exploration_template

April 20, 2021

1 2019.02 Ford Go Bike - tripdata

1.1 by Szymon Debski

1.2 Preliminary Wrangling

This data set is taken from https://www.fordgobike.com/system-data and represents trips taken by members of the service for month of February of 2019.

Data consists of info about trips taken by service's members, their types, their age, their gender, stations of starting and ending trips, duration of trips etc.

[147]:
```
# 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

%matplotlib inline

import warnings
warnings.simplefilter("ignore")
```

Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

[148]:
```
df = pd.read_csv('201902-fordgobike-tripdata.csv')
df.head()
```

[148]:
```
   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    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

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

[149]:
```
df.shape
```

[149]:
```
(183412, 16)
```

[150]:
```
df.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
```

[151]:
```
df.describe()
```

[151]:
```
        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
```

1.2.1 Data Cleaning

[152]:
```
df_clean = df.copy()
```

Remove columns that are not of interest to me

[153]:
```
list(df_clean.columns)
```

[153]:
```
['duration_sec',
 'start_time',
 'end_time',
 'start_station_id',
 'start_station_name',
 'start_station_latitude',
 'start_station_longitude',
 'end_station_id',
 'end_station_name',
 'end_station_latitude',
 'end_station_longitude',
 'bike_id',
 'user_type',
 'member_birth_year',
 'member_gender',
 'bike_share_for_all_trip']
```

[154]:
```
df_clean.drop(['start_station_id',
 'start_station_name',
 'start_station_latitude',
 'start_station_longitude',
 'end_station_id',
 'end_station_name',
 'end_station_latitude',
 'end_station_longitude'], axis=1, inplace=True)
```

[155]:
```
df_clean.head()
```

[155]:
```
   duration_sec                start_time                  end_time  bike_id  \
0         52185  2019-02-28 17:32:10.1450  2019-03-01 08:01:55.9750     4902
1         42521  2019-02-28 18:53:21.7890  2019-03-01 06:42:03.0560     2535
2         61854  2019-02-28 12:13:13.2180  2019-03-01 05:24:08.1460     5905
3         36490  2019-02-28 17:54:26.0100  2019-03-01 04:02:36.8420     6638
4          1585  2019-02-28 23:54:18.5490  2019-03-01 00:20:44.0740     4898

    user_type  member_birth_year member_gender bike_share_for_all_trip
0    Customer             1984.0          Male                      No
1    Customer                NaN           NaN                      No
2    Customer             1972.0          Male                      No
3  Subscriber             1989.0         Other                      No
4  Subscriber             1974.0          Male                     Yes
```

[156]:
```
df_clean.isnull().sum()
```

[156]:
```
duration_sec                 0
start_time                   0
end_time                     0
bike_id                      0
user_type                    0
member_birth_year         8265
member_gender             8265
bike_share_for_all_trip      0
dtype: int64
```

Drop records with null values

[157]:
```
df_clean = df_clean[df_clean['member_birth_year'].isnull() == False]
```

[158]:
```
df_clean.isnull().sum()
```

[158]:
```
duration_sec               0
start_time                 0
end_time                   0
bike_id                    0
user_type                  0
member_birth_year          0
member_gender              0
bike_share_for_all_trip    0
dtype: int64
```

[159]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 175147 entries, 0 to 183411
Data columns (total 8 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             175147 non-null  int64
 1   start_time               175147 non-null  object
 2   end_time                 175147 non-null  object
 3   bike_id                  175147 non-null  int64
 4   user_type                175147 non-null  object
 5   member_birth_year        175147 non-null  float64
 6   member_gender            175147 non-null  object
 7   bike_share_for_all_trip  175147 non-null  object
dtypes: float64(1), int64(2), object(5)
memory usage: 12.0+ MB
```

[160]:
```
df_clean.user_type.value_counts()
```

[160]:
```
Subscriber    158516
Customer       16631
Name: user_type, dtype: int64
```

[161]:
```
df_clean.member_gender.value_counts()
```

[161]:
```
Male      130651
Female     40844
Other       3652
Name: member_gender, dtype: int64
```

Drop 'Other from gender column'

[162]:
```
df_clean = df_clean[df_clean['member_gender'] != 'Other']
```

[163]:
```
df_clean.member_gender.value_counts()
```

[163]:
```
Male      130651
Female     40844
Name: member_gender, dtype: int64
```

[164]:
```
df_clean.duplicated().sum()
```

[164]:
```
0
```

[165]:
```
df_clean.start_time = pd.to_datetime(df_clean['start_time'])
df_clean.end_time = pd.to_datetime(df_clean['end_time'])
```

[166]:
```
df_clean['weekday'] = df_clean['start_time'].dt.day_name()
df_clean['hour']= df_clean['start_time'].dt.hour
```

[167]:
```
df_clean.sample(1)
```

[167]:
```
       duration_sec              start_time                end_time  bike_id  \
28155           359 2019-02-25 08:57:11.110 2019-02-25 09:03:10.381     5633

        user_type  member_birth_year member_gender bike_share_for_all_trip  \
28155  Subscriber             1987.0        Female                      No

      weekday  hour
28155  Monday     8
```

[168]:
```
df_clean.weekday.value_counts()
```

[168]:
```
Thursday     33005
Tuesday      30051
Wednesday    27853
Friday       27102
Monday       25151
```

```
Sunday       14203
Saturday     14130
Name: weekday, dtype: int64
```

Create a column duration in minutes

[171]:
```
df_clean['duration_minutes'] = round(df_clean['duration_sec'] / 60, 0)
```

[172]:
```
df_clean.sample(5)
```

[172]:
```
        duration_sec              start_time                end_time  bike_id  \
182441           714 2019-02-01 08:11:47.664 2019-02-01 08:23:41.687     1469
34008            306 2019-02-24 09:48:33.715 2019-02-24 09:53:40.600     5940
142935           285 2019-02-07 16:32:46.908 2019-02-07 16:37:32.328     2848
17846            456 2019-02-26 20:23:55.220 2019-02-26 20:31:31.586     1576
121410           574 2019-02-11 15:19:28.770 2019-02-11 15:29:03.413     4895

         user_type  member_birth_year member_gender bike_share_for_all_trip  \
182441  Subscriber             1992.0        Female                      No
34008   Subscriber             1987.0          Male                      No
142935  Subscriber             1982.0          Male                      No
17846     Customer             1991.0          Male                      No
121410    Customer             1997.0          Male                      No

         weekday  hour  duration_minutes
182441    Friday     8              12.0
34008     Sunday     9               5.0
142935  Thursday    16               5.0
17846    Tuesday    20               8.0
121410    Monday    15              10.0
```

Calculate age for users of service

[173]:
```
df_clean['age'] = 2019 - df_clean['member_birth_year']
```

[174]:
```
df_clean.sample(5)
```

[174]:
```
        duration_sec              start_time                end_time  bike_id  \
78865            175 2019-02-18 18:34:18.671 2019-02-18 18:37:13.813     4909
33702            625 2019-02-24 10:50:43.535 2019-02-24 11:01:09.124     4065
25297            883 2019-02-25 17:04:49.919 2019-02-25 17:19:33.485     6353
108268           534 2019-02-13 08:57:10.372 2019-02-13 09:06:04.484     3676
157698           579 2019-02-05 20:54:28.249 2019-02-05 21:04:07.592     2859

         user_type  member_birth_year member_gender bike_share_for_all_trip  \
78865   Subscriber             1983.0          Male                      No
33702   Subscriber             1995.0          Male                     Yes
25297   Subscriber             1990.0          Male                      No
108268    Customer             1989.0          Male                      No
```

```
157698  Subscriber          1994.0        Male                        Yes

          weekday  hour  duration_minutes   age
78865      Monday    18               3.0  36.0
33702      Sunday    10              10.0  24.0
25297      Monday    17              15.0  29.0
108268  Wednesday     8               9.0  30.0
157698    Tuesday    20              10.0  25.0
```

[175]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 171495 entries, 0 to 183411
Data columns (total 12 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             171495 non-null  int64
 1   start_time               171495 non-null  datetime64[ns]
 2   end_time                 171495 non-null  datetime64[ns]
 3   bike_id                  171495 non-null  int64
 4   user_type                171495 non-null  object
 5   member_birth_year        171495 non-null  float64
 6   member_gender            171495 non-null  object
 7   bike_share_for_all_trip  171495 non-null  object
 8   weekday                  171495 non-null  object
 9   hour                     171495 non-null  int64
 10  duration_minutes         171495 non-null  float64
 11  age                      171495 non-null  float64
dtypes: datetime64[ns](2), float64(3), int64(3), object(4)
memory usage: 17.0+ MB
```

[176]:
```
df_clean['duration_minutes'] = df_clean['duration_minutes'].astype(int)
df_clean['age'] = df_clean['age'].astype(int)
```

[177]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 171495 entries, 0 to 183411
Data columns (total 12 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             171495 non-null  int64
 1   start_time               171495 non-null  datetime64[ns]
 2   end_time                 171495 non-null  datetime64[ns]
 3   bike_id                  171495 non-null  int64
 4   user_type                171495 non-null  object
 5   member_birth_year        171495 non-null  float64
 6   member_gender            171495 non-null  object
```

```
 7   bike_share_for_all_trip  171495 non-null  object
 8   weekday                  171495 non-null  object
 9   hour                     171495 non-null  int64
 10  duration_minutes         171495 non-null  int32
 11  age                      171495 non-null  int32
dtypes: datetime64[ns](2), float64(1), int32(2), int64(3), object(4)
memory usage: 15.7+ MB
```

1.2.2 What is the structure of your dataset?

The data set consists of approx. 180k bike rides in San Francisco.

