share_for_all_trip            object
dtype: object
```

Issue 5 Create new columns `weekday`, `time` to be used in the analysis

In [19]:
```
# Create weekday column
go_bikes_clean['weekday'] = go_bikes_clean['start_time'].dt.strftime("%A")

# Create time column
go_bikes_clean["time"] = go_bikes_clean['start_time'].dt.hour
```

In [20]:
```
# convert weekday into ordered categorical types
ordinal_var_dict = ['Monday','Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',
ordered_var = pd.api.types.CategoricalDtype(ordered = True,
                                            categories = ordinal_var_dict)
go_bikes_clean['weekday'] = go_bikes_clean['weekday'].astype(ordered_var)
```

In [21]:
```
go_bikes_clean['weekday'].dtypes
```

Out[21]:
```
CategoricalDtype(categories=['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
                  'Saturday', 'Sunday'],
, ordered=True)
```

In [22]:
```
#check new columns
go_bikes_clean[['weekday','time']].sample(5)
```

Out[22]:

	weekday	time
24549	Monday	18
135428	Friday	12
79148	Monday	17
149131	Wednesday	19
2257	Thursday	18

In [23]:
```
#transform time in part of the day
b = [0,4,8,12,16,20,24]
l = ['Late Night','Early Morning','Morning','Noon','Evening','Night']
go_bikes_clean['time'] = pd.cut(go_bikes_clean['time'], bins=b, labels=l, include_lowes
```

In [24]:
```
#check transformation
go_bikes_clean.time.value_counts()
```

Out[24]:
```
Evening          52657
Morning          38855
Noon             37894
Early Morning    34617
Night             8765
Late Night        2164
Name: time, dtype: int64
```

Issue 6 We need transform values wrom `member_birth_year` into age and put them into a new column.

In [25]:
```python
# create new column
go_bikes_clean['member_age'] = 2019 - go_bikes_clean['member_birth_year']
```

In [26]:
```python
#drop unnecessary column
go_bikes_clean.drop(['member_birth_year'], axis=1, inplace=True)
```

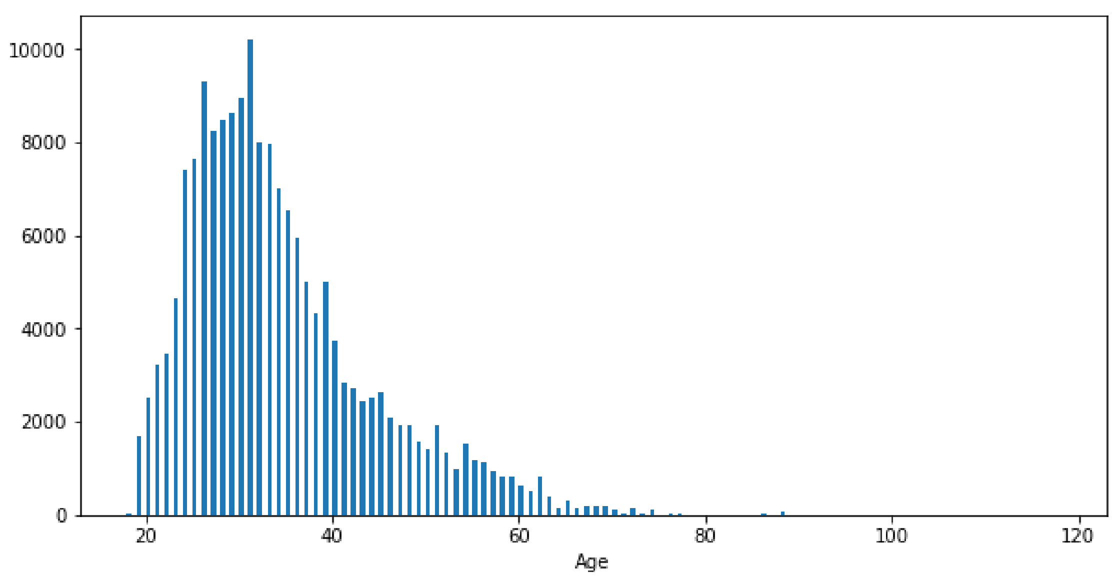
In [27]:
```python
#check for the absence of unnecessary columns
go_bikes_clean.columns
```

Out[27]:
```
Index(['duration_sec', 'start_time', 'end_time', 'start_station_id',
       'start_station_name', 'end_station_id', 'end_station_name', 'bike_id',
       'user_type', 'member_gender', 'bike_share_for_all_trip', 'weekday',
       'time', 'member_age'],
      dtype='object')
```

In [28]:
```python
#check
go_bikes_clean.member_age.describe()
```

Out[28]:
```
count    174952.000000
mean         34.196865
std          10.118731
min          18.000000
25%          27.000000
50%          32.000000
75%          39.000000
max         141.000000
Name: member_age, dtype: float64
```

In [29]:
```python
plt.figure(figsize = [10, 5])
bins = np.arange(18, 118 + 0.5, 0.5)
plt.hist(data = go_bikes_clean, x = 'member_age', bins = bins)
plt.xlabel('Age');
```



Issue 7 We need to delete the rows with data of members over 80 years old.

```
In [30]: # Delete rows with inappropriate values
         go_bikes_clean.drop(go_bikes_clean[go_bikes_clean.member_age >= 80].index, inplace=True
```

```
In [31]: #Check for the absence of inappropriate values
         go_bikes_clean[go_bikes_clean.member_age >= 80]
```

```
Out[31]: Empty DataFrame
         Columns: [duration_sec, start_time, end_time, start_station_id, start_station_name, end
         Index: []
```

Issue 8 We need to replace values 'Yes' and 'No' to 1 and 2 respectively in column `bike_share_for_all_trip`.

```
In [32]: #replace values
         go_bikes_clean.bike_share_for_all_trip.replace('No', 0, inplace = True)
         go_bikes_clean.bike_share_for_all_trip.replace('Yes', 1, inplace = True)
```

```
In [33]: go_bikes_clean.bike_share_for_all_trip.value_counts()
```

```
Out[33]: 0    157457
         1     17292
         Name: bike_share_for_all_trip, dtype: int64
```

1.3.3 Check the improved data specifications

```
In [34]: #check the improved data specifications
         print(go_bikes_clean.shape)
```

```
(174749, 14)
```

```
In [35]: #statistic description
         go_bikes_clean.describe()
```

```
Out[35]:         duration_sec  start_station_id  end_station_id        bike_id  \
         count  174749.000000     174749.000000   174749.000000  174749.000000
         mean      704.300563        139.024092      136.643683    4482.315183
         std      1643.075498        111.651112      111.352470    1659.248113
         min        61.000000          3.000000        3.000000      11.000000
         25%       323.000000         47.000000       44.000000    3799.000000
         50%       511.000000        104.000000      101.000000    4960.000000
         75%       789.000000        239.000000      238.000000    5505.000000
         max     84548.000000        398.000000      398.000000    6645.000000

                bike_share_for_all_trip     member_age
         count            174749.000000  174749.000000
         mean                  0.098953      34.122335
```

