Part_I_exploration_template

November 12, 2022

1 Part I - (201902 FORD-GO-BIKE DATASET)

1.1 by Ighoruemuse Omojevwe Rachael

1.2 Introduction

Ford GoBike, the San Francisco Bay Area's new regional bike share network, is a public-private partnership between the Metropolitan Transportation Commission and Motivate. Motivate, the global leader in bike share, operates tens of thousands of bikes across four continents. Ford Motor Company is the program's title partner, whose support enables Ford GoBike to bring the myriad public benefits of state-of-the-art bike share to San Francisco, San Jose, Oakland, Berkeley and Emeryville — at no cost to taxpayers for capital or operational expenditures. This data set includes information about individual rides made in this 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 sns

%matplotlib inline
```

In [2]:
```
# Load dataset
df = pd.read_csv('201902-fordgobike-tripdata.csv')
df.head()
```

Out[2]:
```
   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
```

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
duration_sec               183412 non-null int64
start_time                 183412 non-null object
end_time                   183412 non-null object
start_station_id           183215 non-null float64
start_station_name         183215 non-null object
start_station_latitude     183412 non-null float64
start_station_longitude    183412 non-null float64
end_station_id             183215 non-null float64
end_station_name           183215 non-null object
```

```
end_station_latitude       183412 non-null float64
end_station_longitude      183412 non-null float64
bike_id                    183412 non-null int64
user_type                  183412 non-null object
member_birth_year          175147 non-null float64
member_gender              175147 non-null object
bike_share_for_all_trip    183412 non-null object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

In [4]:
```
# shape
df.shape
```

Out[4]: (183412, 16)

In [5]:
```
# datatypes
print(df.dtypes)
```

```
duration_sec                 int64
start_time                  object
end_time                    object
start_station_id           float64
start_station_name          object
start_station_latitude     float64
start_station_longitude    float64
end_station_id             float64
end_station_name            object
end_station_latitude       float64
end_station_longitude      float64
bike_id                      int64
user_type                   object
member_birth_year          float64
member_gender               object
bike_share_for_all_trip     object
dtype: object
```

In [6]:
```
# describe the data
df.describe()
```

Out[6]:

	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 [7]:
```python
# checking for missing values
df.isnull().sum()
```

Out[7]:
```
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 [8]:
```python
# checking for duplicated values
sum(df.duplicated())
```

Out[8]: 0

In [9]:
```python
# checking for number of unique values in each column
df.nunique()
```

```
Out[9]: duration_sec                 4752
        start_time                 183401
        end_time                   183397
        start_station_id              329
        start_station_name            329
        start_station_latitude        334
        start_station_longitude       335
        end_station_id                329
        end_station_name              329
        end_station_latitude          335
        end_station_longitude         335
        bike_id                      4646
        user_type                       2
        member_birth_year              75
        member_gender                   3
        bike_share_for_all_trip         2
        dtype: int64
```

1.3.1 Structure of the dataset

The dataset has 183412 observations with 16 features of bike trips. The features included are: trip duration(in sec), start_time, end_time, station informations(start_station_id, start_station_name, start_station_latitude, start_station_longitude, end_station_id, end_station_name, end_station_latitude and end_station_longitude), informations on members(bike_id, user_type, member_birth_year, member_gender, bike_share_for_all_trip).

1.3.2 Main feature(s) of interest

The Trip duration might be the main feature of interest of this dataset, as it does affects the revenue of the company, therefore I will also study the effect of other factors like user_type, trip start and end times, gender and age on the trip duration. Furthermore, i'll explore how riding on different days of the week relate to each rider's characteristics i.e the user type, gender and age to understand how they use the bike sharing service and what it's been used for.

1.3.3 Features in the dataset that will help support the investigation into the feature(s) of interest

- How does the trip duration differ by user_type, age, hour, and day?
- How does gender and age of the users have an effect on the trip duration?
- When are most trips taken during time of day, day of the week, or month of the year?
- What does the distribution of trip duration look like?
- Which day has the highest demand on trips?
- Which hour(s) during the day has the highest demand on trips?

2 DATA WRANGLING PROCESS

2.0.1 Tasks

- Missing values
- Invalid datatypes
- Extract hour, day from start time and end time
- Extract age from birth year

Dealing with missing values

```
In [10]: # since there are no replacement values for the missing stations IDs or names, it's bet
         df = df[(df['start_station_id'].isnull() == False) & (df['start_station_name'].isnull()
            & (df['member_birth_year'].isnull() == False) & (df['member_gender'].isnull() == Fal
```

```
In [11]: # checkng the null values after the dropping.
         df.isnull().sum()
```

```
Out[11]: duration_sec               0
         start_time                 0
         end_time                   0
         start_station_id           0
         start_station_name         0
         start_station_latitude     0
         start_station_longitude    0
         end_station_id             0
         end_station_name           0
         end_station_latitude       0
         end_station_longitude      0
         bike_id                    0
         user_type                  0
         member_birth_year          0
         member_gender              0
         bike_share_for_all_trip    0
         dtype: int64
```

```
In [12]: # checking the new shape of the dataframe.
         df.shape
```

```
Out[12]: (174952, 16)
```

Invalid Datatypes

```
In [13]: # checking the data type of each column of the dataset
         df.dtypes
```

```
Out[13]: duration_sec                  int64
         start_time                   object
         end_time                     object
```

```
start_station_id            float64
start_station_name           object
start_station_latitude      float64
start_station_longitude     float64
end_station_id              float64
end_station_name             object
end_station_latitude        float64
end_station_longitude       float64
bike_id                       int64
user_type                    object
member_birth_year           float64
member_gender                object
bike_share_for_all_trip      object
dtype: object
```

In [14]:
```
# converting the start_time and end_time to datetime type format
df.start_time = pd.to_datetime(df.start_time)
df.end_time = pd.to_datetime(df.end_time)
```

In [15]:
```
# change the user_type data to category data
df['user_type'] = df['user_type'].astype('category')
```

In [16]:
```
# change the data type for bike_share_for_all_trip to be bool
df.bike_share_for_all_trip = (df.bike_share_for_all_trip == 'Yes')
```

In [17]:
```
# change the start_station_id, end_station_id and bike_id to object data type
df['start_station_id'] = df['start_station_id'].astype('object')
df['end_station_id'] = df['end_station_id'].astype('object')
df['bike_id'] = df['bike_id'].astype('object')
```

In [18]:
```
#checking dtypes
df.dtypes
```

Out[18]:
```
duration_sec                         int64
start_time                  datetime64[ns]
end_time                    datetime64[ns]
start_station_id                    object
start_station_name                  object
start_station_latitude             float64
start_station_longitude            float64
end_station_id                      object
end_station_name                    object
end_station_latitude               float64
end_station_longitude              float64
bike_id                             object
user_type                         category
member_birth_year                  float64
member_gender                       object
bike_share_for_all_trip               bool
dtype: object
```

Extracting hour and day from start time

```
In [19]: # Extract start_time_month and day of week from the start_time
         df['start_time_dayofweek']= df['start_time'].dt.strftime('%a')
         df['start_time_month'] = df['start_time'].dt.strftime('%B')
```

Extracting hour and day from end time

```
In [20]: # Extract end_time_month and day of week from end_time
         df['end_time_dayofweek']= df['end_time'].dt.strftime('%a')
         df['end_time_month'] = df['end_time'].dt.strftime('%B')

In [21]: # For better understanding of the dataset(trip duration), change the duration in second
         df['duration_min'] = df['duration_sec'] / 60

In [22]: # let's have a look on the distrubtion of the duration_min
         df['duration_min'].describe()

Out[22]: count    174952.000000
         mean         11.733379
         std          27.370082
         min           1.016667
         25%           5.383333
         50%           8.500000
         75%          13.150000
         max        1409.133333
         Name: duration_min, dtype: float64

In [23]: # Looks like for at least 75% of the data are less than one hour, so end_time_hour will
         df['start_time_hour']= df['start_time'].dt.hour

In [24]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
Data columns (total 22 columns):
duration_sec               174952 non-null int64
start_time                 174952 non-null datetime64[ns]
end_time                   174952 non-null datetime64[ns]
start_station_id           174952 non-null object
start_station_name         174952 non-null object
start_station_latitude     174952 non-null float64
start_station_longitude    174952 non-null float64
end_station_id             174952 non-null object
end_station_name           174952 non-null object
end_station_latitude       174952 non-null float64
end_station_longitude      174952 non-null float64
bike_id                    174952 non-null object
user_type                  174952 non-null category
```

```
member_birth_year          174952 non-null float64
member_gender              174952 non-null object
bike_share_for_all_trip    174952 non-null bool
start_time_dayofweek       174952 non-null object
start_time_month           174952 non-null object
end_time_dayofweek         174952 non-null object
end_time_month             174952 non-null object
duration_min               174952 non-null float64
start_time_hour            174952 non-null int64
dtypes: bool(1), category(1), datetime64[ns](2), float64(6), int64(2), object(10)
memory usage: 28.4+ MB
```