The data contains:

- Trip duration
- Start / Endstation
- Bike ID
- User info (user type, date of birth, gender)

1.2.3 What is the main feature of interest in your dataset?

I'm interested in analyzing trip duration depending on user type

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

- duration_sec
- user_type
- member_birth_year
- member_gender

1.3 Univariate Exploration

In this section, investigate distributions of individual variables. If you see unusual points or outliers, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

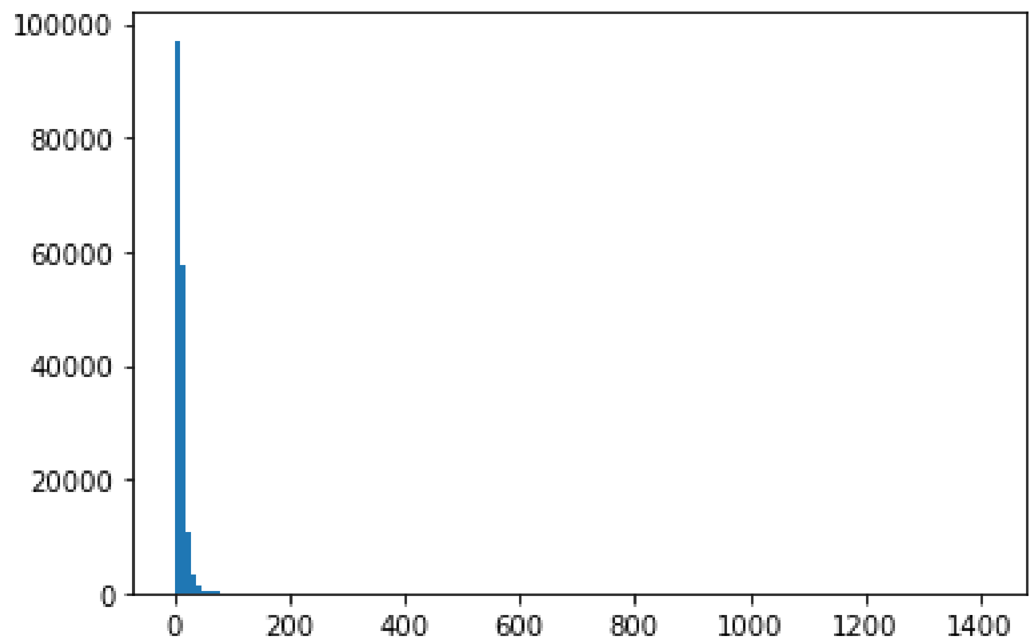
[178]:
```
df_clean.describe()
```

[178]:
```
         duration_sec        bike_id  member_birth_year           hour  \
count  171495.000000  171495.000000      171495.000000  171495.000000
mean      697.987218    4480.962868        1984.842328      13.451698
std      1576.717221    1658.635854          10.113921       4.732831
min        61.000000      11.000000        1878.000000       0.000000
25%       323.000000    3799.000000        1980.000000       9.000000
50%       510.000000    4959.000000        1987.000000      14.000000
75%       787.000000    5505.000000        1992.000000      17.000000
max     84548.000000    6645.000000        2001.000000      23.000000

       duration_minutes            age
```

```
count     171495.000000  171495.000000
mean          11.632992      34.157672
std           26.280664      10.113921
min            1.000000      18.000000
25%            5.000000      27.000000
50%            8.000000      32.000000
75%           13.000000      39.000000
max         1409.000000     141.000000
```

It seems that the 'duration_minutes' data is highly skewed to the right, most rides are short however there are some that are long we will have to take a closer look

[179]:
```
bins = np.arange(0, df_clean['duration_minutes'].max()+10, 10)
plt.hist(df_clean['duration_minutes'], bins = bins);
```



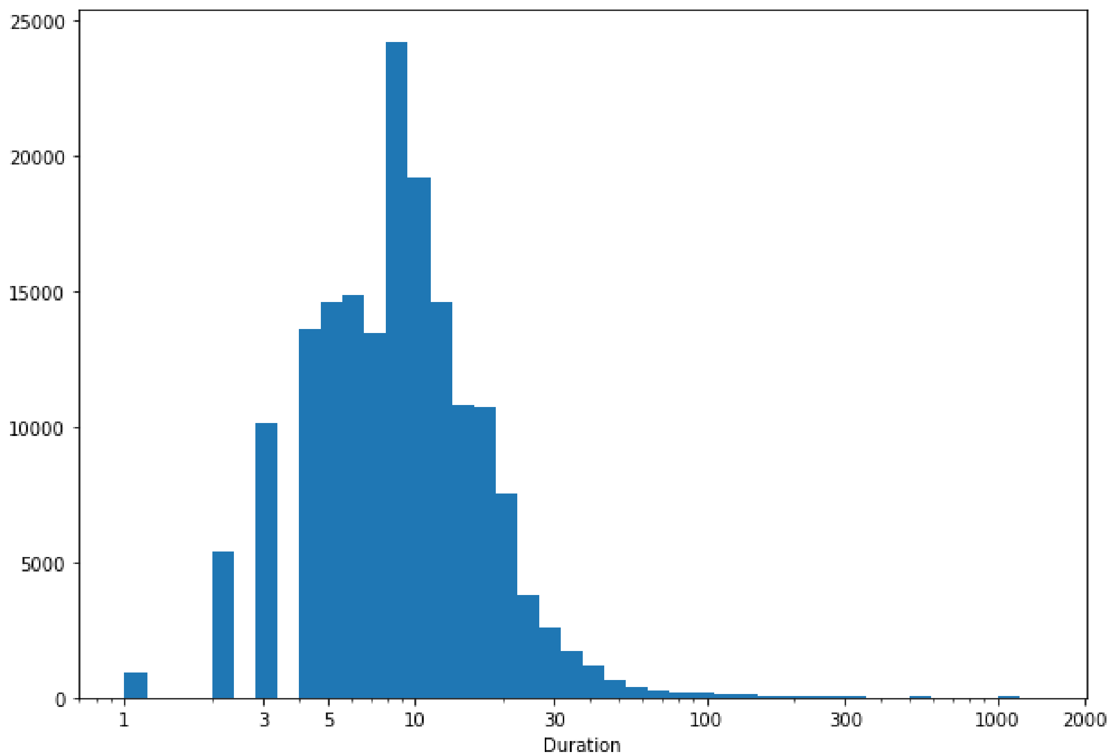
[180]:
```
np.log10(df_clean['duration_minutes'].describe())
```

[180]:
```
count    5.234251
mean     1.065691
std      1.419636
min      0.000000
25%      0.698970
50%      0.903090
75%      1.113943
max      3.148911
Name: duration_minutes, dtype: float64
```

Let's transform the scale so that we have a better look at the data. We will use the log10 transformation for the bins and use a log scale for the x-axis.

[181]:
```
bin_size = 0.075
bins = 10 ** np.arange(0, np.log10(df_clean['duration_minutes'].max()) +␣
 ↪bin_size, bin_size)

plt.figure(figsize=[10, 7]);
plt.hist(data = df_clean, x = 'duration_minutes', bins = bins);
plt.xscale('log');
ticks = [1, 3, 5, 10, 30, 100, 300, 1000, 2000]
labels = ['{}'.format(val) for val in ticks]

plt.xticks(ticks, labels)
plt.xlabel('Duration')
```

[181]:
```
Text(0.5, 0, 'Duration')
```



This looks much better. We can drop the outliers - trips longer than 100 minutes.