```
std                     0.298600     9.871342
min                     0.000000    18.000000
25%                     0.000000    27.000000
50%                     0.000000    32.000000
75%                     0.000000    39.000000
max                     1.000000    78.000000
```

In [36]:
```
go_bikes_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174749 entries, 0 to 183411
Data columns (total 14 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             174749 non-null  int64
 1   start_time               174749 non-null  datetime64[ns]
 2   end_time                 174749 non-null  datetime64[ns]
 3   start_station_id         174749 non-null  int64
 4   start_station_name       174749 non-null  object
 5   end_station_id           174749 non-null  int64
 6   end_station_name         174749 non-null  object
 7   bike_id                  174749 non-null  int64
 8   user_type                174749 non-null  object
 9   member_gender            174749 non-null  category
 10  bike_share_for_all_trip  174749 non-null  int64
 11  weekday                  174749 non-null  category
 12  time                     174749 non-null  category
 13  member_age               174749 non-null  int64
dtypes: category(3), datetime64[ns](2), int64(6), object(3)
memory usage: 16.5+ MB
```

1.3.4 Storing Data

Save gathered, assessed, and cleaned master dataset to a CSV file named "go_bikes_master.csv".

In [37]:
```
#store the clean DataFrame in a CSV file
go_bikes_master = go_bikes_clean.copy()
go_bikes_master.to_csv('go_bikes_master.csv',
                 index=False, encoding = 'utf-8')
```

1.3.5 What is the structure of your dataset?

There are 174,278 rides with 14 features. This dataset provides detailed rides information for February 2019. The original dataset has the following information

1. Ride duration: duration of the rides in seconds;
2. Start and End time: when the ride started and ended;
3. Station Information: the station id, name and location;
4. The user information: user id, year of birth, gender, subscription.

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

I'm most interested in figuring out how subscribers and customers use the service in terms of the duration of the ride, frequency of use, their age and gender.

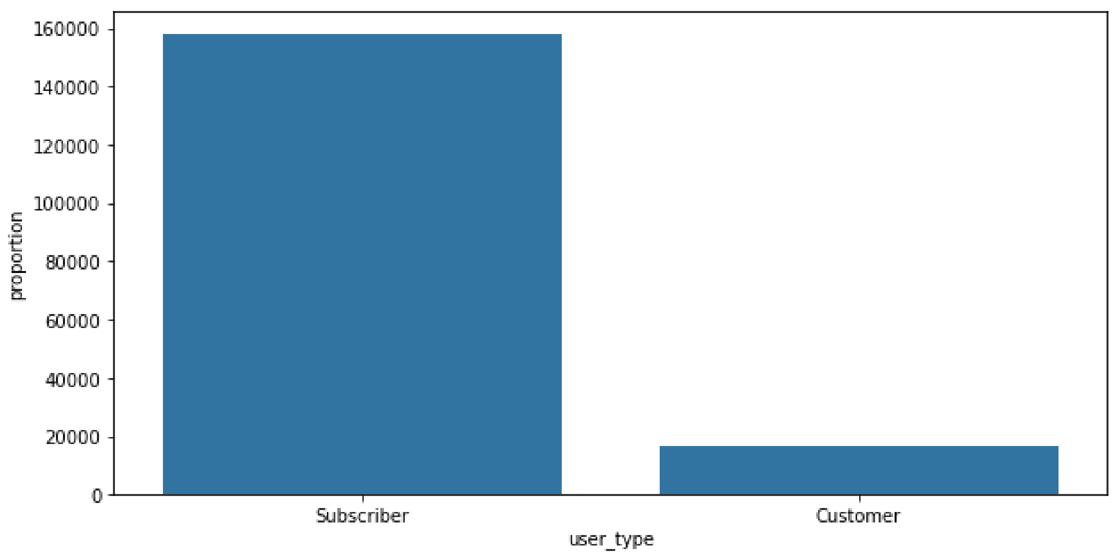
1.3.7 What features in the dataset do you think will help support your investigation into your feature(s) of interest?

I expect that subscribers use the service more often (during day and week), they trips are longer.

1.4 Univariate Exploration

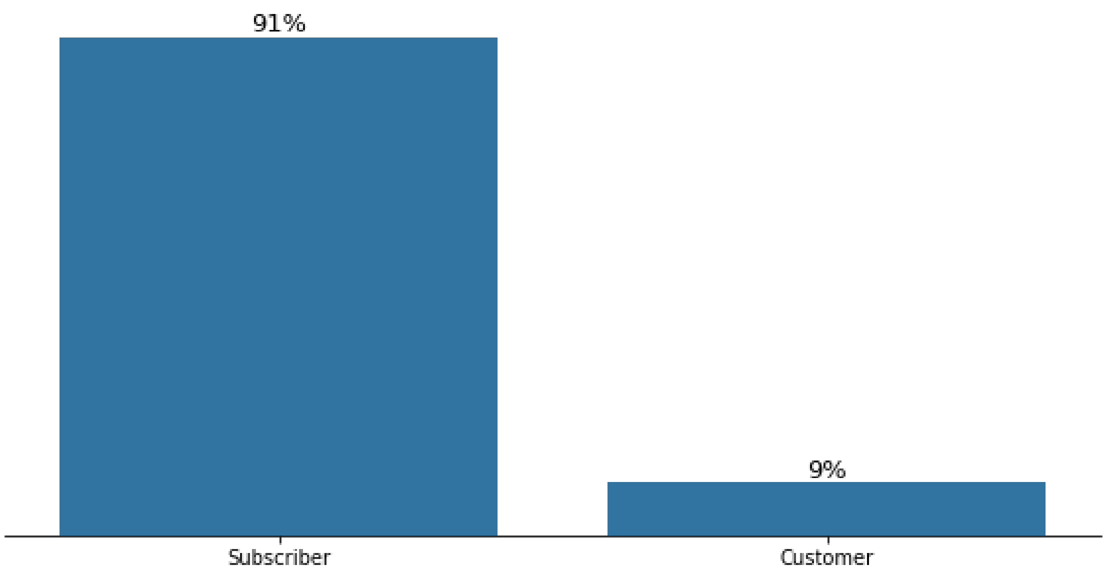
I'll start by looking at the subscribtion destribution

```
In [38]: # establish tick locations and create plot
         fig, ax = plt.subplots(figsize = (10,5))
         base_color = sb.color_palette()[0]
         sb.countplot(data = go_bikes_master, x = 'user_type', color = base_color, order = go_bi
         plt.ylabel('proportion');
```




```
In [65]: #so, let's add percentages to each bar
         fig, ax = plt.subplots(figsize = (10,5))
         base_color = sb.color_palette()[0]

         sb.countplot(x = "user_type", data = go_bikes_master,
                       order = go_bikes_master['user_type'].value_counts().index,
                       color = base_color)

         # Calculate % for each user types
```

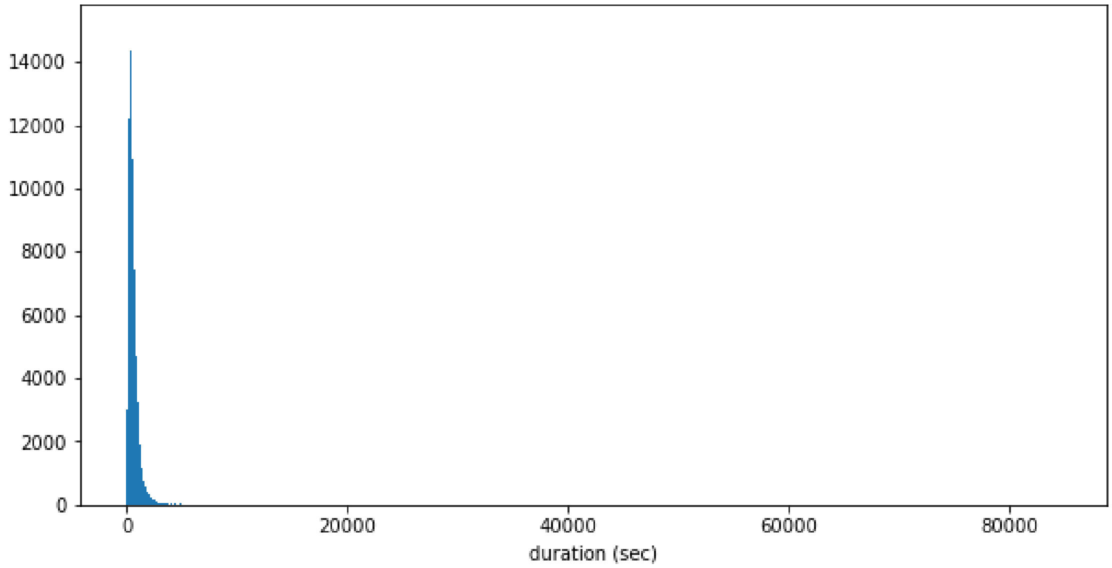
```
perc_list = []
type_sum = go_bikes_master['user_type'].value_counts().to_list()
total_sum = go_bikes_master.shape[0]
for i in range(0,len(type_sum)):
    percent = int(round(100 * type_sum[i] / total_sum))
    perc_list.append(percent)
# Annotate bars
i=0
for p in ax.patches:
    ax.annotate('{:.0f}%'.format(perc_list[i]),
                (p.get_x()+p.get_width()/2, p.get_height()),
                ha="center", va="bottom", color='black', size=13)
    i+=1
plt.ylim([0, 170000])
cur_axes = plt.gca()
cur_axes.axes.get_yaxis().set_visible(False)
plt.xlabel("")
sb.despine(fig, left = True);
```



As we can see on the plot, most of the users (91%) have a subscription.
Let's look at the distribution of the main variable of interest: duration.

In [40]:
```
# start with a standard-scaled plot
binsize = 60
bins = np.arange(61, go_bikes_master['duration_sec'].max()+binsize, binsize)

plt.figure(figsize=[10, 5])
plt.hist(data = go_bikes_master, x = 'duration_sec', bins = bins)
```

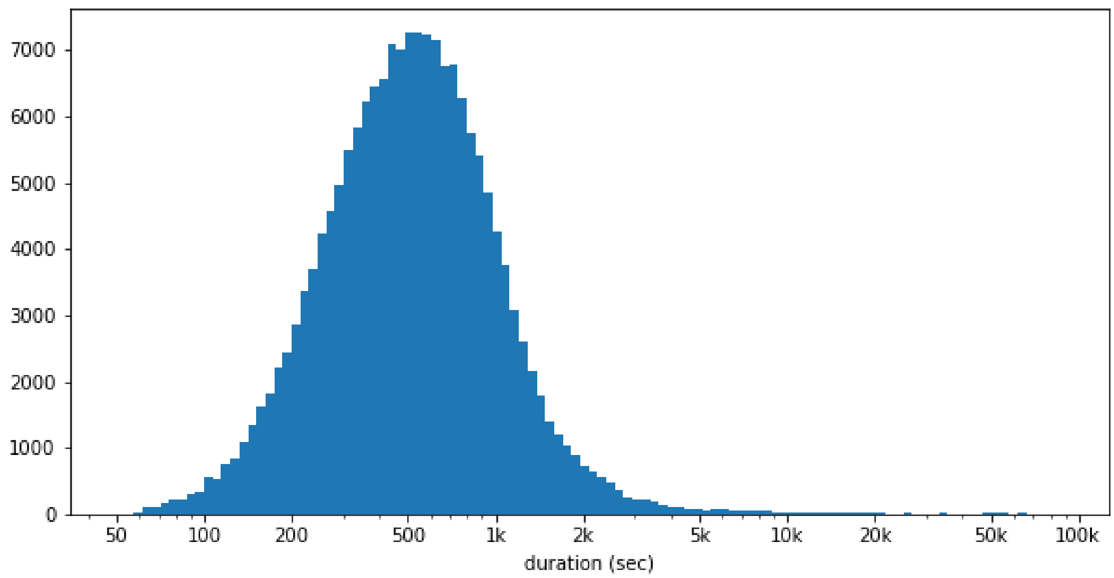
```
plt.xlabel('duration (sec)')
plt.show()
```



In [41]:
```
np.log10(go_bikes_master['duration_sec'].describe())
```

Out[41]:
```
count    5.242415
mean     2.847758
std      3.215658
min      1.785330
25%      2.509203
50%      2.708421
75%      2.897077
max      4.927103
Name: duration_sec, dtype: float64
```

In [42]:
```
# there is a very long tail in the distribution, so let's put it on a log scale instead
log_binsize = 0.03
bins = 10 ** np.arange(1.7, np.log10(go_bikes_master['duration_sec'].max())+log_binsize
tick = [50, 100, 200, 500, 1e3, 2e3, 5e3, 1e4, 2e4, 5e4, 1e5]
label = [50, 100, 200, 500, '1k', '2k', '5k', '10k', '20k','50k', '100k']