In [25]:
```python
# Notice that the start_time_dayofweek is object type. For better analysis, convert it
weekdays = ['Fri','Sat','Sun','Mon','Tue','Wed','Thu']
ordered_weekdays = pd.api.types.CategoricalDtype(ordered = True, categories = weekdays)
df['start_time_dayofweek'] = df['start_time_dayofweek'].astype(ordered_weekdays)
```

In [26]:
```python
# checking the unique values of the start_time_month
df['start_time_month'].unique()
```

Out[26]:
```
array(['February'], dtype=object)
```

In [27]:
```python
# The timestamp proves of the fact that all trips record for this dataset happended at
df['start_time'].max() , df['start_time'].min()
```

Out[27]:
```
(Timestamp('2019-02-28 23:59:18.548000'),
 Timestamp('2019-02-01 00:00:20.636000'))
```

In [28]:
```python
# There's no need for the duration_sec column
df= df.drop('duration_sec' , axis = 1)
```

In [29]:
```python
# Birth Year column is not important data to analyze, but we can get the age from this
df['member_age'] = 2019 - df['member_birth_year']
```

In [30]:
```python
# Changing the dtype of both member_birth_year and member_age to int datatype.
df['member_age'] = df['member_age'].astype(int)
df['member_birth_year'] = df['member_birth_year'].astype(int)
```

In [31]:
```python
# Checking All the changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
Data columns (total 22 columns):
start_time                 174952 non-null datetime64[ns]
end_time                   174952 non-null datetime64[ns]
start_station_id           174952 non-null object
start_station_name         174952 non-null object
```

```
start_station_latitude     174952 non-null float64
start_station_longitude    174952 non-null float64
end_station_id             174952 non-null object
end_station_name           174952 non-null object
end_station_latitude       174952 non-null float64
end_station_longitude      174952 non-null float64
bike_id                    174952 non-null object
user_type                  174952 non-null category
member_birth_year          174952 non-null int64
member_gender              174952 non-null object
bike_share_for_all_trip    174952 non-null bool
start_time_dayofweek       174952 non-null category
start_time_month           174952 non-null object
end_time_dayofweek         174952 non-null object
end_time_month             174952 non-null object
duration_min               174952 non-null float64
start_time_hour            174952 non-null int64
member_age                 174952 non-null int64
dtypes: bool(1), category(2), datetime64[ns](2), float64(5), int64(3), object(9)
memory usage: 27.2+ MB
```

In [32]:
```
df.sample(5)
```

Out[32]:
```
                    start_time                end_time start_station_id  \
170916 2019-02-04 07:24:58.309 2019-02-04 07:31:18.956               67
178306 2019-02-01 17:26:47.278 2019-02-01 17:33:35.337              368
143598 2019-02-07 14:45:38.549 2019-02-07 15:01:15.355              363
85847  2019-02-17 13:07:49.790 2019-02-17 14:21:09.822              155
31221  2019-02-24 17:06:10.013 2019-02-24 17:23:26.188              285

                                      start_station_name  \
170916  San Francisco Caltrain Station 2  (Townsend St...
178306                                Myrtle St at Polk St
143598    Salesforce Transit Center (Natoma St at 2nd St)
85847                             Emeryville Public Market
31221                             Webster St at O'Farrell St

        start_station_latitude  start_station_longitude end_station_id  \
170916               37.776639              -122.395526            350
178306               37.785434              -122.419622             58
143598               37.787492              -122.398285            130
85847                37.840521              -122.293528            351
31221                37.783521              -122.431158            377

                  end_station_name  end_station_latitude  \
170916       8th St at Brannan St              37.771431
178306       Market St at 10th St              37.776619
```

```
143598   22nd St Caltrain Station             37.757288
85847   10th St at University Ave             37.869060
31221       Fell St at Stanyan St             37.771917

        end_station_longitude     ...     member_birth_year member_gender  \
170916            -122.405787     ...                  1995        Female
178306            -122.417385     ...                  2000          Male
143598            -122.392051     ...                  1961          Male
85847             -122.293400     ...                  1962          Male
31221             -122.453704     ...                  1983          Male

        bike_share_for_all_trip start_time_dayofweek  start_time_month  \
170916                    False                  Mon          February
178306                    False                  Fri          February
143598                    False                  Thu          February
85847                     False                  Sun          February
31221                     False                  Sun          February

       end_time_dayofweek end_time_month duration_min start_time_hour  \
170916                Mon       February     6.333333               7
178306                Fri       February     6.800000              17
143598                Thu       February    15.600000              14
85847                 Sun       February    73.333333              13
31221                 Sun       February    17.266667              17

        member_age
170916          24
178306          19
143598          58
85847           57
31221           36

[5 rows x 22 columns]
```

2.1 Univariate Exploration

Let's look deeply by investigating distributions of individual variables if we'll see unusual points or outliers so as to tidy the data in order to prepare ourselves further in looking at the relationships between variables. Let's start with the trip duration (duration_min).

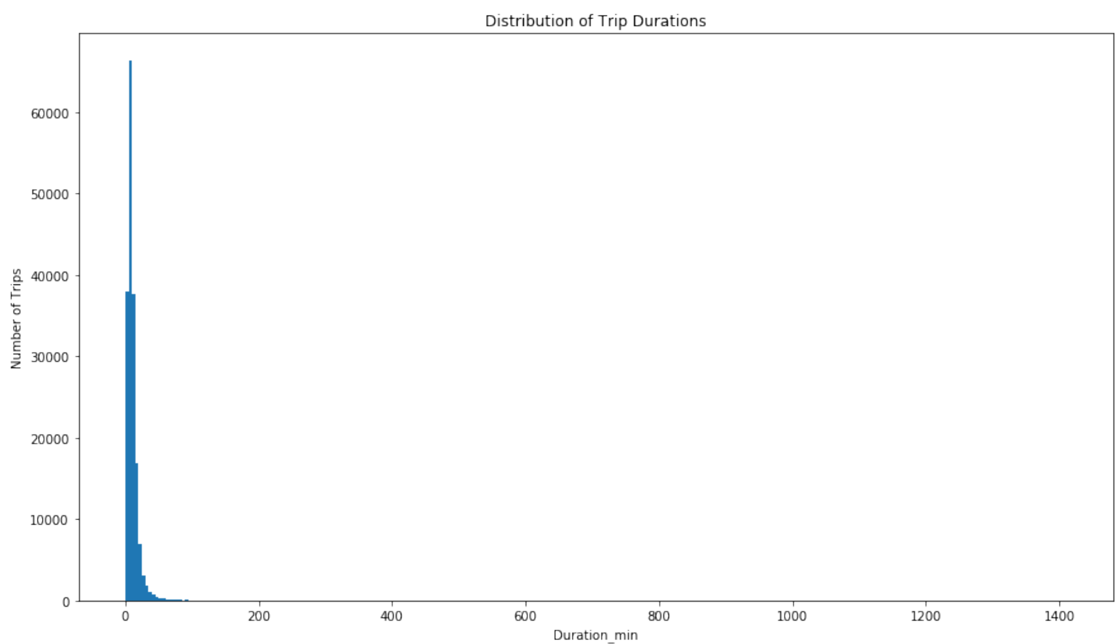
In [33]:
```
df['duration_min'].describe()
```

Out[33]:
```
count    174952.000000
mean         11.733379
std          27.370082
min           1.016667
25%           5.383333
```