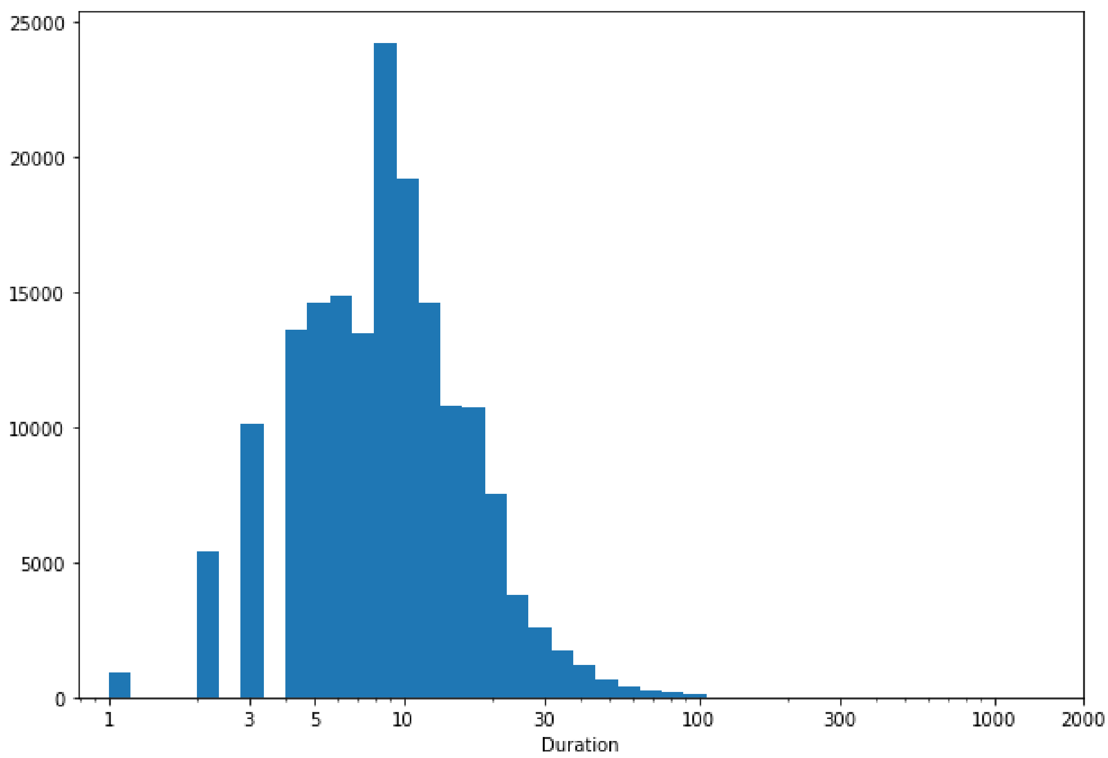
[182]:
```
df_clean = df_clean[df_clean['duration_minutes'] <= 100]
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 170834 entries, 4 to 183411
```

```
Data columns (total 12 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             170834 non-null  int64
 1   start_time               170834 non-null  datetime64[ns]
 2   end_time                 170834 non-null  datetime64[ns]
 3   bike_id                  170834 non-null  int64
 4   user_type                170834 non-null  object
 5   member_birth_year        170834 non-null  float64
 6   member_gender            170834 non-null  object
 7   bike_share_for_all_trip  170834 non-null  object
 8   weekday                  170834 non-null  object
 9   hour                     170834 non-null  int64
 10  duration_minutes         170834 non-null  int32
 11  age                      170834 non-null  int32
dtypes: datetime64[ns](2), float64(1), int32(2), int64(3), object(4)
memory usage: 15.6+ MB
```

[183]:
```
bin_size = 0.075
bins = 10 ** np.arange(0, np.log10(df_clean['duration_minutes'].max()) +␣
 ↪bin_size, bin_size)

plt.figure(figsize=[10, 7]);
plt.hist(data = df_clean, x = 'duration_minutes', bins = bins);
plt.xscale('log');
ticks = [1, 3, 5, 10, 30, 100, 300, 1000, 2000]
labels = ['{}'.format(val) for val in ticks]

plt.xticks(ticks, labels)
plt.xlabel('Duration')
```

[183]:
```
Text(0.5, 0, 'Duration')
```

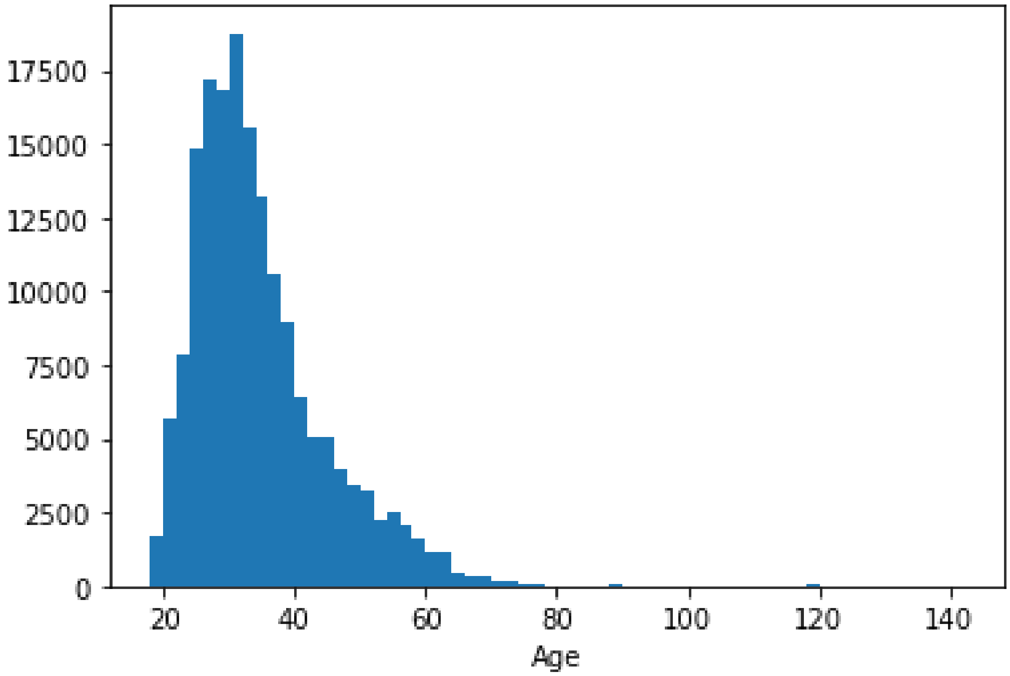


[184]:
```
df_clean['age'].describe()
```

[184]:
```
count    170834.000000
mean         34.153084
std          10.113001
min          18.000000
25%          27.000000
50%          32.000000
75%          39.000000
max         141.000000
Name: age, dtype: float64
```

Data skewed to the right plus oldest customer is 141 years old this can't be correct

[185]:
```
bins = np.arange(18, df_clean['age'].max()+2, 2)
plt.hist(df_clean['age'], bins = bins);
plt.xlabel('Age');
```



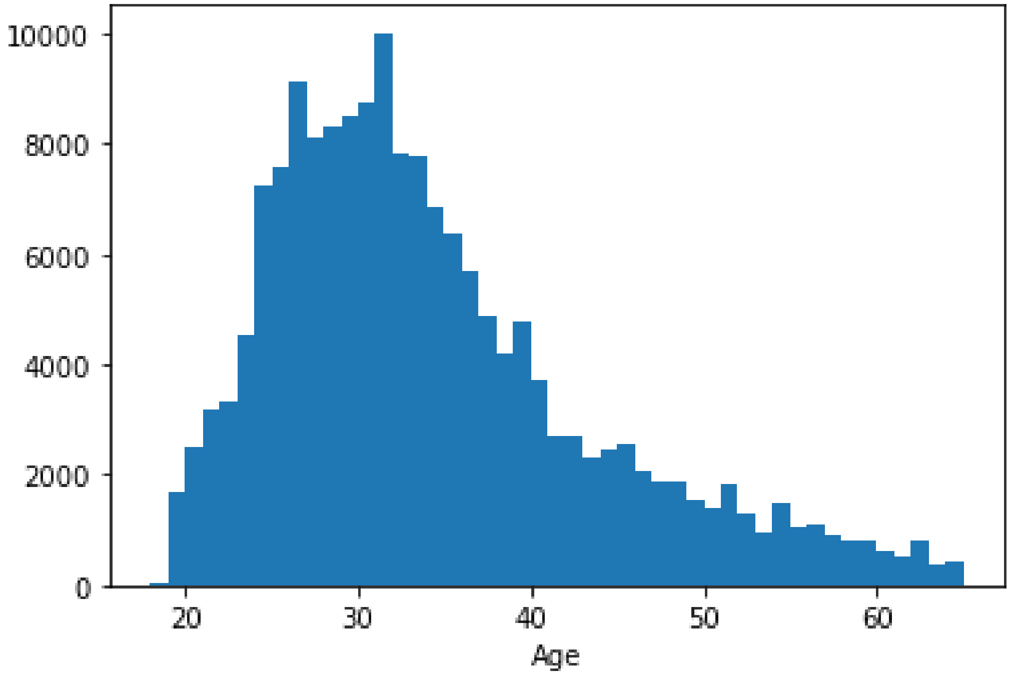
The distribution does not look good, let's drop the outliers

[186]:
```
df_clean = df_clean[df_clean['age'] <= 65]
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 169513 entries, 4 to 183411
Data columns (total 12 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   duration_sec            169513 non-null  int64
 1   start_time              169513 non-null  datetime64[ns]
 2   end_time                169513 non-null  datetime64[ns]
 3   bike_id                 169513 non-null  int64
 4   user_type               169513 non-null  object
 5   member_birth_year       169513 non-null  float64
 6   member_gender           169513 non-null  object
 7   bike_share_for_all_trip 169513 non-null  object
 8   weekday                 169513 non-null  object
 9   hour                    169513 non-null  int64
 10  duration_minutes        169513 non-null  int32
 11  age                     169513 non-null  int32
dtypes: datetime64[ns](2), float64(1), int32(2), int64(3), object(4)
memory usage: 15.5+ MB
```

This looks much better still right-skewed but in reason

[187]:
```
bins = np.arange(18, df_clean['age'].max()+1, 1)
plt.hist(df_clean['age'], bins = bins);
plt.xlabel('Age');
```