plt.figure(figsize=[10, 5])
plt.hist(data = go_bikes_master, x = 'duration_sec', bins = bins)
plt.xscale('log')
plt.xticks(tick, label)
plt.xlabel('duration (sec)')
plt.show()
```

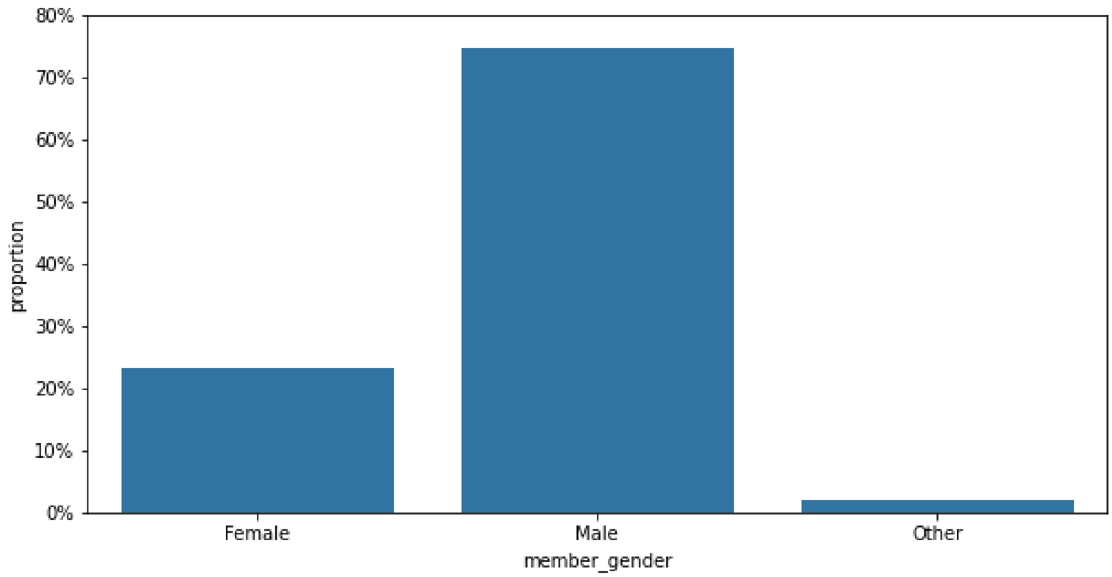


Duration has a very long-tailed distribution, most trips lasted from 120 seconds (2 minutes) to 2000 seconds (around 33 minutes), and some trips lasted much longer (almost 24 hours). When plotted on a log-scale, the duration distribution looks unimodal, with a single peak between 400 and 700 seconds (7 - 12 minutes).

Let's look at the gender destribution. Who uses the bike sharing service most often - a men or a women?

In [43]:
```
# Compute proportion
sum_gender = go_bikes_master['member_gender'].value_counts().sum()
gender_counts = go_bikes_master['member_gender'].value_counts()
max_gend_count = gender_counts[0]
max_prop = max_gend_count/sum_gender
```

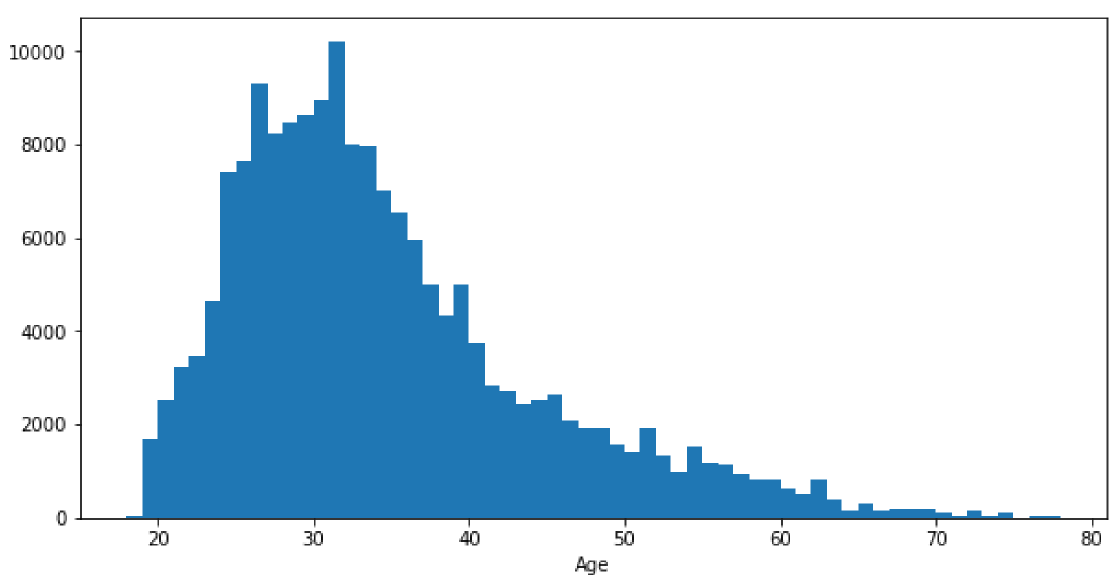
In [44]:
```
# establish tick locations and create plot
fig, ax = plt.subplots(figsize = (10,5))
tick_props = np.arange(0, max_prop +0.1, 0.1)
tick_names = [f'{int(v*100)}%' for v in tick_props]
ax = sb.countplot(data = go_bikes_master, x = 'member_gender', color = base_color)
plt.yticks(tick_props * sum_gender, tick_names)
plt.ylabel('Proportion');
```



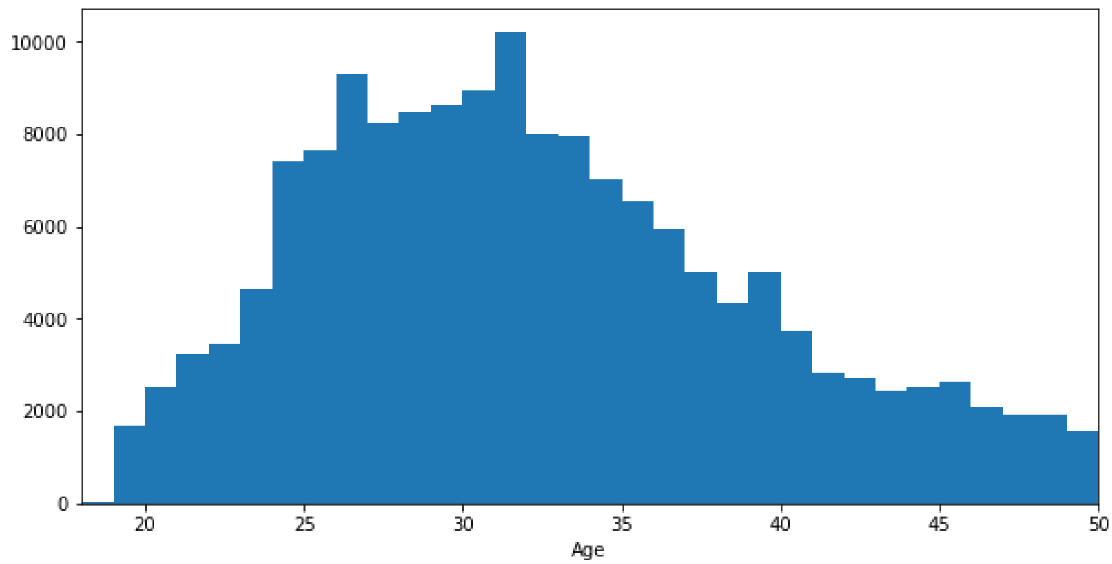
According to the plot, the majority of members around 75% are male, around 25% are female and around 1% are others.

Move on to age destribution. People of what age are more likely to use the bike sharing service?

In [45]:
```
# create plot
binsize = 1
bins = np.arange(18, go_bikes_master['member_age'].max()+binsize, binsize)