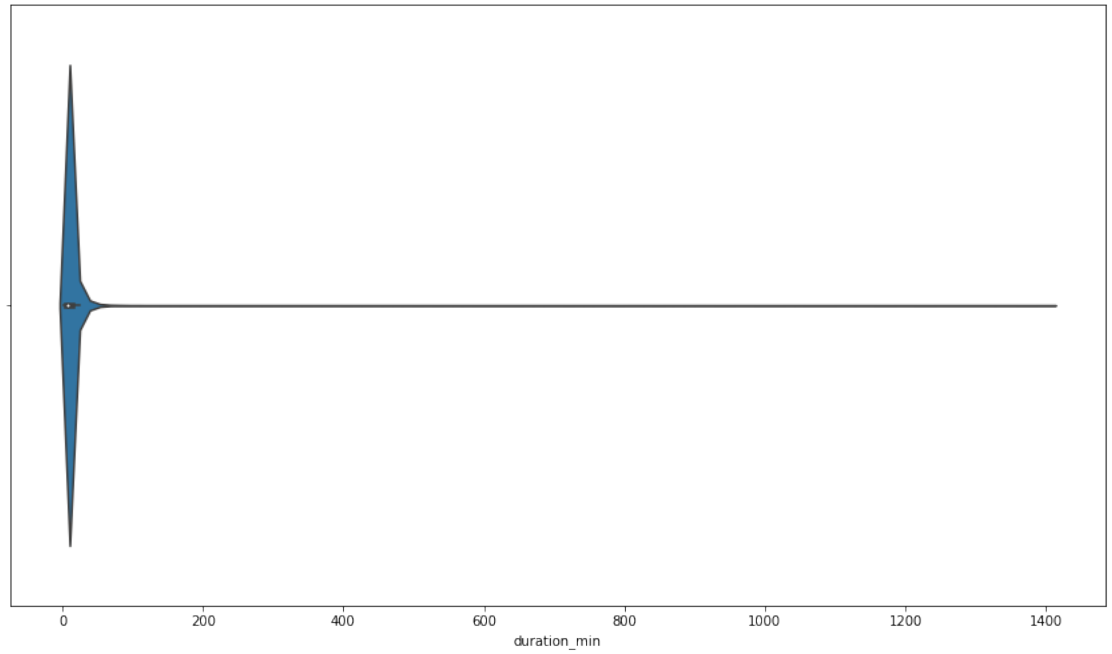
```
50%             8.500000
75%            13.150000
max          1409.133333
Name: duration_min, dtype: float64
```

- How does the duration affect the number of trips?

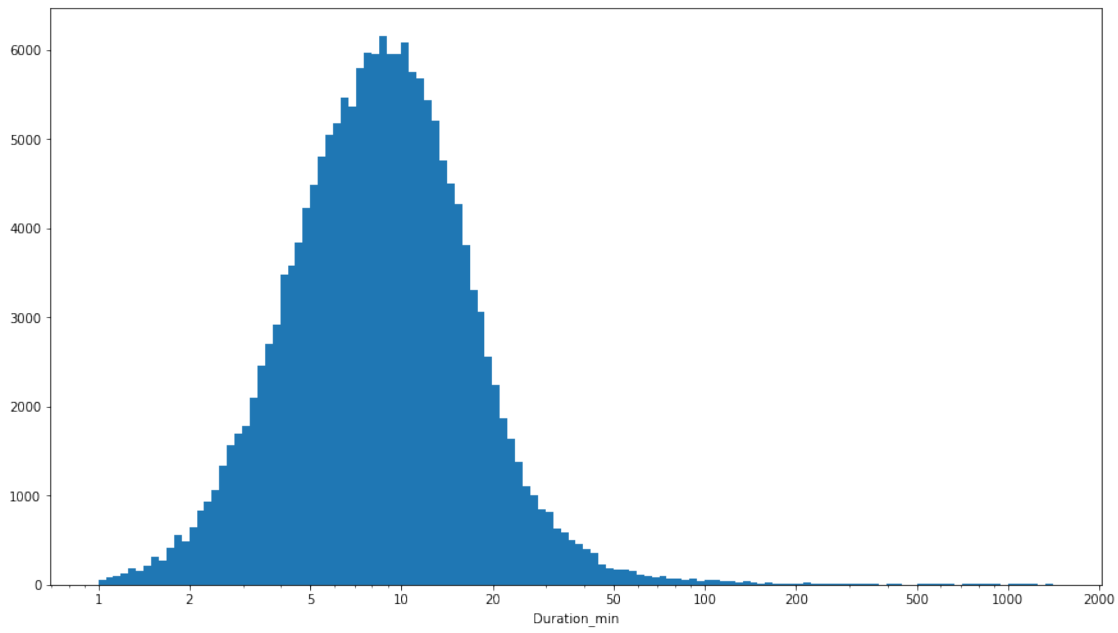
```
In [49]: # plotting the duration_min data on a normal scale
         binsize = 5
         bins = np.arange(0, df['duration_min'].max()+binsize, binsize)

         plt.figure(figsize=[14.70, 8.27])
         plt.tight_layout()
         plt.hist(data = df, x = 'duration_min', bins = bins)
         plt.title('Distribution of Trip Durations')
         plt.xlabel('Duration_min')
         plt.ylabel('Number of Trips')
         plt.show()
```




```
In [50]: # using violinplot to have a second look at the distribution
         plt.figure(figsize=[14.70, 8.27])
         sns.violinplot(data = df, x = 'duration_min');
```




```
In [51]: # Due to this long tail of the distribution, it's better to use the log scale to visuall
         log_binsize = 0.025
         bins = 10 ** np.arange(0, np.log10(df['duration_min'].max())+log_binsize, log_binsize)

         plt.figure(figsize=[14.70, 8.27])
         plt.hist(data = df, x = 'duration_min', bins = bins);
         plt.xscale('log');
         plt.xticks([1, 2, 5, 10, 20, 50, 100, 200, 500, 1000, 2000], [1, 2, 5, 10, 20, 50, 100,
         plt.xlabel('Duration_min');
```



The longer the duration the shorter the number of trips

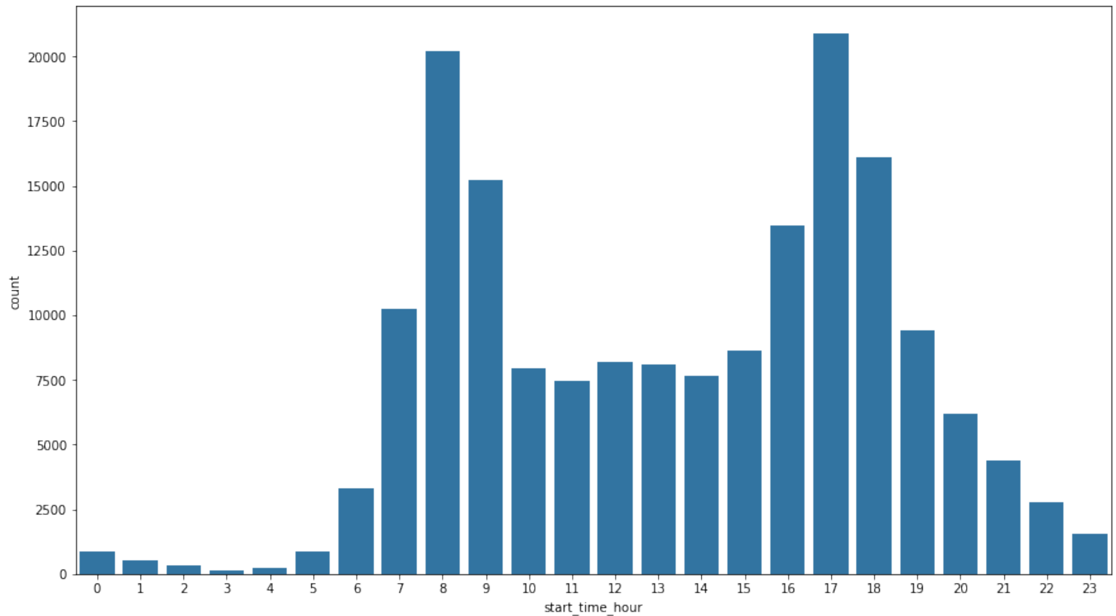
Let's check the start_time_hour data

```
In [52]: base_color = sns.color_palette()[0]
```