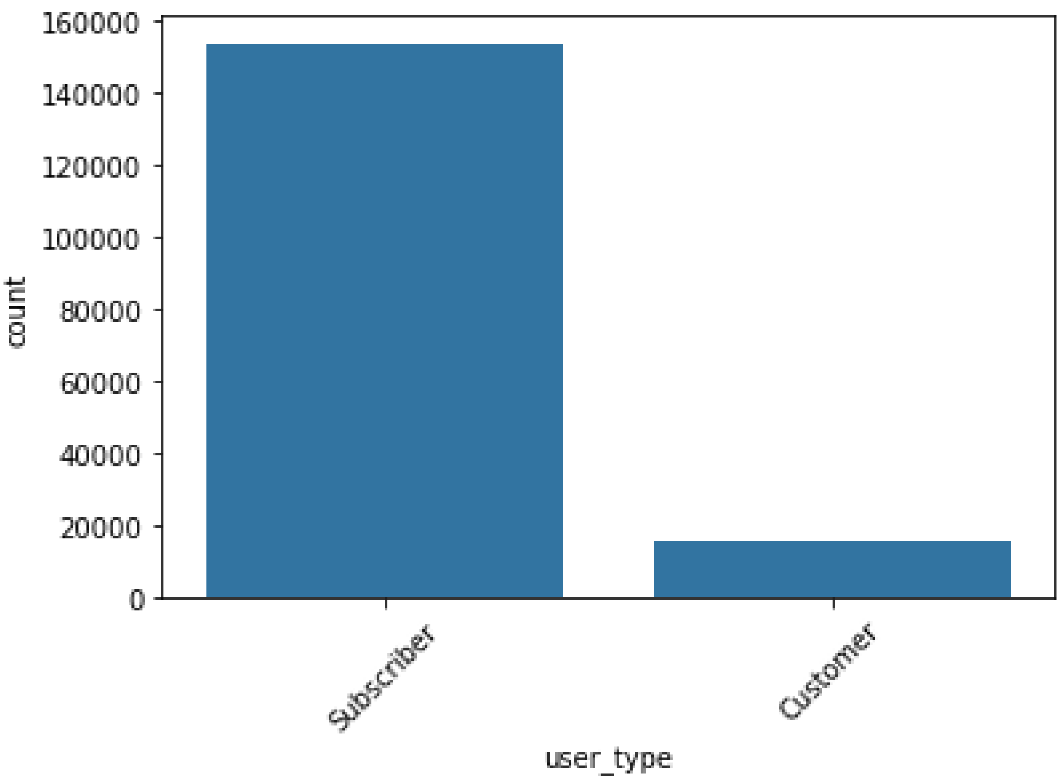
[188]:
```
df_clean.head()
```

[188]:
```
   duration_sec               start_time                 end_time  bike_id  \
4          1585 2019-02-28 23:54:18.549 2019-03-01 00:20:44.074     4898
5          1793 2019-02-28 23:49:58.632 2019-03-01 00:19:51.760     5200
6          1147 2019-02-28 23:55:35.104 2019-03-01 00:14:42.588     3803
7          1615 2019-02-28 23:41:06.766 2019-03-01 00:08:02.756     6329
9          1049 2019-02-28 23:49:47.699 2019-03-01 00:07:17.025     6488

    user_type  member_birth_year member_gender bike_share_for_all_trip  \
4  Subscriber             1974.0          Male                     Yes
5  Subscriber             1959.0          Male                      No
6  Subscriber             1983.0        Female                      No
7  Subscriber             1989.0          Male                      No
9  Subscriber             1992.0          Male                      No

    weekday  hour  duration_minutes  age
4  Thursday    23                26   45
5  Thursday    23                30   60
6  Thursday    23                19   36
```

```
7   Thursday    23                  27   30
9   Thursday    23                  17   27
```

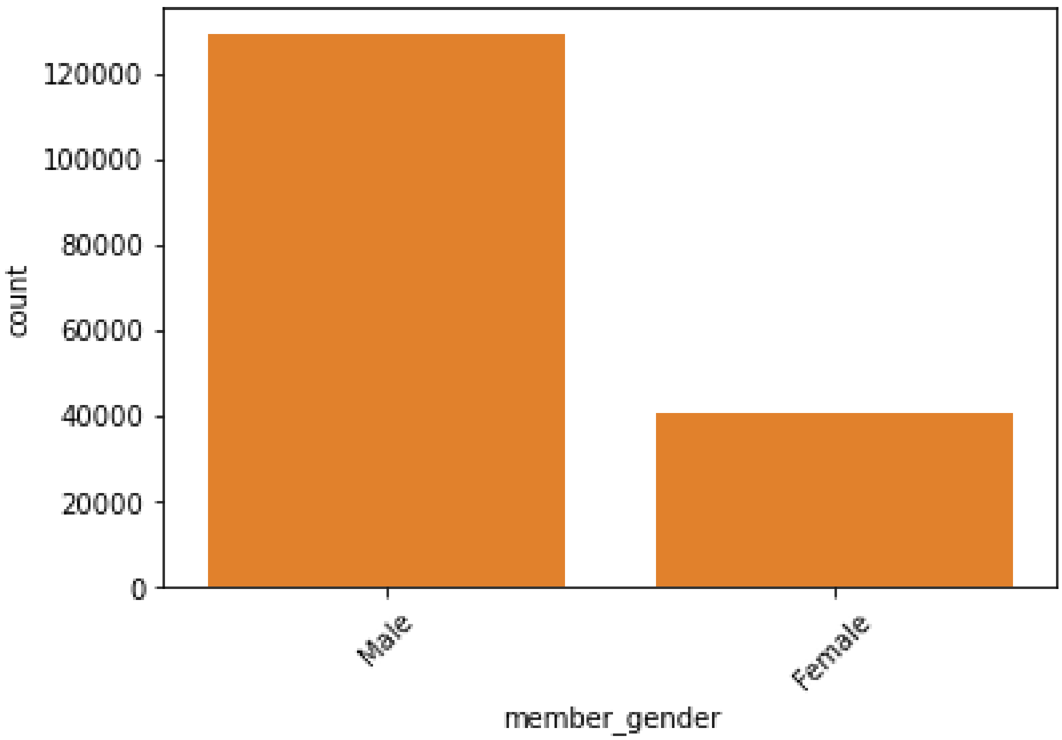
When looking at our customer base we can see that most people which use the bikes are subscribers

[189]:
```
sb.countplot(data = df_clean, x = 'user_type', color = sb.color_palette()[0])
plt.xticks(rotation = 45);
```



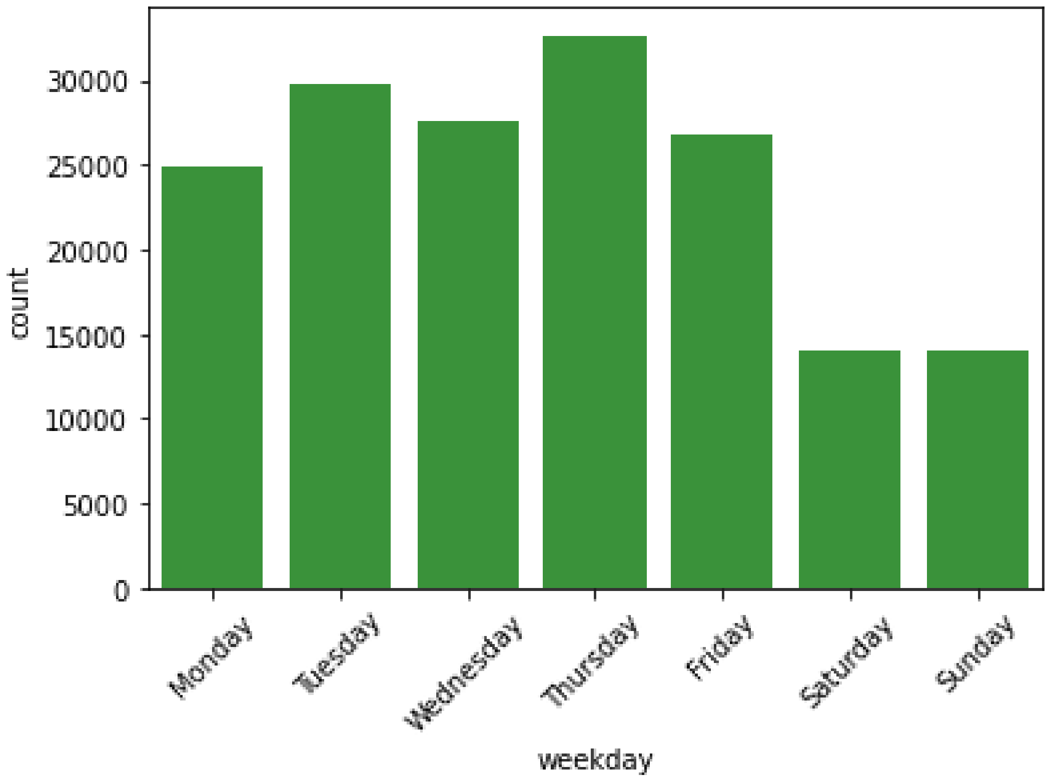
Most people using the service are Male

[190]:
```
sb.countplot(data = df_clean, x = 'member_gender', color = sb.
 ↪color_palette()[1])
plt.xticks(rotation = 45);
```



The highest numbers of rides occurred on Thursday

[191]:
```
days = [ 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
 ↪'Sunday']

sb.countplot(data = df_clean, x = 'weekday', color = sb.color_palette()[2],␣
 ↪order = days)
plt.xticks(rotation = 45);
```



Make sure that, after every plot or related series of plots, that you include a Markdown cell with comments about what you observed, and what you plan on investigating next.