plt.figure(figsize=[10, 5])
plt.hist(data = go_bikes_master, x = 'member_age', bins = bins)
plt.xlabel('Age')
plt.show()
```



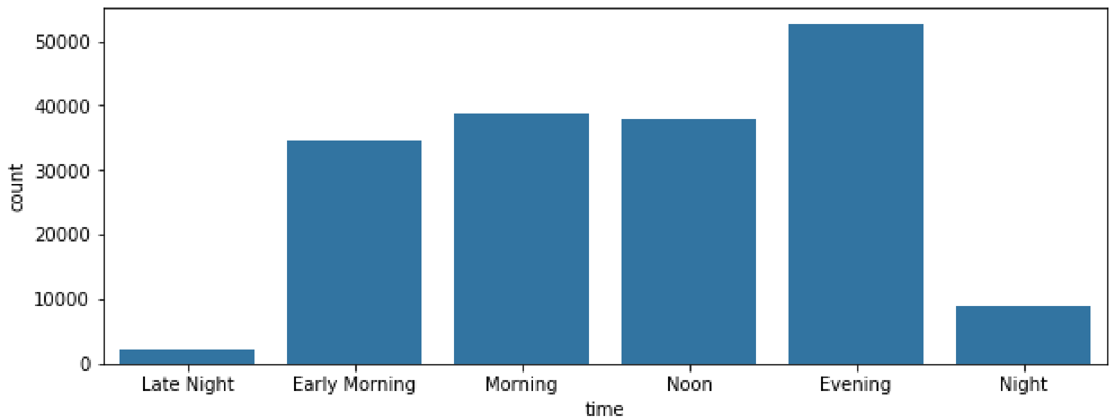
```
In [46]: #let's zoom the plot
         binsize = 1
         bins = np.arange(18, go_bikes_master['member_age'].max()+binsize, binsize)

         plt.figure(figsize=[10, 5])
         plt.hist(data = go_bikes_master, x = 'member_age', bins = bins)
         plt.xlabel('Age')
         plt.xlim([18, 50])
         plt.show()
```

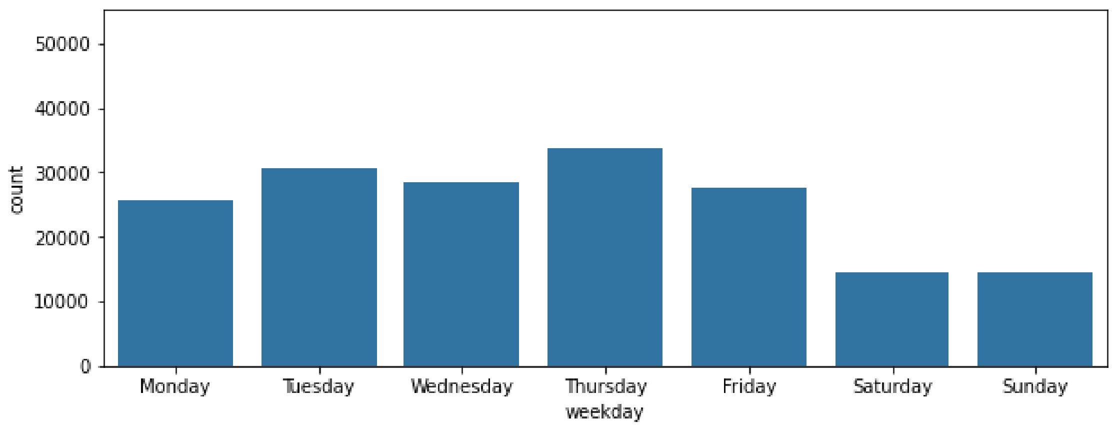


According to the plot, the distribution is more concentrated between 25 and 35 years old.

At the end of this section we will take a look at period of day and weekday. When the most popular time to share bike?

```
In [47]: fig, ax = plt.subplots(nrows=2, figsize = [10, 8])