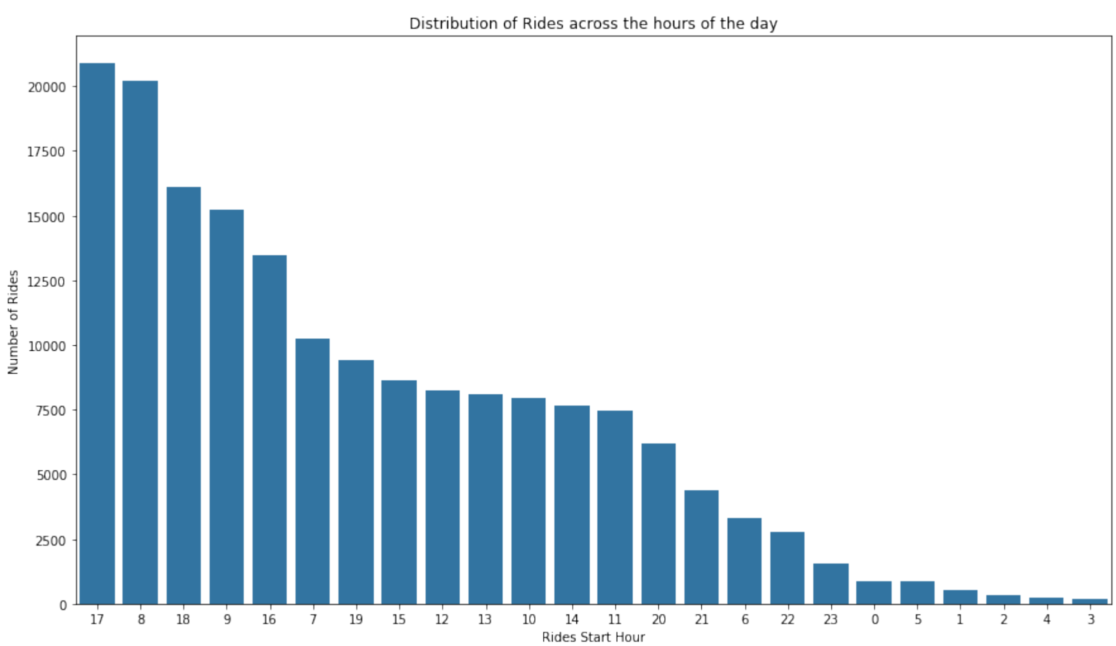
```
In [53]: hour_order = df['start_time_hour'].value_counts().index
```

- What's the distribution of the rides during the day?

```
In [54]: # distribution of rides during the day
         plt.figure(figsize=[14.70, 8.27])
         sns.countplot(data = df , x= 'start_time_hour', color = base_color);
```




```
In [55]: # in order
         plt.figure(figsize=[14.70, 8.27])
         sns.countplot(data = df , x= 'start_time_hour', color=base_color, order=hour_order)
         plt.title('Distribution of Rides across the hours of the day')
         plt.xlabel('Rides Start Hour')
         plt.ylabel('Number of Rides')
         plt.show()
```



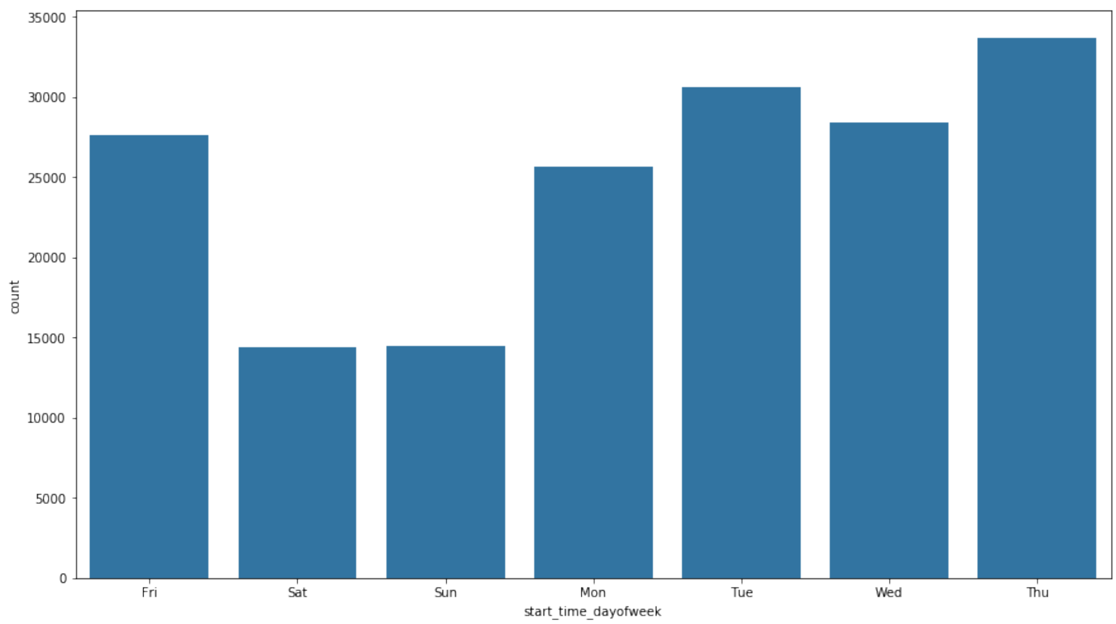
Peak hours for riding is 5 P.M (17:00) and 8 A.M (Those two hours are matching closely with the normal working hours for riders)

Let's know the day of the week with the most rides.

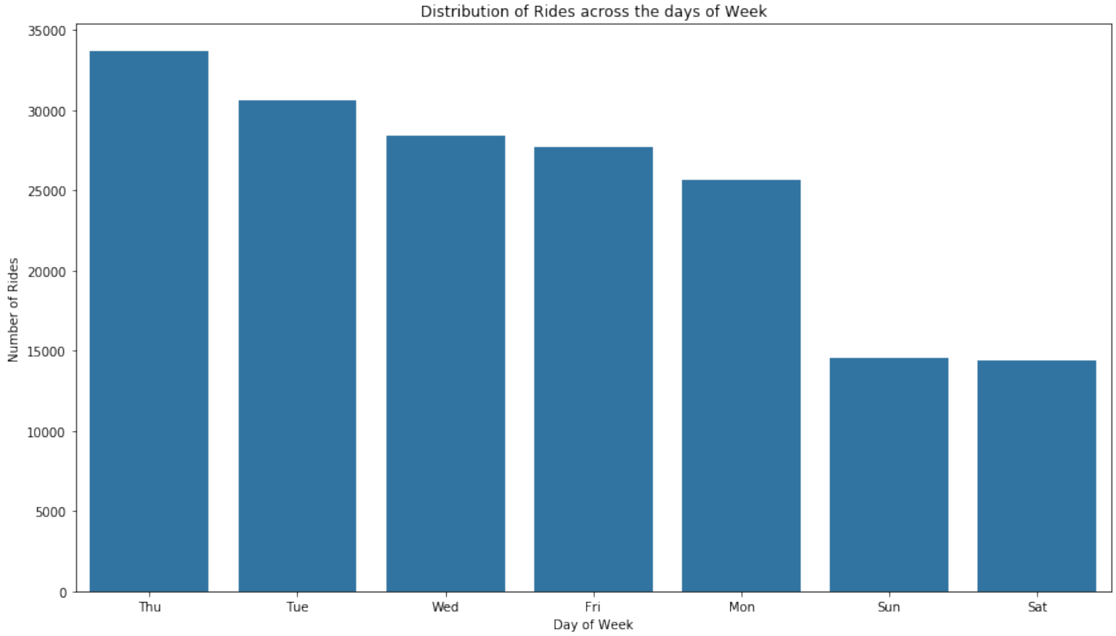
- What day of the week has the most rides?

```
In [56]: # day of the week with the most rides
         plt.tight_layout()
         plt.figure(figsize=[14.70, 8.27])
         sns.countplot(data = df, x = 'start_time_dayofweek', color = base_color);
```

```
<matplotlib.figure.Figure at 0x7f8da0c20780>
```




```
In [57]: # in order
         row_order = df['start_time_dayofweek'].value_counts().index
         plt.figure(figsize=[14.70, 8.27])
         sns.countplot(data = df, x = 'start_time_dayofweek', color = base_color, order = row_or
         plt.title('Distribution of Rides across the days of Week')
         plt.xlabel('Day of Week')
         plt.ylabel('Number of Rides')
         plt.show()
```