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

First we analyzed the 'duration in minutes' as it is our main variable of interest. It was heavily right-skewed. We had to transform the data using a log scale which helped us get a normal distribution. We also dropped trips longer than 100 minutes which made the data even cleaner. At first glance, we can see that most trips were around 10 minutes long.

1.3.2 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?

The distribution of the 'age' variable was also heavily right-skewed. When looking closely at the age data there were some unusual data points - the oldest customer was 141 years old - which for sure is a mistake. For our analysis, I decided to drop customers older than 65 years old. This in turn made our distribution nicer - still right-skewed but in reason.

1.4 Bivariate Exploration

In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

[192]:
```
df_clean.describe()
```

[192]:

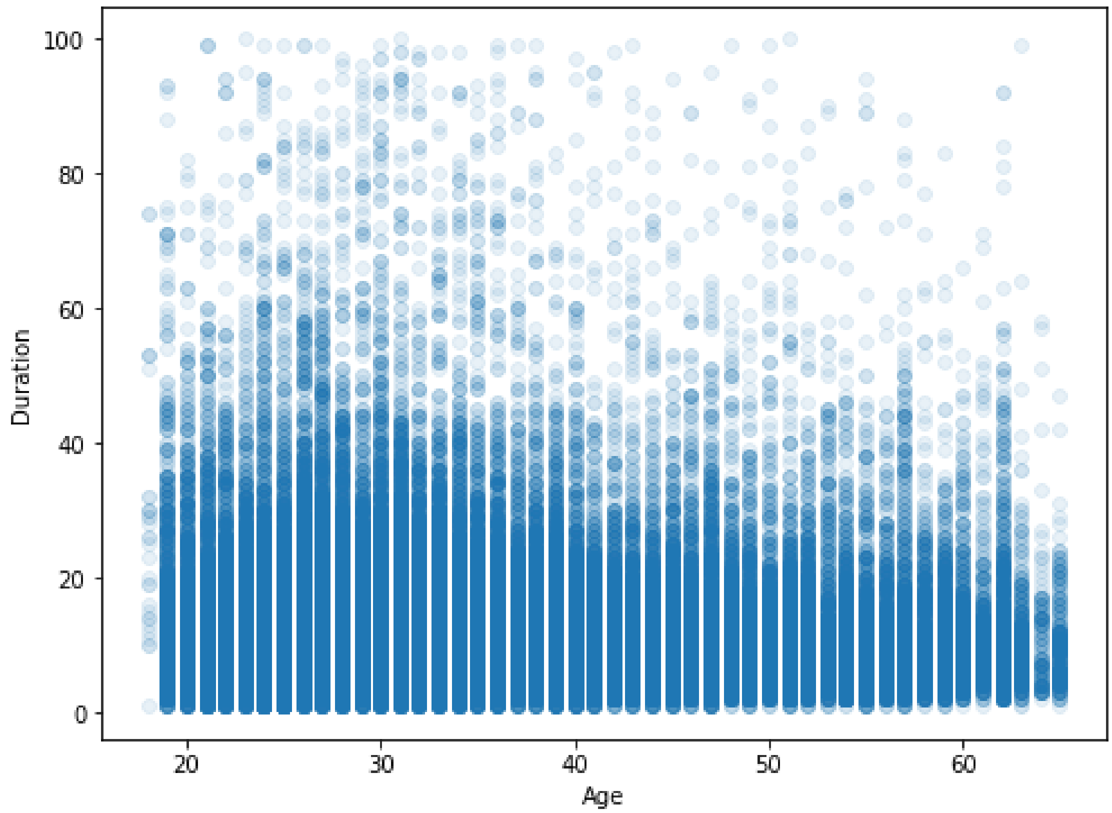
	duration_sec	bike_id	member_birth_year	hour
count	169513.000000	169513.000000	169513.000000	169513.000000
mean	632.194392	4481.961047	1985.156489	13.457404
std	504.899629	1657.785239	9.460529	4.738949
min	61.000000	11.000000	1954.000000	0.000000
25%	322.000000	3802.000000	1980.000000	9.000000
50%	508.000000	4959.000000	1987.000000	14.000000
75%	782.000000	5504.000000	1992.000000	17.000000
max	6020.000000	6645.000000	2001.000000	23.000000

\

	duration_minutes	age
count	169513.000000	169513.000000
mean	10.536478	33.843511
std	8.418791	9.460529
min	1.000000	18.000000
25%	5.000000	27.000000
50%	8.000000	32.000000
75%	13.000000	39.000000
max	100.000000	65.000000

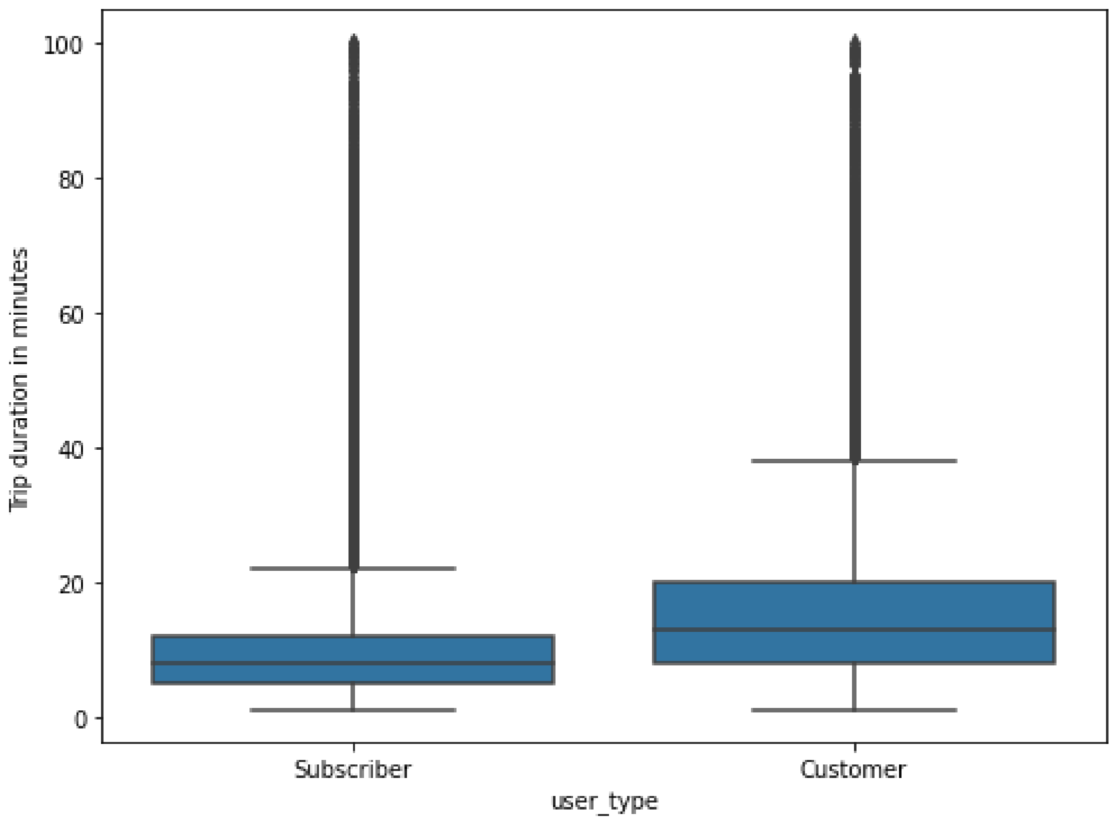
We can see a negative relationship between age and the duration of the ride - which is understandable - however, this does not mean that older people only ride for a short time there are many cases where over 65 rode for over 80 minutes.