         ax1 = sb.countplot(data = go_bikes_master, x = 'time', color = base_color, ax = ax[0])
         sb.countplot(data = go_bikes_master, x = 'weekday', color = base_color, ax = ax[1])
         plt.ylim(ax1.get_ylim())
         plt.show()
```





As we can see on the "time" bar chart, the number of trips during the day is distributed evenly, but in the evening it increases by almost a third. However, Night is not a popular time for cycling

On the weekday bar plot, we can see that weekdays are much more popular than weekends, especially on Thursday.

1.4.1 Discuss the distribution(s) of your variable(s) of interest. Were there any unusual points? Did you need to perform any transformations?

First of all, most of the users (91%) have a subscription. Than I explored the duration variable. It took a large range of values, so I used a log transformation for the data. Under the transformation, the data looked unimodal, with a single peak between 400 and 700 seconds (7 - 12 minutes).

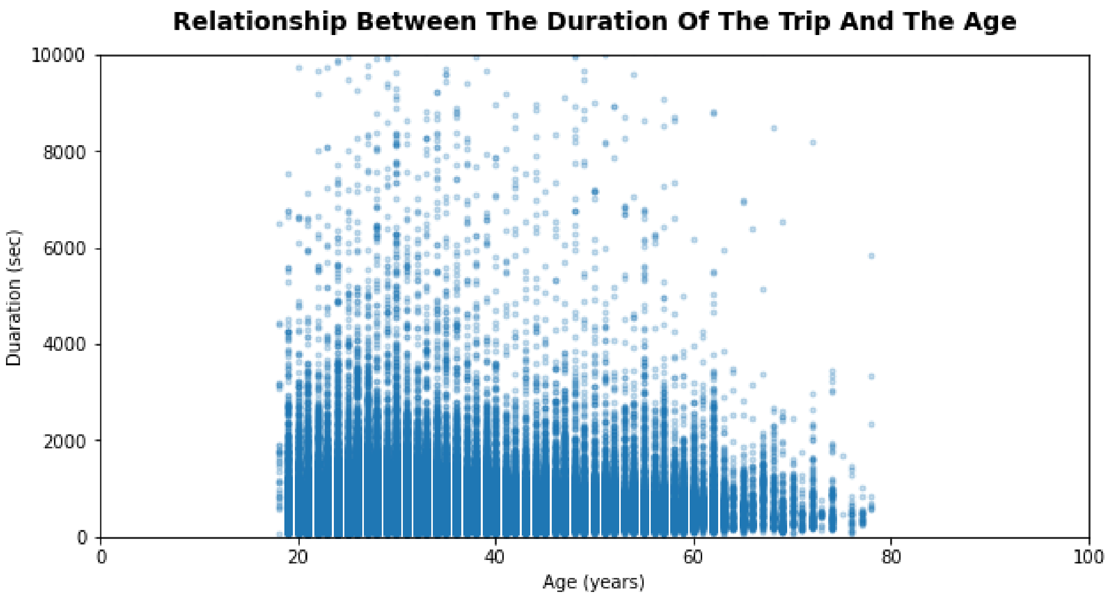
1.4.2 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

I extracted data about the start time of the trip and the day of the week when the trip starts from the "start time" to see the most popular time of using the service. In column year of birth were outliers, so I decidet to remove them also I converted the "year of birth" column to the "age" column for the convenience of information perception. The duration variable took a large range of values, so I used a log transformation for the data. Under the transformation, the data looked unimodal, with a single peak between 400 and 700 seconds (7 - 12 minutes).

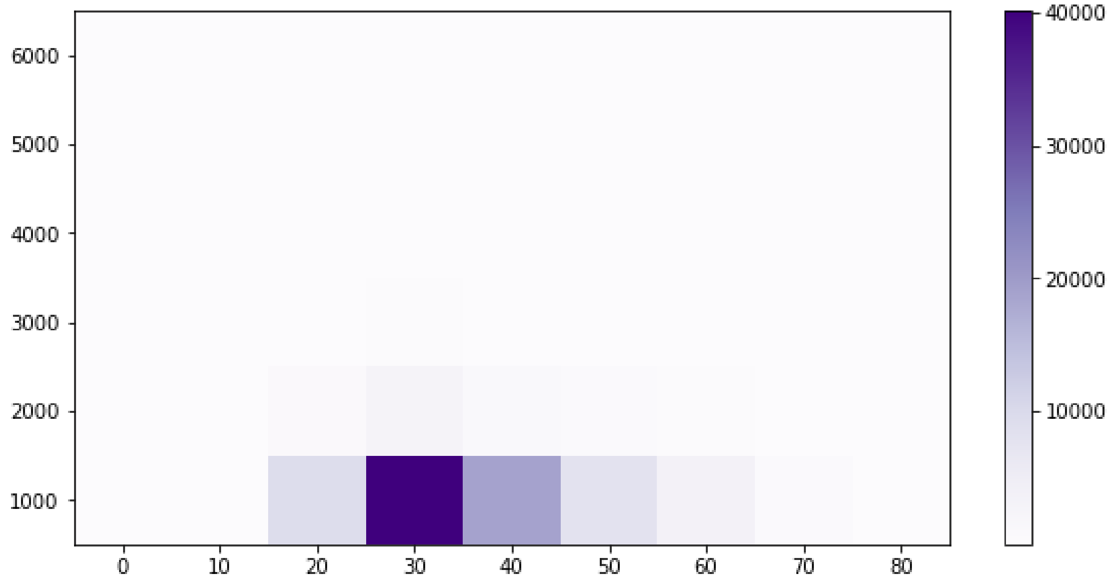
1.5 Bivariate Exploration

First, Let's look at the relationship between two numeric variables the duration of the trip and the age of the members.

In [48]:
```
#let's plot scatterplot
plt.figure(figsize=[10,5])
plt.scatter(data = go_bikes_master, x = 'member_age', y='duration_sec', alpha = 0.25, m
plt.axis([0, 100, 0, 1e4])
plt.xlabel('Age (years)')
plt.ylabel('Duaration (sec)')
plt.title('Relationship Between The Duration Of The Trip And The Age',
            y=1.03, fontsize=14, fontweight='semibold')
plt.show()
```



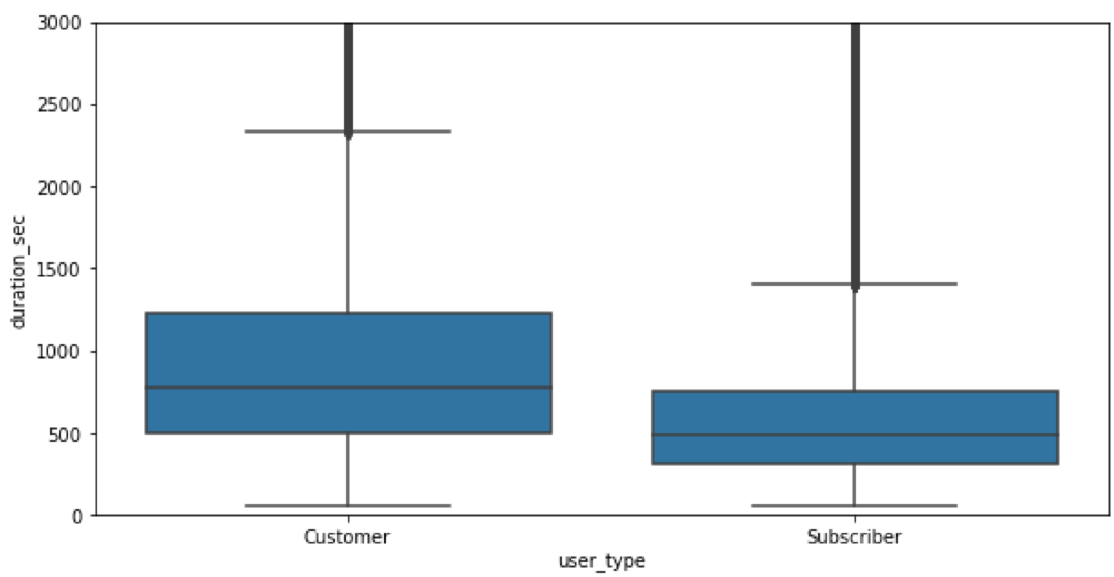
In [49]:
```
#the plot above looks a bit messy, let's use a heat map to depict the data.
plt.figure(figsize=[10,5])
bins_y = np.arange(500, 6500+1, 1000)
bins_x = np.arange(-5, 85+1, 10)
plt.hist2d(data = go_bikes_master, x = 'member_age', y='duration_sec',
           bins = [bins_x, bins_y], cmap ='Purples')
plt.colorbar(ticks=[1e4, 2e4, 3e4, 4e4])
plt.show()
```



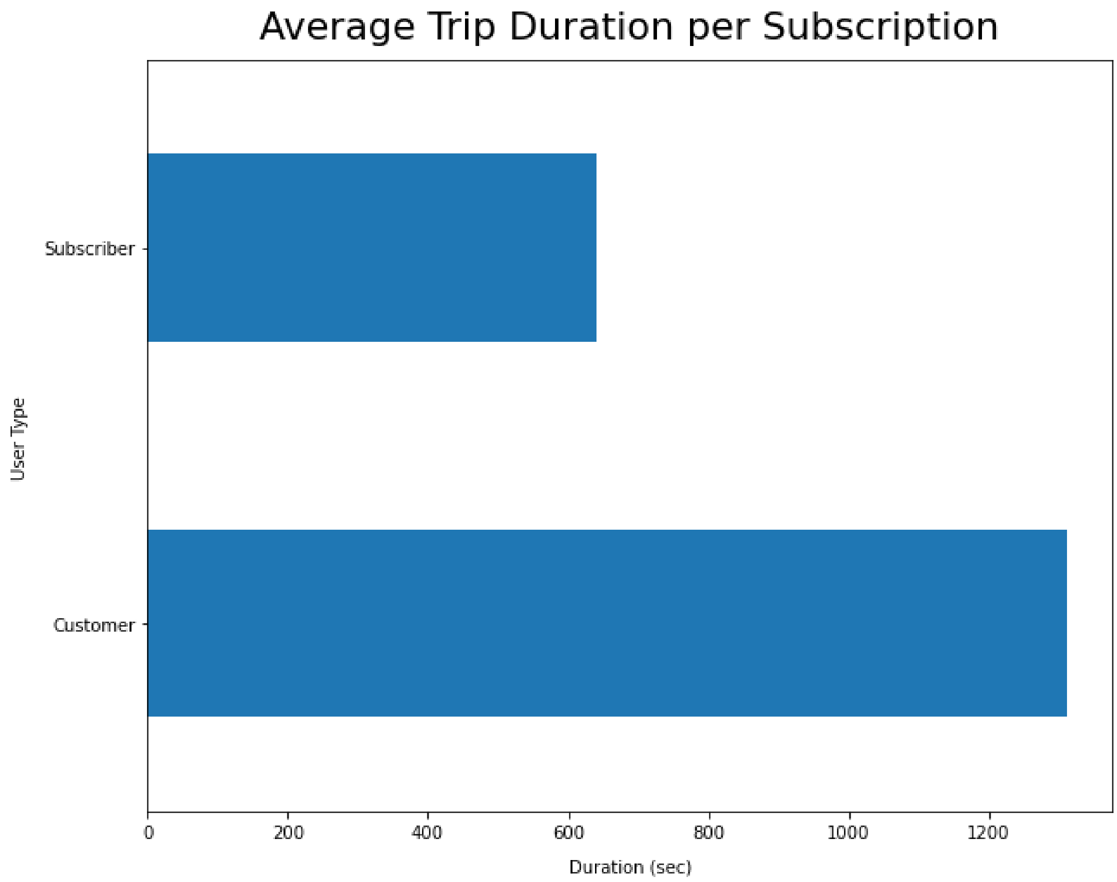
The relationship between the two variables is negative. Visualization shows that the longest trips were made by people aged 25 to 35 years. As we already know, this age group is the most popular among users.

Now, let's look at relationship between the numeric variables - duration of the trip and categorical variables - subscriptions

In [50]:
```
fig, ax = plt.subplots(figsize = (10,5))
sb.boxplot(data=go_bikes_master, x='user_type', y='duration_sec', color=base_color)
plt.ylim([0, 3e3])
plt.show()
```

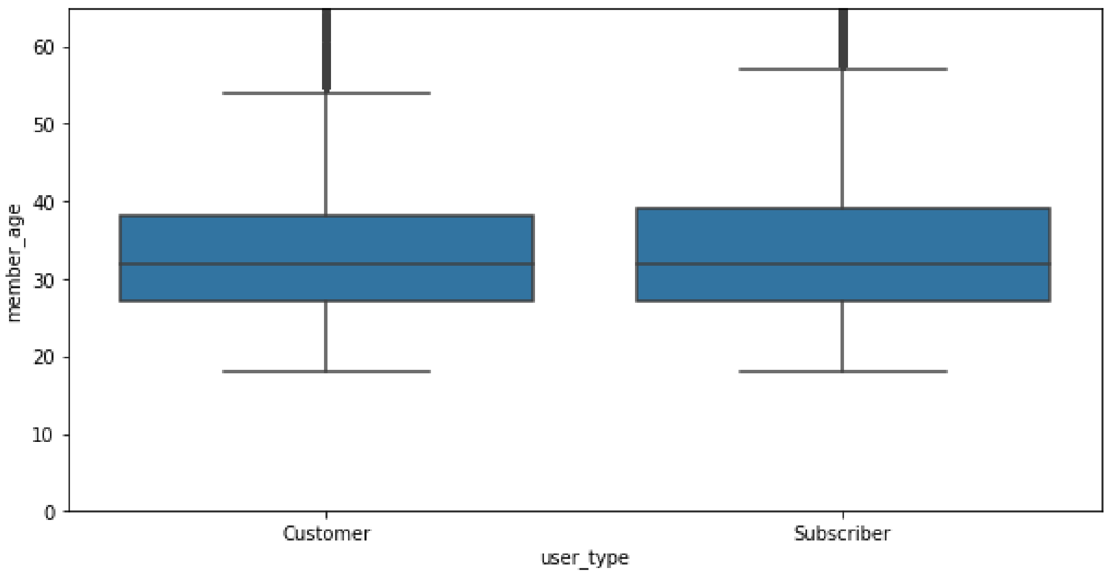