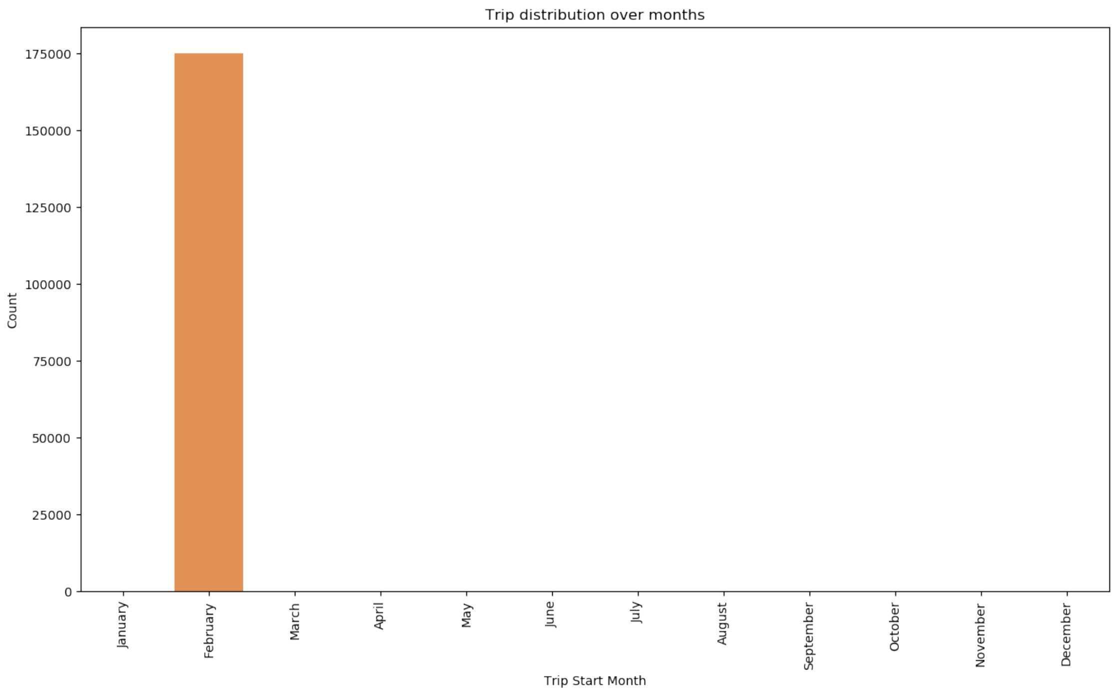


Apparently bikers have higher rides at weekdays more than weekends making Thursday the highest day of rides with the other workdays close to it.

The month with the most rides

- In what month were most of the rides taken?

```
In [58]: # trip distribution over months
         plt.figure(figsize = (14.70,8.27), dpi = 100)

         month = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'Sep
         month_categ = pd.api.types.CategoricalDtype(ordered=True, categories=month)
         df['start_time_month'] = df['start_time_month'].astype(month_categ)

         sns.countplot(data=df, x='start_time_month')
         plt.xticks(rotation=90)
         plt.xlabel('Trip Start Month')
         plt.ylabel('Count')

         plt.title("Trip distribution over months")

         plt.show()
```



Apparently, all the trips took place in the month of February.

2.2 Now Let's pay more attention to the bikers, their gender, age and user_type

2.3 1. Bikers' Gender

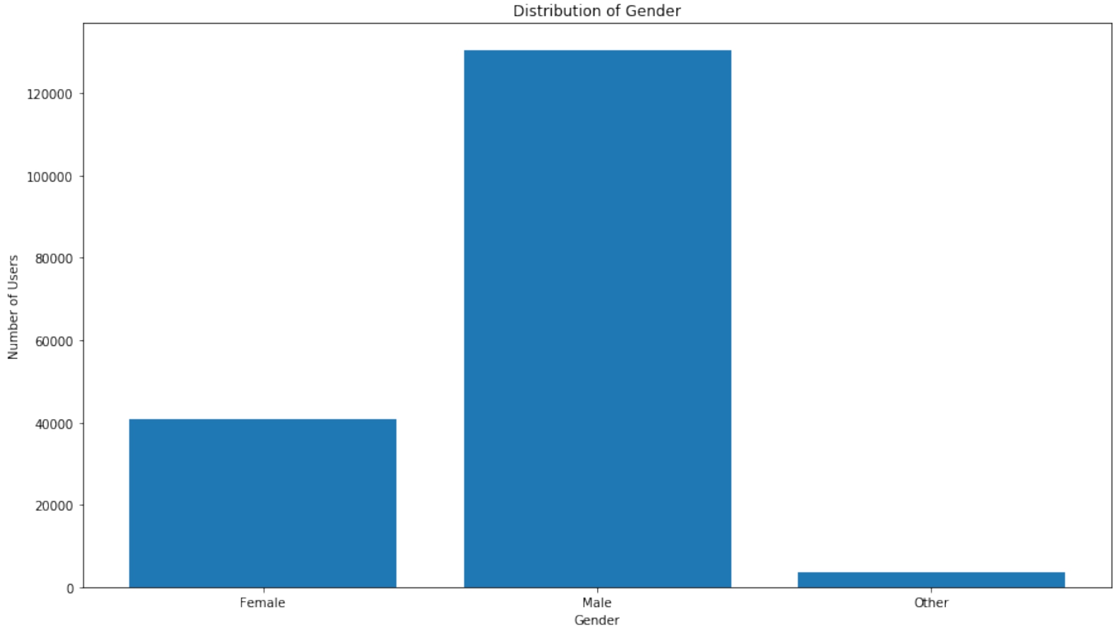
```
In [59]: df['member_gender'].value_counts()
```

```
Out[59]: Male      130500
         Female     40805
         Other       3647
         Name: member_gender, dtype: int64
```

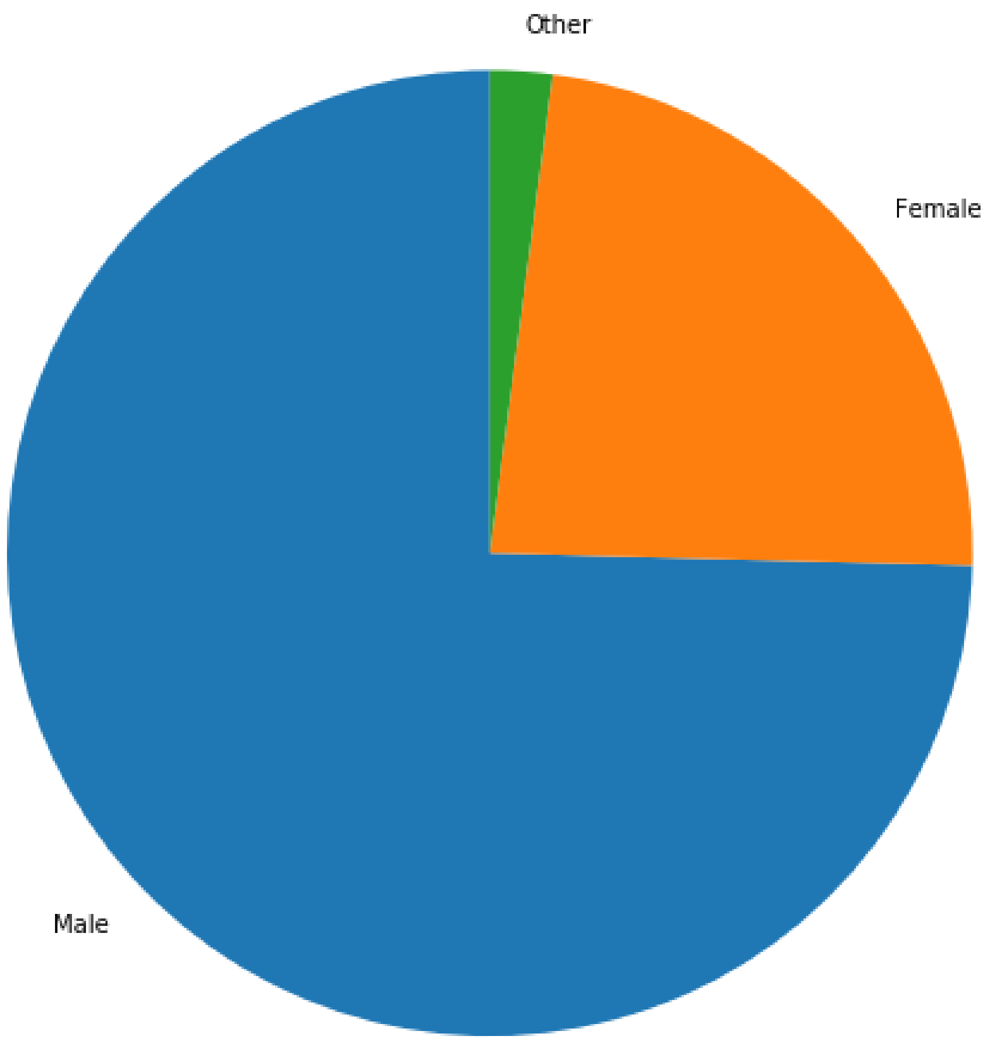
- What gender rode bikes the most?

```
In [60]: # distribution of genders by number of users
         plt.tight_layout()
         plt.figure(figsize=[14.70, 8.27])
         plt.bar(x = df['member_gender'].value_counts().keys(), height = df['member_gender'].val
         plt.title('Distribution of Gender')
         plt.xlabel('Gender')
         plt.ylabel('Number of Users')
         plt.show();
```

```
<matplotlib.figure.Figure at 0x7f8da0c64f98>
```