[193]:
```
plt.figure(figsize = [8, 6])
plt.scatter(data = df_clean, x = 'age', y = 'duration_minutes', alpha = 1/10);
plt.xlabel('Age');
plt.ylabel('Duration');
```



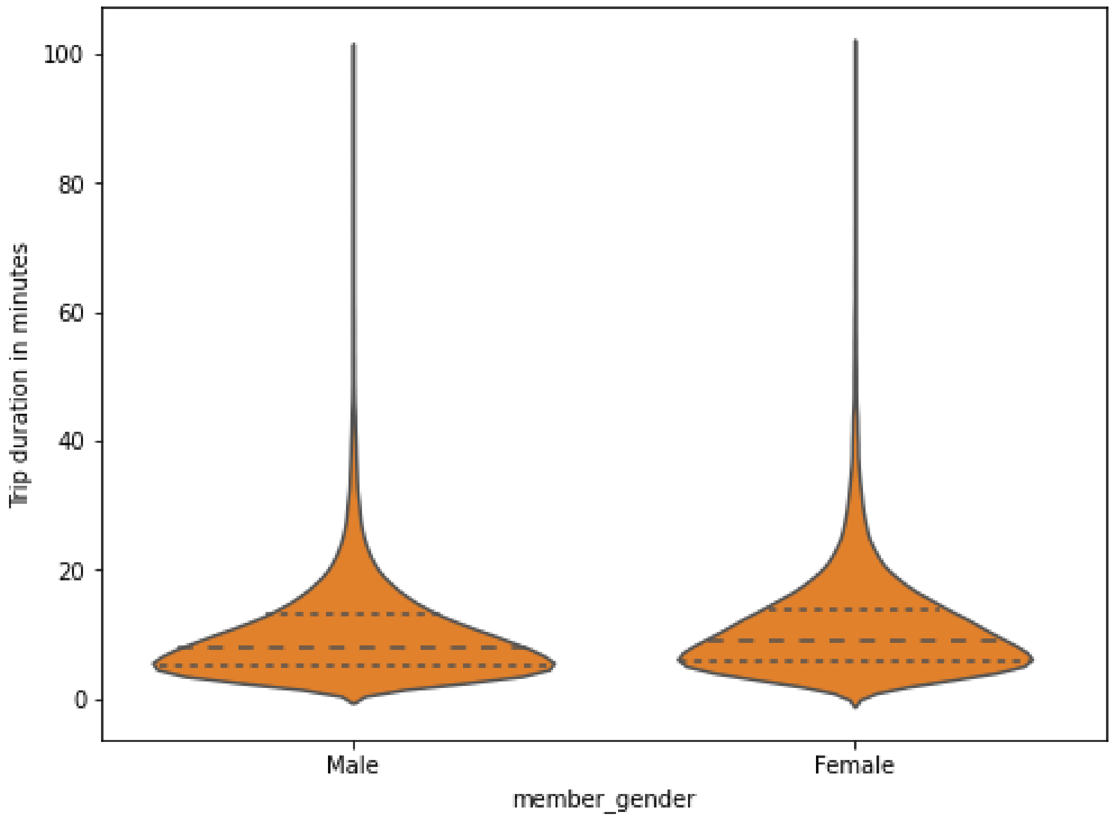
From the graph below we can see that customers overall ride for a longer time - we will take a closer look later at this relationship.

[194]:
```
plt.figure(figsize = [8, 6])
sb.boxplot(data=df_clean, x='user_type', y='duration_minutes', color=sb.
 ↪color_palette()[0]);
plt.xlabel('user_type');
plt.ylabel('Trip duration in minutes');
```



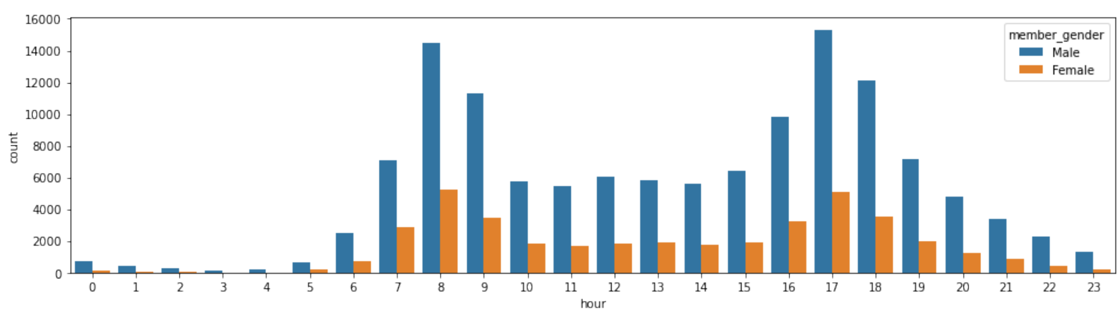
We can also see that Female users are going for longer rides on average

[195]:
```
plt.figure(figsize = [8, 6])
sb.violinplot(data=df_clean, x='member_gender', y='duration_minutes', color=sb.
 ↪color_palette()[1], inner='quartile');
plt.xlabel('member_gender');
plt.ylabel('Trip duration in minutes');
```

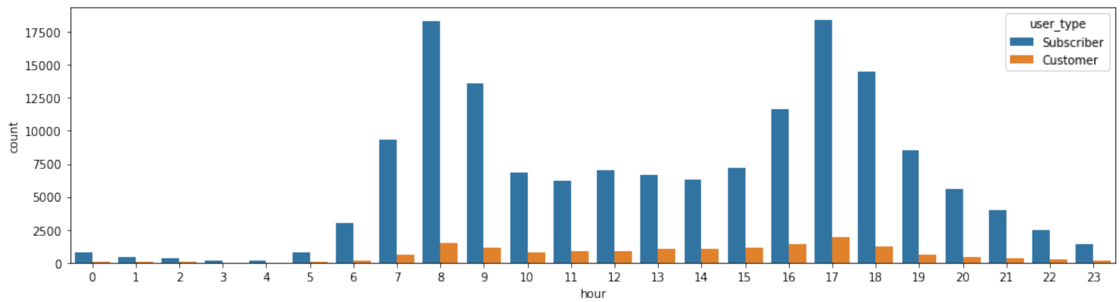


The hour at which the bikes are rented is also interesting. We can see that people mostly use the bikes around 8 AM and 5 PM. Which indicates that they are used for commuting.

[196]:
```
fig = plt.figure(figsize = [16,4])
sb.countplot(data = df_clean, x = 'hour', hue = 'member_gender');
```

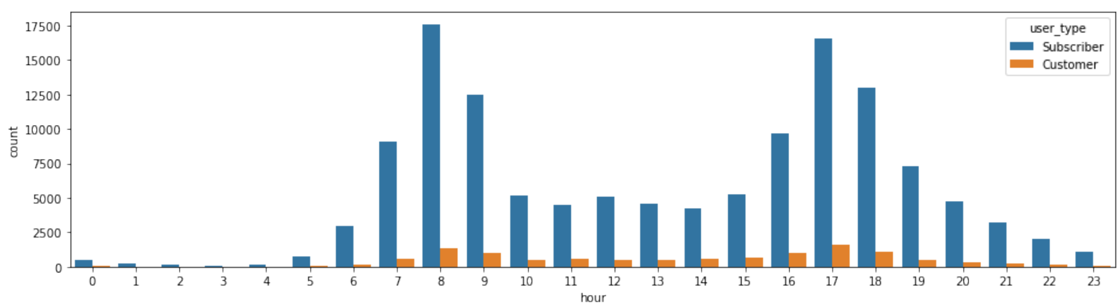


[197]:
```
fig = plt.figure(figsize = [16,4])
sb.countplot(data = df_clean, x = 'hour', hue = 'user_type');
```

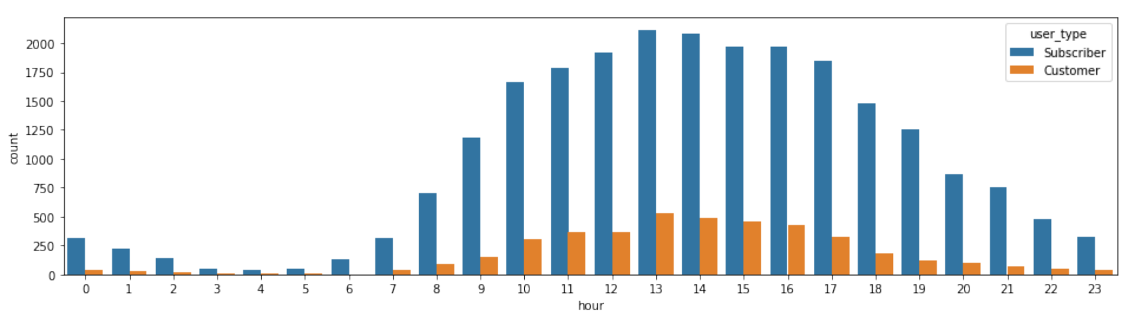


As we can see in the graph below bike renting patterns differ a lot based on whether it's the weekend or a weekday. On weekdays the bikes are used mostly during rush hours. On the weekend, on the other hand, usage is more spread out with a peak during the midday.