```
In [51]: #let's create bar charwith the average duration of trips
         ax = go_bikes_master.groupby('user_type')['duration_sec'].mean().plot(kind='barh', figs
         ax.set_title('Average Trip Duration per Subscription', fontsize=22, y=1.015)
         ax.set_ylabel('User Type', labelpad=8)
         ax.set_xlabel('Duration (sec)', labelpad=10);
```



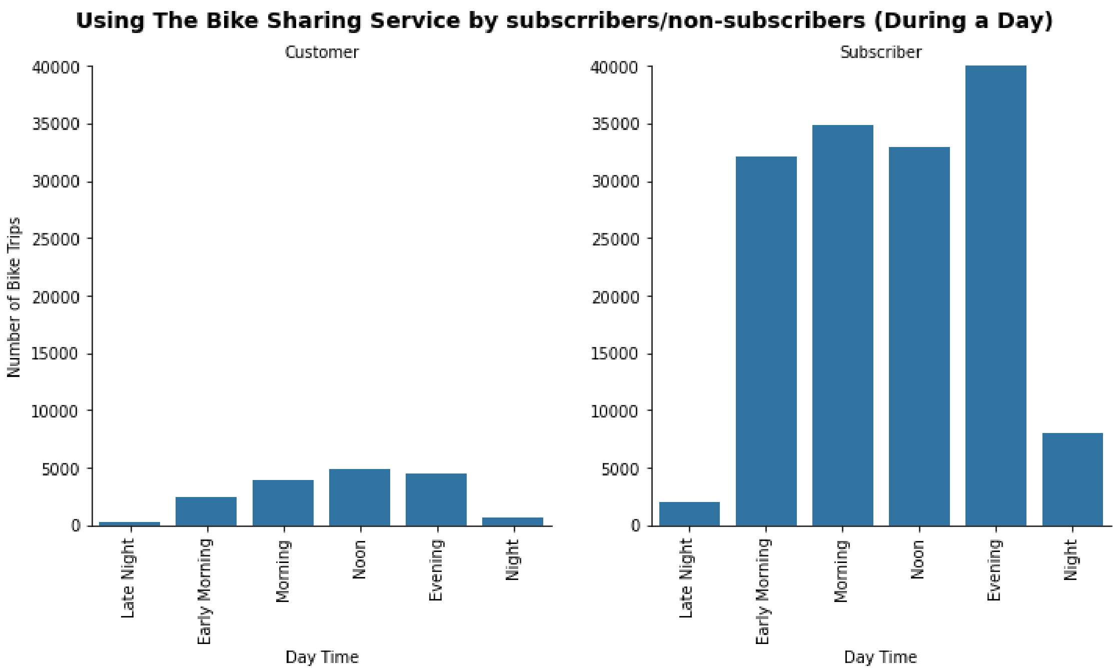
Visualization shows that on average, customers took longer rides than subscribers. let's look at relationship between members age and subscriptions

```
In [52]: fig, ax = plt.subplots(figsize = (10,5))
         sb.boxplot(data=go_bikes_master, x='user_type', y='member_age', color=base_color)
         plt.ylim([0, 65])
         plt.title('',
                       y=1.03, fontsize=14, fontweight='semibold')
         plt.show()
```

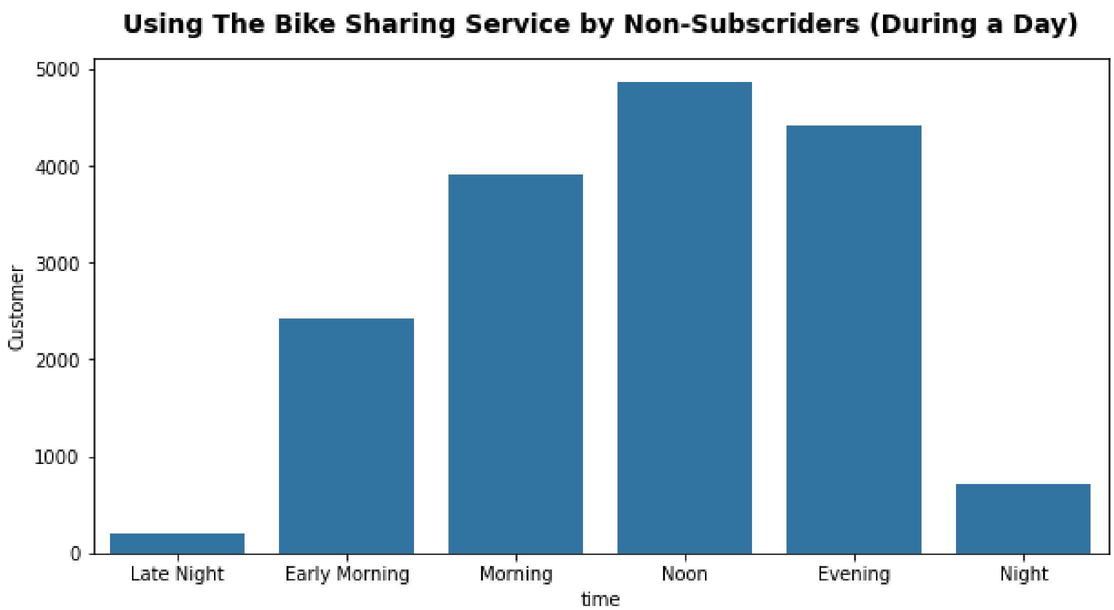


It seems that both groups have the same age distribution
Next, let's look at how subscribers and non-subscribers use the service during day and week

In [53]:
```
#let's plot the difference in the use of the service during the day
g = sb.catplot(data=go_bikes_master, x='time', col='user_type', kind='count', sharex =
            color = base_color)
g.set_axis_labels('Day Time', 'Number of Bike Trips')
g.set_titles("{col_name}")
g.fig.suptitle('Using The Bike Sharing Service by subscrribers/non-subscribers (During
               y=1.03, fontsize=14, fontweight='semibold')
g.set_xticklabels(rotation=90)
g.set(ylim=(0, 4e4));
```

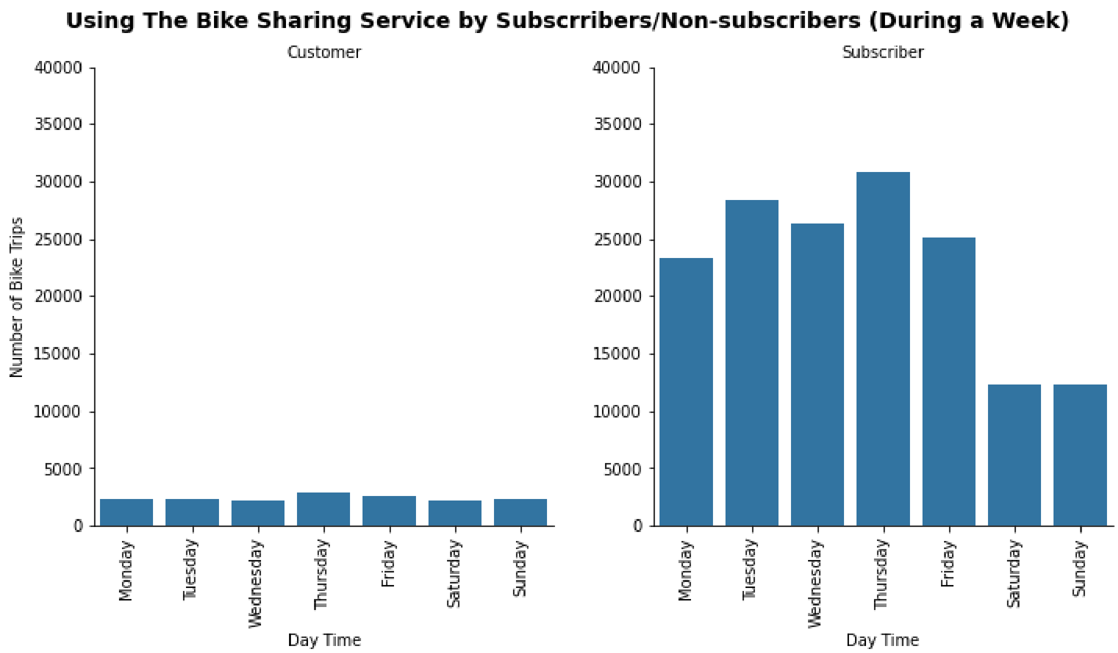


In [54]:
```
#let's zoom the plot for customers
n_time_cust = go_bikes_master.groupby(['time', 'user_type']).size()
n_time_cust = n_time_cust.reset_index(name='count')
n_time_cust = n_time_cust.pivot(index = 'time', columns = 'user_type', values = 'count'
n_time_cust=n_time_cust.reset_index()