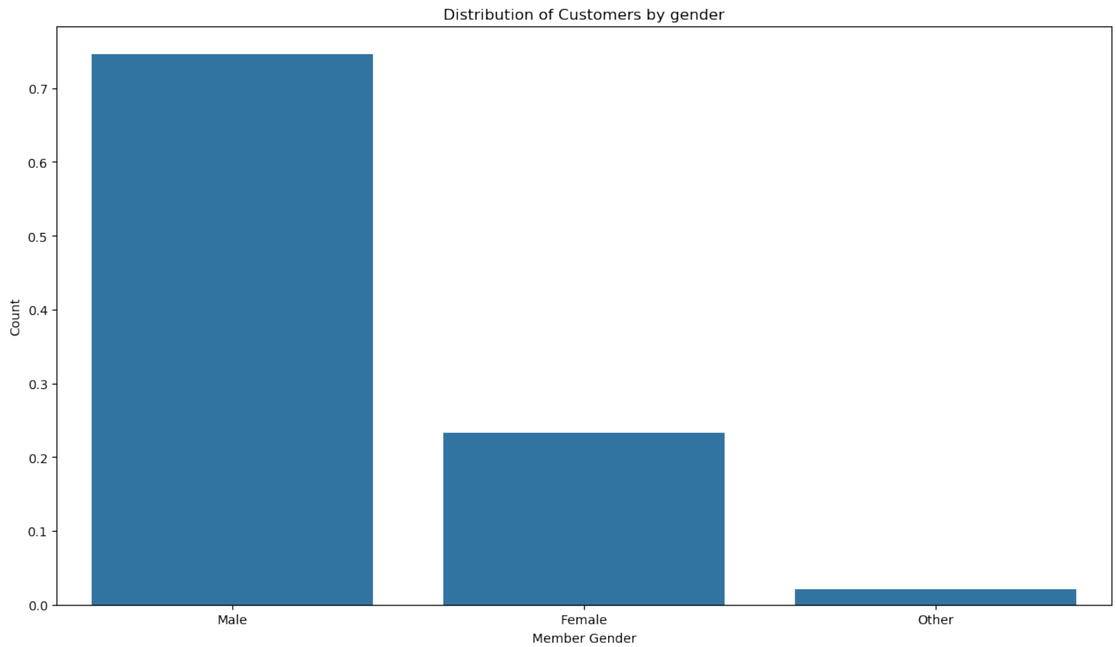
In [61]:
```
# Viewing the gender also on a pie chart
sorted_counts = df['member_gender'].value_counts()

plt.figure(figsize=[14.70, 8.27])

plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90);

plt.axis('square');
```




```
In [62]: # Viewing the gender in percentage
         plt.figure(figsize=[14.70, 8.27], dpi = 100)

         counts = df['member_gender'].value_counts(normalize = True)
         sns.barplot(x = counts.index, y = counts.values, color=base_color)
         plt.xlabel('Member Gender')
         plt.ylabel('Count')
         print(counts * 100)
         plt.title("Distribution of Customers by gender")

         plt.show()
```

```
Male      74.591888
Female    23.323540
```

```
Other      2.084572
Name: member_gender, dtype: float64
```



We can come to the conclusion that male bikers are more with the distribution at 74.59% while the female bikers are at 23.32% and others at 2.09%.

3 2. Bikers' Age

In [ ]:
```
df['member_age'].value_counts()
```

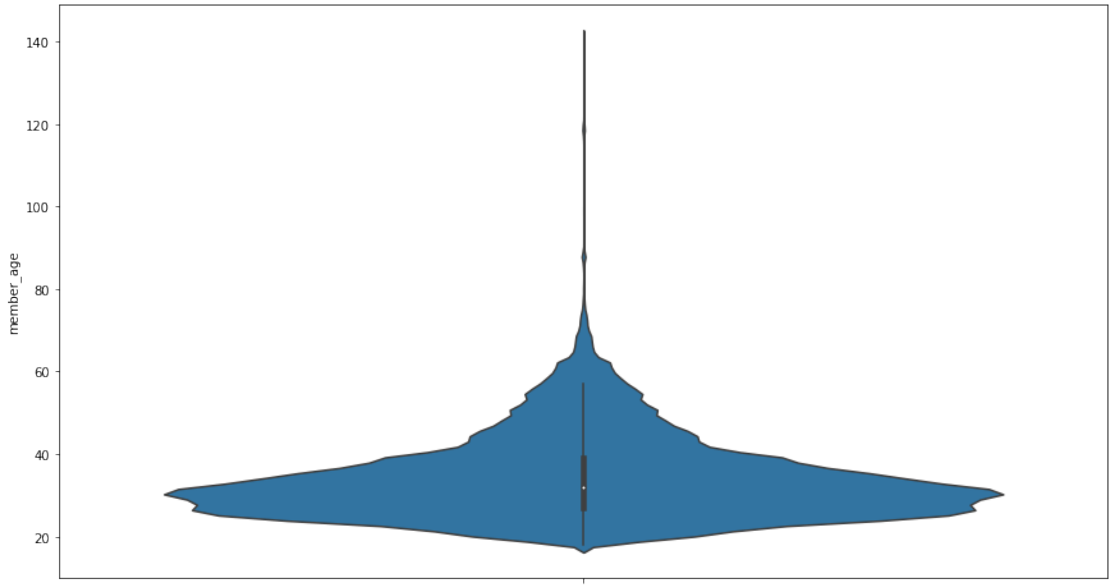
Ages 141, 119, 118, 117 are almost impossible, so we're not sure if it's an outlier. Let's just keep that in mind as we go further

In [63]:
```
df['member_age'].describe()
```

Out[63]:
```
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
```

- What age group are most active?

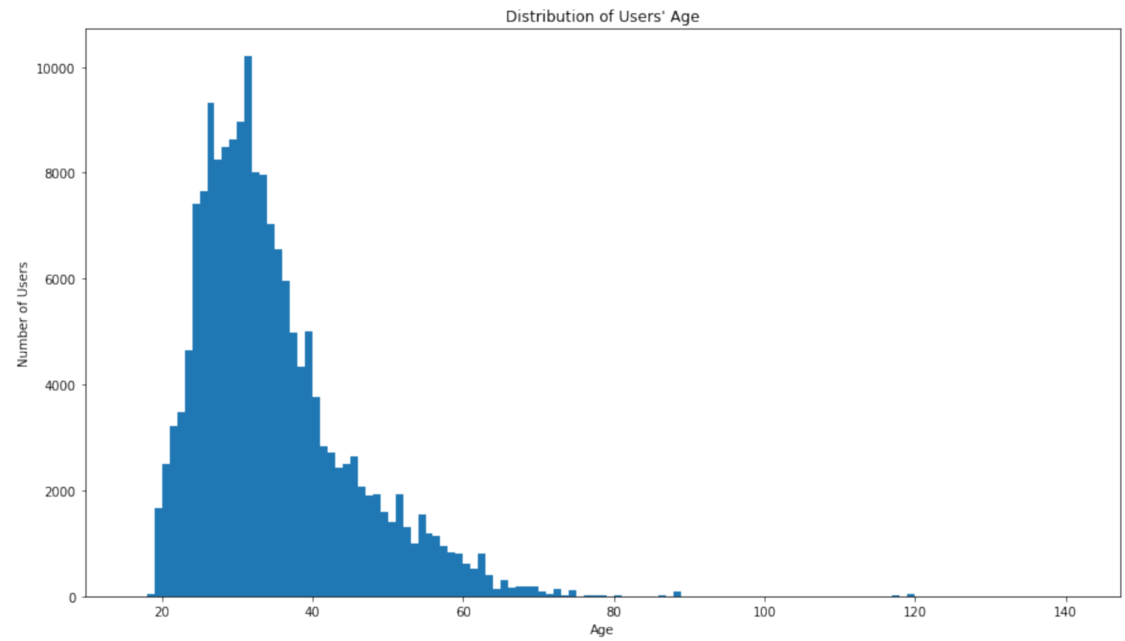
In [64]:
```
plt.figure(figsize=[14.70, 8.27])
sns.violinplot(data = df, y = 'member_age');
```