[198]:
```
fig = plt.figure(figsize = [16,4])
sb.countplot(data = df_clean.query('weekday == ["Monday", "Tuesday",␣
↪"Wednesday", "Thursday", "Friday"]'), x = 'hour', hue = 'user_type');
```



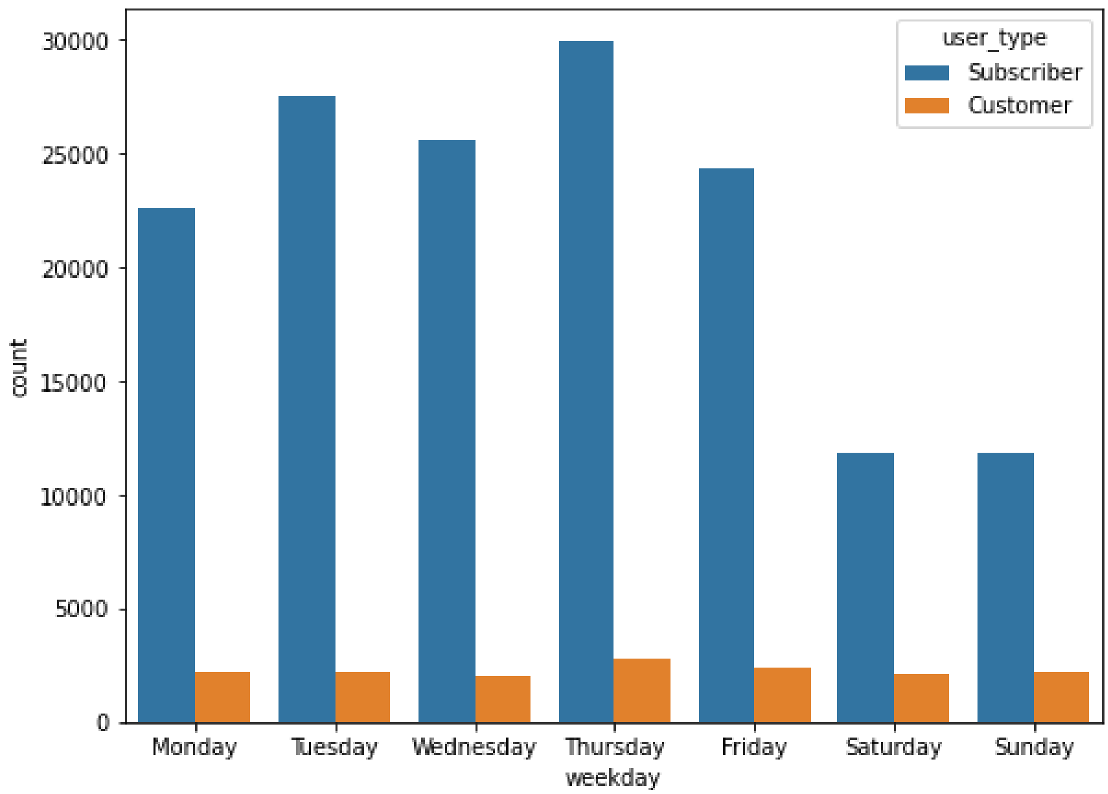
[199]:
```
fig = plt.figure(figsize = [16,4])
sb.countplot(data = df_clean.query('weekday == ["Saturday", "Sunday"]'), x =␣
↪'hour', hue = 'user_type');
```



[200]:
```
days = [ 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
↪'Sunday']
days_dtype = pd.api.types.CategoricalDtype(categories=days, ordered=True)
df_clean['weekday'] = df_clean['weekday'].astype(days_dtype)
```

Below I wanted to look at the relationship between user type and the day on which the bike is rented. Unfortunately due to the much higher number of subscribers vs customers, it's hard to make any conclusions. Let's try to transform the data.

[201]:
```
plt.figure(figsize = [8, 6])
sb.countplot(data=df_clean, x='weekday', hue='user_type');
plt.xlabel('weekday');
plt.ylabel('count');
```



[202]:
```
df_clean.user_type.value_counts()
```

[202]:
```
Subscriber    153739
Customer       15774
Name: user_type, dtype: int64
```

I will create a new data frame where I will calculate a ratio for subscribers and customer's which will help us analyze the data better.

[203]:
```
df_ratio = df_clean.groupby(['weekday', 'user_type'])['duration_sec'].count()
df_ratio = df_ratio.reset_index()
```

[204]:
```
df_ratio.rename(columns={'duration_sec': 'quantity'}, inplace=True)
```

[205]:
```
df_ratio
```

[205]:

	weekday	user_type	quantity
0	Monday	Customer	2216
1	Monday	Subscriber	22619
2	Tuesday	Customer	2197
3	Tuesday	Subscriber	27563
4	Wednesday	Customer	1997
5	Wednesday	Subscriber	25590
6	Thursday	Customer	2729
7	Thursday	Subscriber	29934
8	Friday	Customer	2418
9	Friday	Subscriber	24374
10	Saturday	Customer	2067
11	Saturday	Subscriber	11864
12	Sunday	Customer	2150
13	Sunday	Subscriber	11795

[206]:
```
df_ratio_cust = df_ratio.query('user_type == "Customer"')
df_ratio_cust
```

[206]:

	weekday	user_type	quantity
0	Monday	Customer	2216
2	Tuesday	Customer	2197
4	Wednesday	Customer	1997
6	Thursday	Customer	2729
8	Friday	Customer	2418
10	Saturday	Customer	2067
12	Sunday	Customer	2150

[207]:
```
df_ratio_sub = df_ratio.query('user_type == "Subscriber"')
df_ratio_sub
```

[207]:

	weekday	user_type	quantity
1	Monday	Subscriber	22619
3	Tuesday	Subscriber	27563
5	Wednesday	Subscriber	25590
7	Thursday	Subscriber	29934
9	Friday	Subscriber	24374
11	Saturday	Subscriber	11864
13	Sunday	Subscriber	11795

[208]:
```
df_ratio_cust = df_ratio_cust.assign(ratio=df_ratio_cust.quantity.
    ↪transform(lambda x: x / x.sum()))
```

[209]:
```
df_ratio_sub = df_ratio_sub.assign(ratio=df_ratio_sub.quantity.transform(lambda␣
    ↪x: x / x.sum()))
```

[210]:
```
df_ratio_sub
```

[210]:

	weekday	user_type	quantity	ratio
1	Monday	Subscriber	22619	0.147126
3	Tuesday	Subscriber	27563	0.179284
5	Wednesday	Subscriber	25590	0.166451
7	Thursday	Subscriber	29934	0.194707
9	Friday	Subscriber	24374	0.158541
11	Saturday	Subscriber	11864	0.077170
13	Sunday	Subscriber	11795	0.076721

[211]:
```
ratios = df_ratio_cust.append(df_ratio_sub)
```

[212]:
```
ratios
```

[212]:

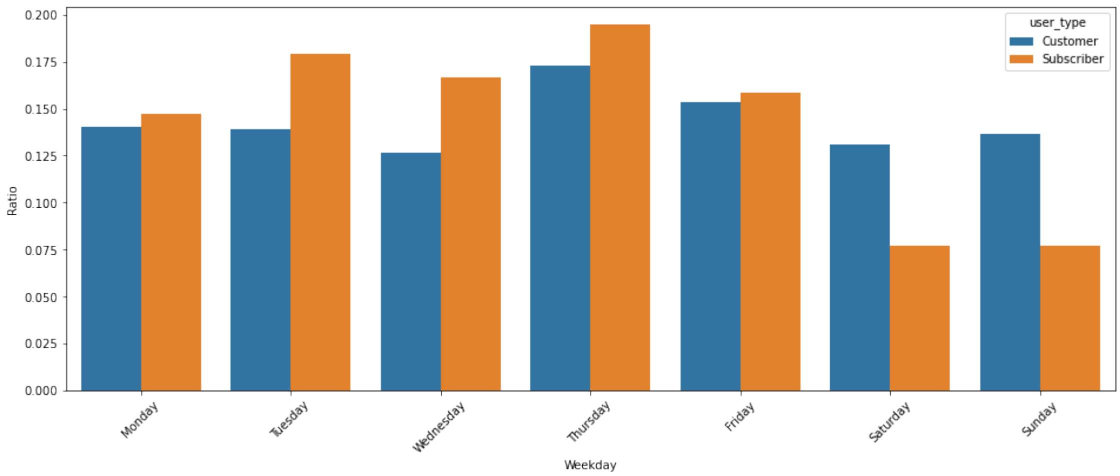
	weekday	user_type	quantity	ratio
0	Monday	Customer	2216	0.140484
2	Tuesday	Customer	2197	0.139280
4	Wednesday	Customer	1997	0.126601
6	Thursday	Customer	2729	0.173006
8	Friday	Customer	2418	0.153290
10	Saturday	Customer	2067	0.131038
12	Sunday	Customer	2150	0.136300
1	Monday	Subscriber	22619	0.147126
3	Tuesday	Subscriber	27563	0.179284
5	Wednesday	Subscriber	25590	0.166451
7	Thursday	Subscriber	29934	0.194707
9	Friday	Subscriber	24374	0.158541
11	Saturday	Subscriber	11864	0.077170
13	Sunday	Subscriber	11795	0.076721

[213]:
```
ratios.to_csv(r'ratios.csv', index = False, header=True)
```

After transforming the data we can see an interesting observation. During the working week proportionally subscribers used the service more, however, on the weekend regular customer used it proportionally more often. This means that on the weekend many casual bike riders use the service and people that use it during the week for commuting don't use the service as often.

[214]:
```
plt.figure(figsize=(16,6))
sb.barplot(x='weekday', y='ratio', hue='user_type', data=ratios);
plt.xlabel('Weekday');
```

```
plt.ylabel('Ratio');
plt.xticks(rotation = 45);
```



1.4.1 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?

From my visual analysis I can conclude that:

- With age people take shorter rides
- Customer rent the bikes for a longer time vs subscribers
- People use mostly bikes for commuting (around 8 AM and 5 PM)

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

A very interesting observation is that on weekdays on average subscribers use the bikes more - probably for commuting. However, on the weekend random customers on average use the service more - probably leisurely bike riders :)

1.5 Multivariate Exploration

Create plots of three or more variables to investigate your data even further. Make sure that your investigations are justified, and follow from your work in the previous sections.