plt.figure(figsize = (10,5))
sb.barplot(data=n_time_cust, x='time', y='Customer', color=base_color)
plt.title('Using The Bike Sharing Service by Non-Subscriders (During a Day)',
               y=1.03, fontsize=14, fontweight='semibold')
plt.show()
```

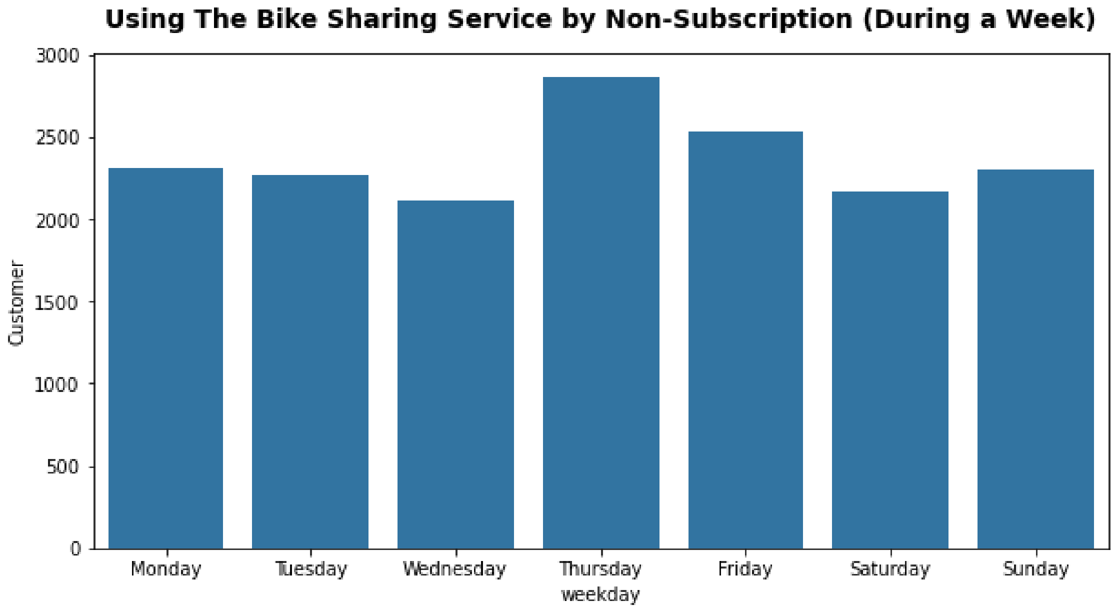


As we already know, subscribers exceed the number of non-subscribers, so we see this in the graphs above. Subscribers used the service from early morning to evening, and customers mostly use the service closer to noon and at evening. Both groups rarely use the service at night.

```
In [55]: #let's plot the difference in the use of the service during the week
         g = sb.catplot(data=go_bikes_master, x='weekday', col='user_type', kind='count', sharex
                     color = base_color)
         g.set_axis_labels('Day Time', 'Number of Bike Trips')
         g.set_titles("{col_name}")
         g.fig.suptitle('Using The Bike Sharing Service by Subscrribers/Non-subscribers (During
                        y=1.03, fontsize=14, fontweight='semibold')
         g.set_xticklabels(rotation=90)
         g.set(ylim=(0, 4e4));
```

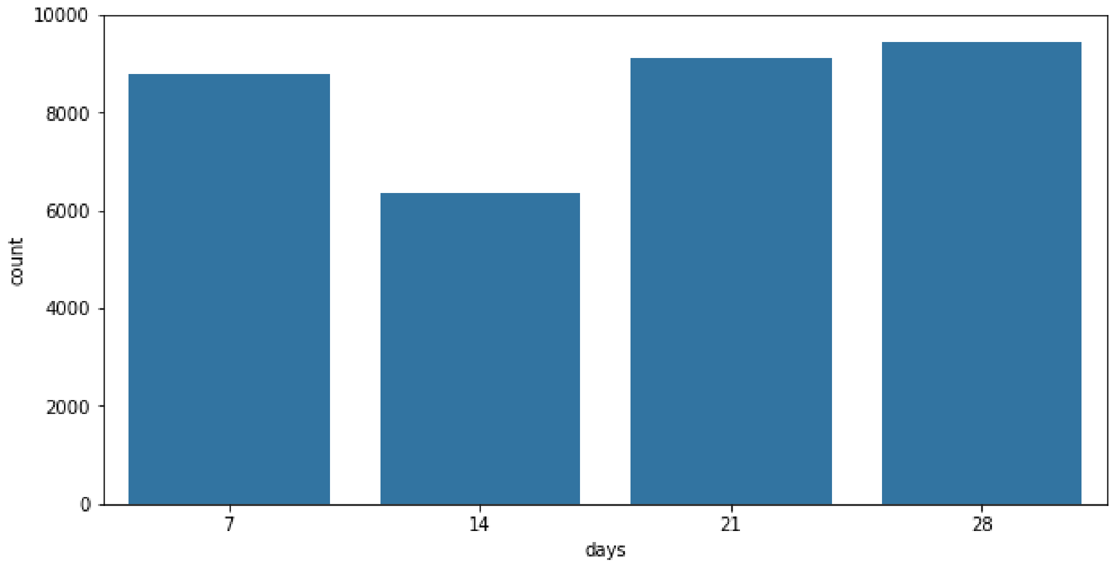


In [56]:
```
#let's zoom the plot for customers
n_week_cust = go_bikes_master.groupby(['weekday', 'user_type']).size()
n_week_cust = n_week_cust.reset_index(name='count')
n_week_cust = n_week_cust.pivot(index = 'weekday', columns = 'user_type', values = 'cou
n_week_cust=n_week_cust.reset_index()

plt.figure(figsize = (10,5))
sb.barplot(data=n_week_cust, x='weekday', y='Customer', color=base_color)
plt.title('Using The Bike Sharing Service by Non-Subscription (During a Week)',
               y=1.03, fontsize=14, fontweight='semibold')
plt.show()
```



Subscribers most often used the service on working days, in contrast to customers who used the service throughout a week. Interestingly, both groups used the service most on Thursday, perhaps this is due to the fact that February 14 was on Thursday.

```
In [57]: #so, let's check this assumption
         # sort data by Thursdays
         thursdays = go_bikes_master.query('weekday =="Thursday"').copy()
         thursdays['days'] = thursdays['start_time'].dt.strftime("%d")
         thursdays['days'] = thursdays['days'].astype(int)

         plt.figure(figsize = (10,5))
         sb.countplot(data = thursdays, x = 'days', color = base_color)
         plt.ylim([0, 10e3])
         plt.show()
```

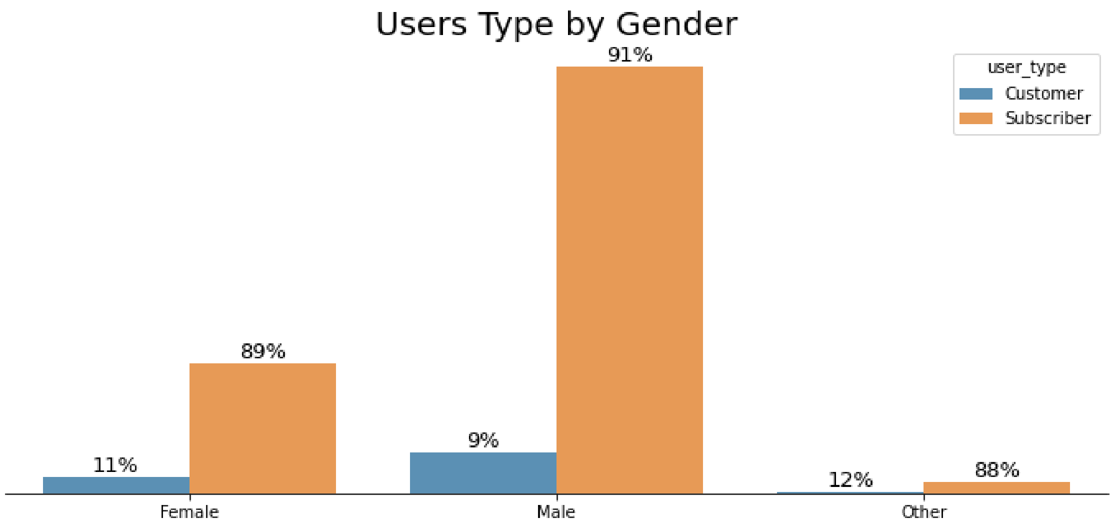


This assumption was not confirmed, on February 14, fewer trips were made than on other Thursdays.

Let's look at the gender distribution by user type

```
In [58]: fig, ax = plt.subplots(figsize = (12,5))
         sb.countplot(data = go_bikes_master, x = 'member_gender',
                      hue = "user_type", alpha = 0.8)
         # Percentage for each gender
         perc_list_customer, perc_list_subscriber, perc_list = [], [], []
         type_sum = go_bikes_master.groupby('member_gender')['user_type'].value_counts().sort_in
         total_sum = go_bikes_master['member_gender'].value_counts().sort_index().to_list()

         # arrange the % list in same as annotate loop order
         for i in range(0,len(total_sum)):
             perc_customer = int(round(100 * type_sum[2*i] / total_sum[i]))
             perc_list_customer.append(perc_customer)
         for i in range(0,len(total_sum)):
             perc_subscriber = int(round(100 * type_sum[2*i+1]/ total_sum[i]))
             perc_list_subscriber.append(perc_subscriber)
         perc_list = perc_list_customer + perc_list_subscriber

         # annotate each bar
         i=0
         for p in ax.patches:
             ax.annotate('{:.0f}%'.format(perc_list[i]),
                         (p.get_x()+p.get_width()/2, p.get_height()),
                         ha="center", va="bottom", color='black', size=13)
             i+=1
```