In [65]:
```
df['member_age'].describe()
```

Out[65]:
```
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 [66]:
```
# distribution of users' age
binsize = 1
bins = np.arange(16, df['member_age'].max()+binsize, binsize)
plt.figure(figsize=[14.70, 8.27])
plt.hist(data = df, x = 'member_age', bins = bins);
plt.title("Distribution of Users' Age")
plt.xlabel('Age')
plt.ylabel('Number of Users')
plt.show()
```



Using this distribution, which is skewed to the right, one can conclude that the major age range of bikers which are 25-35 belongs to either the working class or students or one can easily say they are the most active set of the population.

4 3. Bikers Type

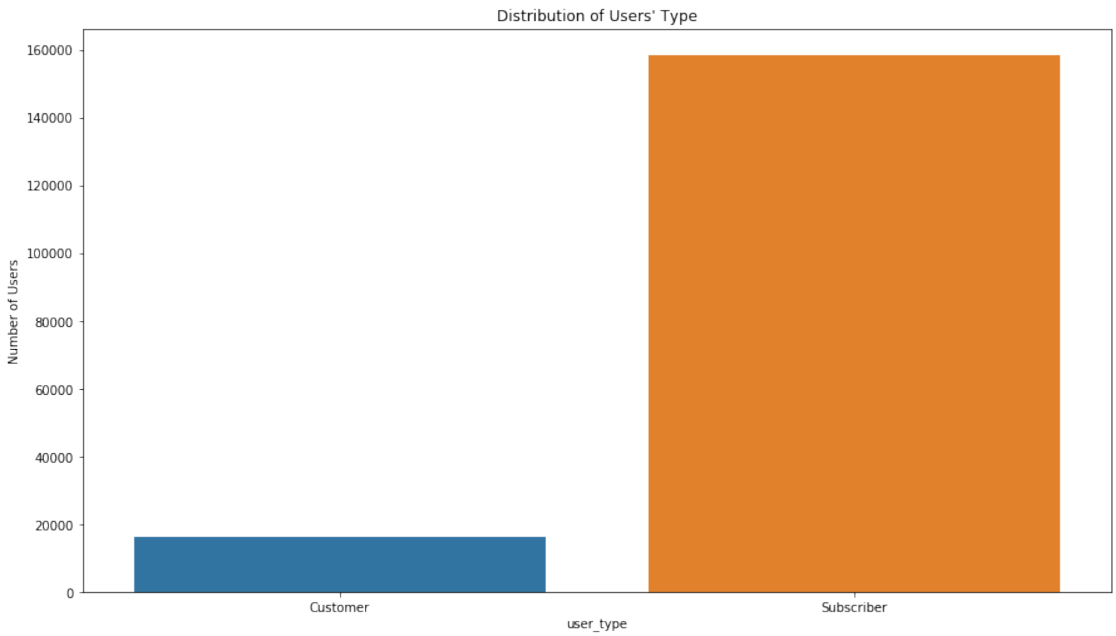
In [67]:
```
df['user_type'].value_counts()
```

Out[67]:
```
Subscriber    158386
Customer       16566
Name: user_type, dtype: int64
```

- What is the distribution of the number of users by type?

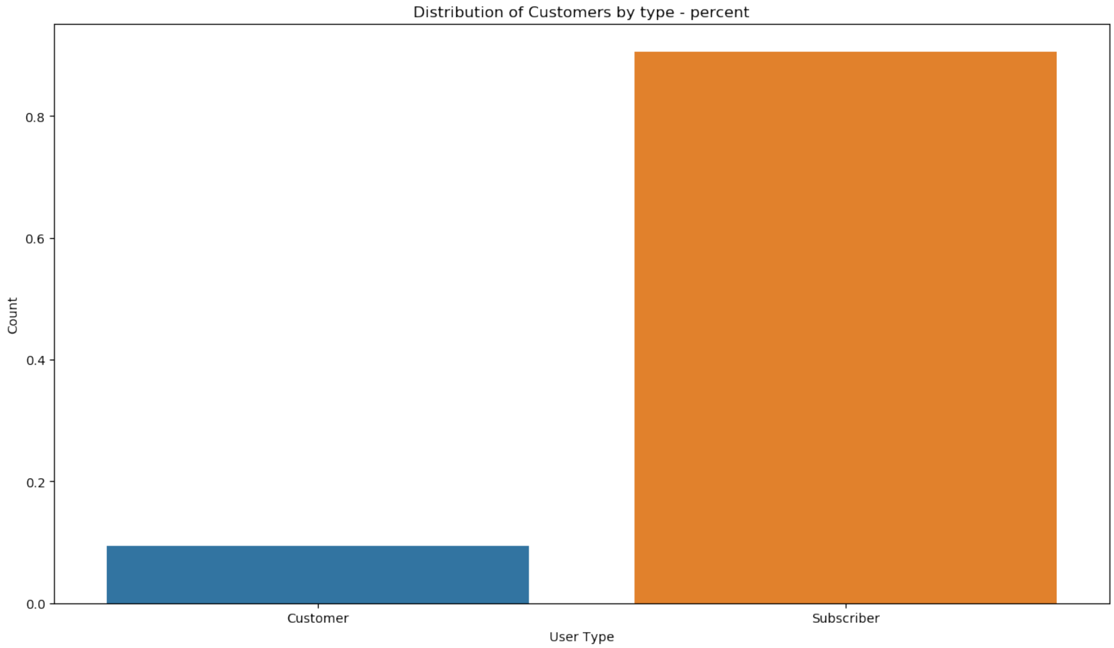
In [68]:
```
# distribution by type
plt.tight_layout()
plt.figure(figsize=[14.70, 8.27])
sns.countplot(data = df, x = 'user_type');
plt.title("Distribution of Users' Type")
plt.xlabel('user_type')
plt.ylabel('Number of Users')
plt.show();
```

```
<matplotlib.figure.Figure at 0x7f8da231ee10>
```




```
In [69]: # distribution in percentage
         plt.figure(figsize=[14.70, 8.27], dpi = 100)

         counts = df['user_type'].value_counts(normalize = True)
         sns.barplot(x = counts.index, y = counts.values)
         plt.xlabel('User Type')
         plt.ylabel('Count')
         print(counts * 100)

         plt.title("Distribution of Customers by type - percent")
         plt.show()
```

```
Subscriber    90.531117
Customer       9.468883
Name: user_type, dtype: float64
```



Apparently, the subscribers are more than 9 times the customers and that shows a long term relationship and satisfaction from the users with the services provided to them.

Removing Outliers

```
In [70]: # going further, using the duration not more than 60 mins and members' age not more tha
         df_1 = df[df["duration_min"] <= 60]
         df_2 = df_1[df["member_age"] <= 80]
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:3: UserWarning: Boolean Series key
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
In [72]: df_2.sample(20)
```

```
Out[72]:                     start_time                end_time start_station_id  \
         123820 2019-02-11 09:01:02.447 2019-02-11 09:09:18.340               81
         49494  2019-02-21 21:28:54.770 2019-02-21 21:35:23.740              171
         41001  2019-02-22 19:10:56.425 2019-02-22 19:20:37.116               24
         168763 2019-02-04 13:40:36.695 2019-02-04 13:44:02.445              151
         51371  2019-02-21 17:59:29.920 2019-02-21 18:14:08.737              324
         156330 2019-02-06 08:01:11.084 2019-02-06 08:10:52.963               67
         157632 2019-02-05 21:12:52.602 2019-02-05 21:18:33.217              109
         1806   2019-02-28 18:34:20.938 2019-02-28 18:48:56.253               81
         115893 2019-02-12 08:08:59.734 2019-02-12 08:27:03.211              373
         27996  2019-02-25 08:51:12.503 2019-02-25 09:10:10.317              137
         57273  2019-02-21 08:24:53.966 2019-02-21 08:32:57.547               81
```

```
148578 2019-02-06 21:17:47.438 2019-02-06 21:30:37.063              311
162343 2019-02-05 11:57:15.795 2019-02-05 12:01:21.253               99
67111  2019-02-20 08:08:32.698 2019-02-20 08:22:55.313               16
178490 2019-02-01 17:02:57.969 2019-02-01 17:12:51.084               58
24719  2019-02-25 17:54:55.685 2019-02-25 17:59:56.010              267
117103 2019-02-12 05:54:08.705 2019-02-12 05:56:57.437              385
157519 2019-02-05 21:31:51.266 2019-02-05 21:45:23.201               34
24292  2019-02-25 18:24:13.263 2019-02-25 18:36:11.269               58
106335 2019-02-13 18:19:24.457 2019-02-13 18:30:28.447               81