[215]:
```
df_clean.head(1)
```

[215]:
```
   duration_sec               start_time                 end_time  bike_id  \
4          1585 2019-02-28 23:54:18.549 2019-03-01 00:20:44.074     4898

    user_type  member_birth_year member_gender bike_share_for_all_trip  \
```

```
4  Subscriber              1974.0         Male                        Yes

    weekday  hour  duration_minutes  age
4  Thursday    23                26   45
```

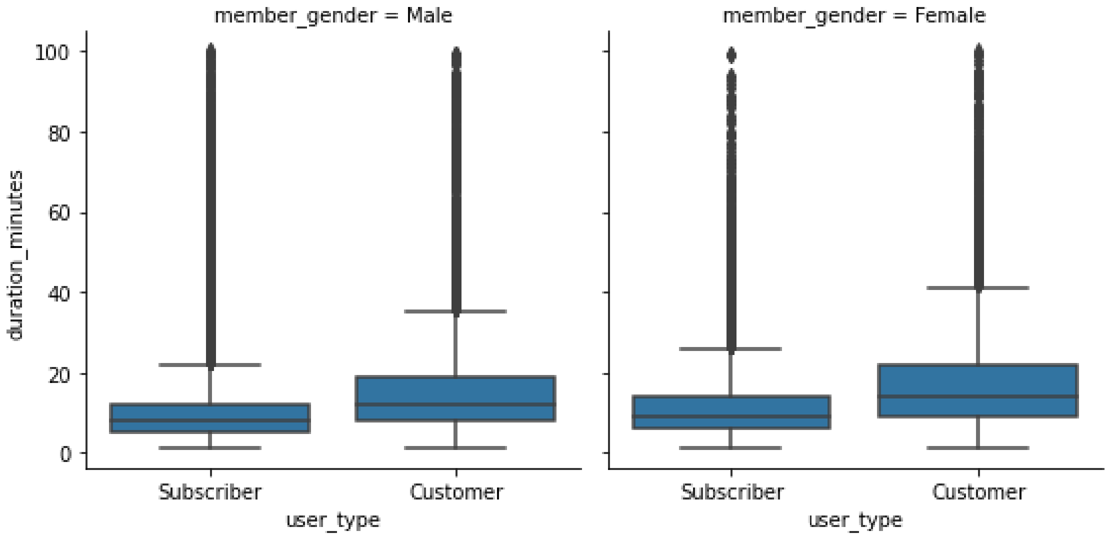
[216]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 169513 entries, 4 to 183411
Data columns (total 12 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             169513 non-null  int64
 1   start_time               169513 non-null  datetime64[ns]
 2   end_time                 169513 non-null  datetime64[ns]
 3   bike_id                  169513 non-null  int64
 4   user_type                169513 non-null  object
 5   member_birth_year        169513 non-null  float64
 6   member_gender            169513 non-null  object
 7   bike_share_for_all_trip  169513 non-null  object
 8   weekday                  169513 non-null  category
 9   hour                     169513 non-null  int64
 10  duration_minutes         169513 non-null  int32
 11  age                      169513 non-null  int32
dtypes: category(1), datetime64[ns](2), float64(1), int32(2), int64(3),
object(3)
memory usage: 18.4+ MB
```

When analyzing the graph below we can see no clear differences in bike usage depending on user type and gender. The relationship is similar - customers be it male or female on average rent the bike for longer periods

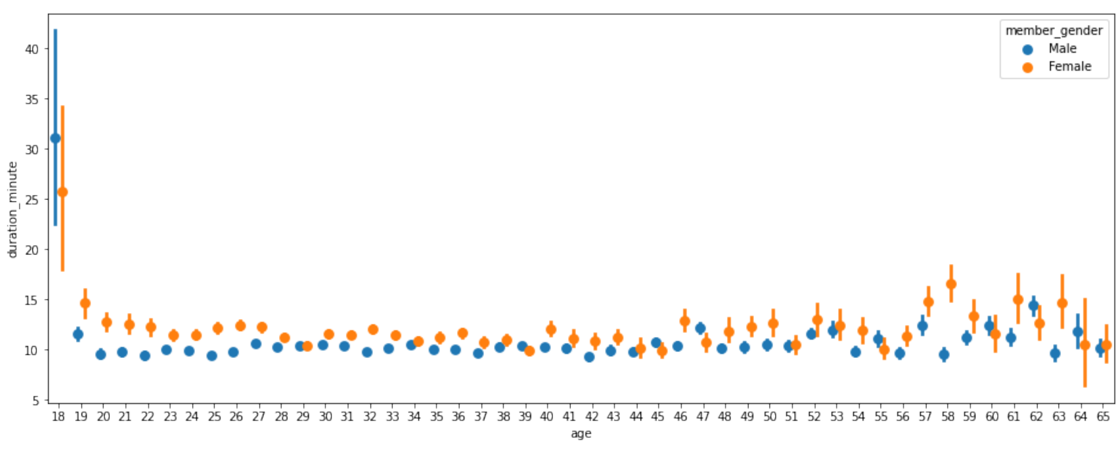
[217]:
```
g = sb.FacetGrid(data = df_clean, col = 'member_gender', size = 4)
g.map(sb.boxplot, 'user_type', 'duration_minutes')
```

[217]: <seaborn.axisgrid.FacetGrid at 0x249689ab160>



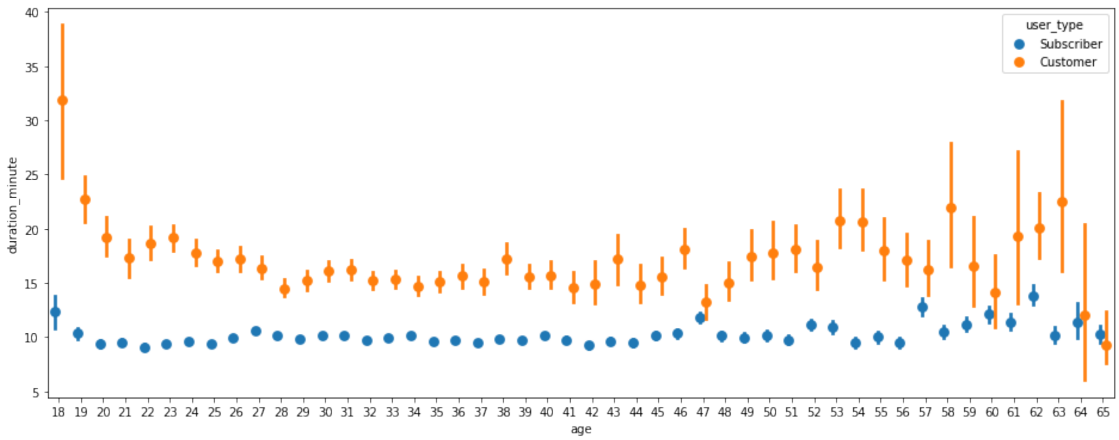
Below we can see an interesting observation. We can verify that female bike riders tend to rent the bike for longer. Also, we can verify that the youngest people rent the bike for the longer periods of time. However, one interesting thing to note is that people that are older than 50 years tend to rent the bike for longer compared to 30 - 50 year olds. We did not see this when analyzing the graph comparing age and rental duration.

[218]:
```
fig = plt.figure(figsize = [16,6])
sb.pointplot(data=df_clean, x='age', y='duration_minutes', hue='member_gender',␣
 ↪dodge=0.3, linestyles="");
plt.xlabel('age');
plt.ylabel('duration_minute');
```



The graph below also confirms our previous findings. Customers on average rent the bike for longer periods. The youngest people rent also for the longest duration. However here we can also see the confirmation that bike riders over 50 years old start to ride for longer periods.

[219]:
```
fig = plt.figure(figsize = [16,6])
sb.pointplot(data=df_clean, x='age', y='duration_minutes', hue='user_type',␣
↪dodge=0.3, linestyles="");
plt.xlabel('age');
plt.ylabel('duration_minute');
```



1.5.1 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?

Most of our previous findings were strengthened in the Multivariate exploration.

- Female riders rent bikes for longer periods
- The youngest people rent a bike for the longest
- Customer rent bikes for a longer duration vs subscribers

1.5.2 Were there any interesting or surprising interactions between features?

The most surprising feature was the age analysis. As previously stated I confirmed that 'The youngest people rent a bike for the longest'. However, what we did not see on our scatter plot is that after the age of 50 people start going for longer rides which is very interesting. It may be connected with a fact that the bike stops being a tool for commuting and starts being a tool for exercising. Mostly we can see this trend when looking at customers. Which as we previously assumed use bikes mostly on weekends for leisure.

All in all this was a very interesting analysis

At the end of your report, make sure that you export the notebook as an html file from the `File > Download as... > HTML` menu. Make sure you keep track of where the

> exported file goes, so you can put it in the same folder as this notebook for project submission. Also, make sure you remove all of the quote-formatted guide notes like this one before you finish your report!

[220]:
```
df_clean.to_csv(r'df_clean.csv', index = False, header=True)
```