```
cur_axes = plt.gca()
cur_axes.axes.get_yaxis().set_visible(False)
sb.despine(fig, left = True)
plt.title('Users Type by Gender', fontsize= 20)
plt.xlabel('');
```



1.5.1 Talk about some of the relationships you observed in this part of the investigation. How did the feature(s) of interest vary with other features in the dataset?

Subscribers used the service more often from early morning until the end of the working day, mainly on working days. This may mean that they used the service for commuting or for work. Customers used the service throughout a week. Interestingly, both groups used the service most on Thursday. I assumed that this was due to the fact that February 14 is Thursday, but this assumption was not confirmed. In addition, it was unexpected to find that customers made longer trips than subscribers

1.5.2 Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

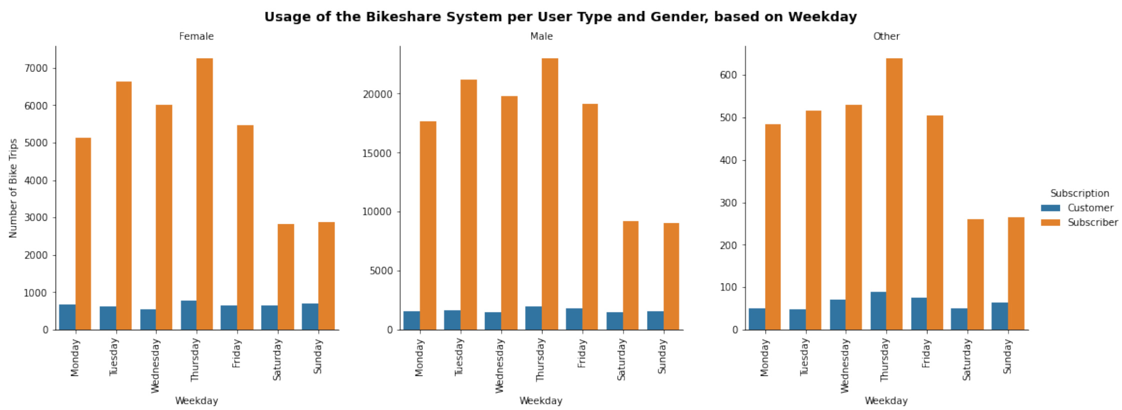
The longest trips were made by people aged 25 to 35 years

1.6 Multivariate Exploration

First, I will analyze the distributions between customer and subscriber, depending on gender and usage on weekdays.

```
In [59]: #let's plot
         g = sb.catplot(data=go_bikes_master, x='weekday', col='member_gender', hue='user_type',
                        kind='count', sharey = False)
         g.set_axis_labels("Weekday", "Number of Bike Trips")
```

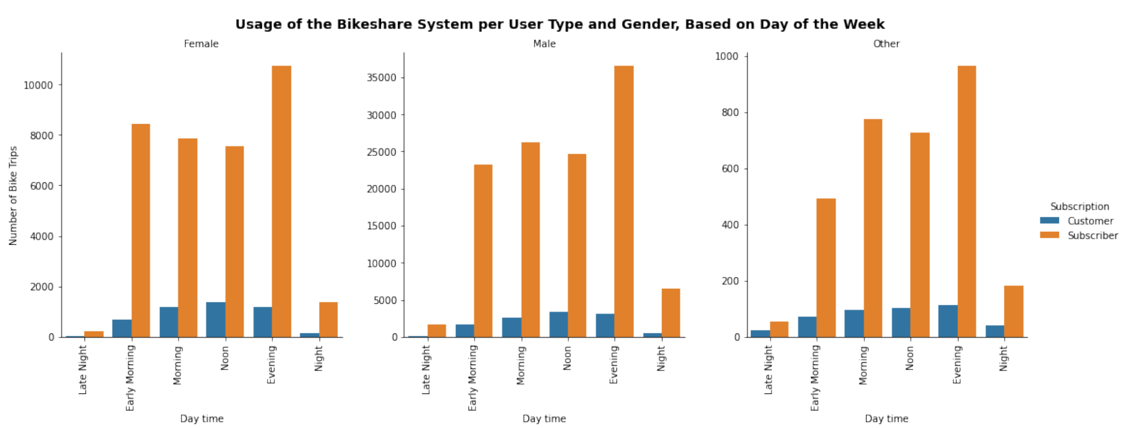
```
g._legend.set_title('Subscription')
g.set_titles("{col_name}")
g.fig.suptitle('Usage of the Bikeshare System per User Type and Gender, based on Weekda
               y=1.03, fontsize=14, fontweight='semibold')
g.set_xticklabels(rotation=90);
```



The distribution of the number of trips made by women corresponds to the distribution of the number of trips made by men

Now, I will analyze the distributions between customer and subscriber, depending on gender and usage during the day.

```
In [60]: #create faceted plot
         g = sb.catplot(data=go_bikes_master, x='time', col='member_gender', hue='user_type',
                        kind='count', sharey = False)
         g.set_axis_labels("Day time", "Number of Bike Trips")
         g._legend.set_title('Subscription')
         g.set_titles("{col_name}")
         g.fig.suptitle('Usage of the Bikeshare System per User Type and Gender, Based on Day of
                        y=1.03, fontsize=14, fontweight='semibold')
         g.set_xticklabels(rotation=90);
```

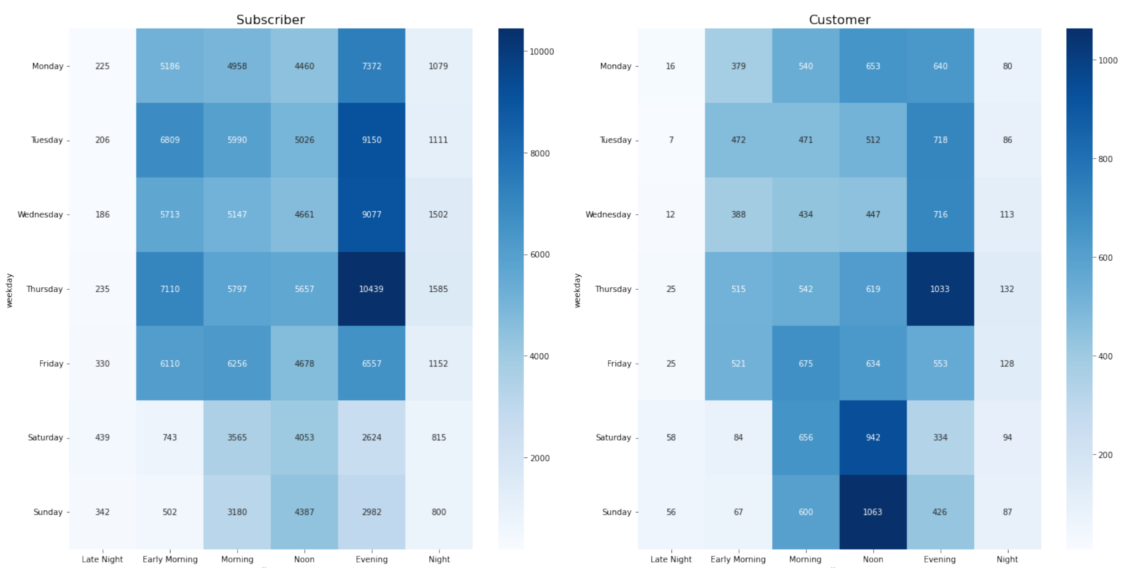


It seems that women with subscriptions started their trips earlier than men.

Let's create a heat map to visualize when trips most often start among subscribers and customers

In [61]:
```
# create dataframe for subscriber
subscriber = go_bikes_master.query('user_type == "Subscriber"').groupby(['time','weekda
                                                                        ).agg({'bike_id'
subscriber = subscriber.pivot_table(index='weekday', columns='time', values='bike_id')
# create dataframe for customer
customer = go_bikes_clean.query('user_type == "Customer"').groupby(['weekday','time']).
customer = customer.pivot_table(index='weekday', columns='time', values='bike_id')
```

In [62]:
```
#plot heatmap
plt.subplots(figsize=(20,10))

fig1 = plt.subplot(1,2,1)
ax1 = sb.heatmap(subscriber, annot=True, fmt='d', cmap='Blues')

plt.title('Subscriber',size=16)
plt.yticks(rotation=360)

fig2 = plt.subplot(1,2,2)
ax2 = sb.heatmap(customer, annot=True, fmt='d', cmap='Blues')

plt.title('Customer',size=16)
plt.yticks(rotation=360)
plt.tight_layout();
```



According to the heatmat above, subscribers used the service more often in the evening - the most popular time to use the service was Thursday evening. Customers used the service mainly in the evening as subscribers, but also on weekends afternoon.

1.6.1 Talk about some of the relationships you observed in this part of the investigation. Were there features that strengthened each other in terms of looking at your feature(s) of interest?

Multivariate charts have strengthened the previously observed relationships. Subscribers most often used the service on weekdays (especially in the evening), and customers preferred to use the bike sharing service on weekends. It was almost unaffected by gender.

1.6.2 Were there any interesting or surprising interactions between features?

Interestingly, women with subscriptions started their trips earlier than men.

1.7 Conclusions

1. Most of users Ford GoBike service are subscribers (91%);
2. The majority of users are men both among subscribers and customers;
3. The majority of users are people between the ages of 25 and 35, both among subscribers and customers;
4. Subscribers mostly use the service during the working week, especially in the evening, while customers use the service throughout the week, especially around noon on weekends. Perhaps subscribers used the service to travel to work or at work, and customers for entertainment. It is worth noting that the trips of customers on average lasted much longer.

```
In [ ]:
```