                                       start_station_name  \
123820                                 Berry St at 4th St
49494                              Rockridge BART Station
41001                                Spear St at Folsom St
168763                                53rd St at Hollis St
51371               Union Square (Powell St at Post St)
156330  San Francisco Caltrain Station 2  (Townsend St...
157632                             17th St at Valencia St
1806                                   Berry St at 4th St
115893         Potrero del Sol Park (25th St at Utah St)
27996                              Jersey St at Castro St
57273                                  Berry St at 4th St
148578                      Paseo De San Antonio at 2nd St
162343                                Folsom St at 15th St
67111                              Steuart St at Market St
178490                                Market St at 10th St
24719                              Derby St at College Ave
117103                        Woolsey St at Sacramento St
157519                      Father Alfred E Boeddeker Park
24292                                 Market St at 10th St
106335                                 Berry St at 4th St

        start_station_latitude  start_station_longitude end_station_id  \
123820               37.775880              -122.393170             16
49494                37.844279              -122.251900             18
41001                37.789677              -122.390428             30
168763               37.836182              -122.287180            148
51371                37.788300              -122.408531             54
156330               37.776639              -122.395526             44
157632               37.763316              -122.421904            133
1806                 37.775880              -122.393170             87
115893               37.751792              -122.405216             28
27996                37.750506              -122.433950            349
57273                37.775880              -122.393170             15
148578               37.333798              -121.886943            296
162343               37.767037              -122.415443             89
67111                37.794130              -122.394430            126
178490               37.776619              -122.417385             30
```

```
24719              37.861804           -122.253569           239
117103             37.850578           -122.278175           241
157519             37.783988           -122.412408            72
24292              37.776619           -122.417385            67
106335             37.775880           -122.393170           116

                                         end_station_name  \
123820                           Steuart St at Market St
49494                        Telegraph Ave at Alcatraz Ave
41001     San Francisco Caltrain (Townsend St at 4th St)
168763                              Horton St at 40th St
51371             Alamo Square (Steiner St at Fulton St)
156330  Civic Center/UN Plaza BART Station (Market St ...
157632                            Valencia St at 22nd St
1806                                Folsom St at 13th St
115893                     The Embarcadero at Bryant St
27996                               Howard St at Mary St
57273   San Francisco Ferry Building (Harry Bridges Pl...
148578                             5th St at Virginia St
162343                         Division St at Potrero Ave
67111                                        Esprit Park
178490    San Francisco Caltrain (Townsend St at 4th St)
24719                        Bancroft Way at Telegraph Ave
117103                                Ashby BART Station
157519                               Page St at Scott St
24292   San Francisco Caltrain Station 2  (Townsend St...
106335                          Mississippi St at 17th St

        end_station_latitude  end_station_longitude     ...      \
123820             37.794130            -122.394430     ...
49494              37.850222            -122.260172     ...
41001              37.776598            -122.395282     ...
168763             37.829705            -122.287610     ...
51371              37.777547            -122.433274     ...
156330             37.781074            -122.411738     ...
157632             37.755213            -122.420975     ...
1806               37.769757            -122.415674     ...
115893             37.787168            -122.388098     ...
27996              37.781010            -122.405666     ...
57273              37.795392            -122.394203     ...
148578             37.325998            -121.877120     ...
162343             37.769218            -122.407646     ...
67111              37.761634            -122.390648     ...
178490             37.776598            -122.395282     ...
24719              37.868813            -122.258764     ...
117103             37.852477            -122.270213     ...
157519             37.772406            -122.435650     ...
24292              37.776639            -122.395526     ...
```

```
106335           37.764802           -122.394771     ...

       member_birth_year member_gender  bike_share_for_all_trip  \
123820              1982          Male                    False
49494               1972        Female                    False
41001               1978          Male                    False
168763              1984          Male                    False
51371               1989          Male                    False
156330              1973          Male                    False
157632              1985        Female                    False
1806                1982          Male                    False
115893              1991          Male                    False
27996               1989        Female                    False
57273               1994        Female                    False
148578              1996          Male                     True
162343              1984          Male                    False
67111               1959          Male                    False
178490              1982          Male                    False
24719               1988          Male                    False
117103              1979        Female                    False
157519              1994          Male                    False
24292               1973          Male                    False
106335              1990          Male                    False

       start_time_dayofweek  start_time_month end_time_dayofweek  \
123820                  Mon          February                Mon
49494                   Thu          February                Thu
41001                   Fri          February                Fri
168763                  Mon          February                Mon
51371                   Thu          February                Thu
156330                  Wed          February                Wed
157632                  Tue          February                Tue
1806                    Thu          February                Thu
115893                  Tue          February                Tue
27996                   Mon          February                Mon
57273                   Thu          February                Thu
148578                  Wed          February                Wed
162343                  Tue          February                Tue
67111                   Wed          February                Wed
178490                  Fri          February                Fri
24719                   Mon          February                Mon
117103                  Tue          February                Tue
157519                  Tue          February                Tue
24292                   Mon          February                Mon
106335                  Wed          February                Wed

       end_time_month duration_min start_time_hour  member_age
123820       February     8.250000               9          37
```

```
49494          February     6.466667            21           47
41001          February     9.666667            19           41
168763         February     3.416667            13           35
51371          February    14.633333            17           30
156330         February     9.683333             8           46
157632         February     5.666667            21           34
1806           February    14.583333            18           37
115893         February    18.050000             8           28
27996          February    18.950000             8           30
57273          February     8.050000             8           25
148578         February    12.816667            21           23
162343         February     4.083333            11           35
67111          February    14.366667             8           60
178490         February     9.883333            17           37
24719          February     5.000000            17           31
117103         February     2.800000             5           40
157519         February    13.516667            21           25
24292          February    11.966667            18           46
106335         February    11.050000            18           29

[20 rows x 22 columns]
```

In [73]:
```
df_2["member_age"].describe()
```

Out[73]:
```
count    173374.000000
mean         34.119389
std           9.873882
min          18.000000
25%          27.000000
50%          32.000000
75%          39.000000
max          80.000000
Name: member_age, dtype: float64
```

In [74]:
```
df_2["duration_min"].describe()
```

Out[74]:
```
count    173374.000000
mean         10.311936
std           7.396501
min           1.016667
25%           5.366667
50%           8.450000
75%          13.000000
max          59.933333
Name: duration_min, dtype: float64
```

4.0.1 Distribution(s) of your variable(s) of interest.

1. The feature of interest was the trip duration, and we can conclude that the users used the biking system for a wide range of trip duration, and after cleaning the trip duration data and

removing the outliers, we have found that the major trips had a trip duration on average of 7-12 mins.

2. The duration_min data were not showing a proper distribution while plotting them on a linear scale, hence the logarithmic scale in order to show proper distribution.

3. I found that the work days were the most days that the users use the bike share system especially Thursdays for this study.

4. I also found that the peak hours for the users were from 7-9am and from 4-6pm and the hours are closely matching with the regular start and end working hours. This might be related to the time when employees and students go to and leave work and school. This is was also consistent with the distribution of trips over weekdays, where work days have the most demand for trips.

5. Regarding the users, the males were almost 3 times the female users, the most age range is 20-40 which belonged to the most active population either at work or studying. the subscribers are more than 9 times the customers. Customers represent 9.35% of users, whereas subscribers represents 90.65%. Males represent 74.62% of users, whereas Females represents 23.30%, the remainder is others with 2.07%

4.0.2 Unusual distributions

1. The trip duration was initially at seconds but I had them converted to minutes for easy analysis. The duration_min distribution had outliers so I also had them removed based on 120 mins as a cut point after studying the effect of these cut data on the whole datset.

2. The hour of the day and the day of the week were extracted from the timestamp.

3. The age of the users is calculated using the member_birth_year.

4. New features were created out of the time variable

4.0.3 Saving the cleaned Dataset

In [75]:
```
# Before moving to the next exploration, save the cleaned dataset on a new csv file.
df_2.to_csv('clean_2019fordgobike.csv', index=False)
```

In [76]:
```
# to confirm it the cleaned dataset was saved
df_2.head()
```

Out[76]:
```
                start_time                 end_time start_station_id  \
4 2019-02-28 23:54:18.549 2019-03-01 00:20:44.074                7
5 2019-02-28 23:49:58.632 2019-03-01 00:19:51.760               93
6 2019-02-28 23:55:35.104 2019-03-01 00:14:42.588              300
7 2019-02-28 23:41:06.766 2019-03-01 00:08:02.756               10
8 2019-02-28 23:41:48.790 2019-03-01 00:07:59.715               10

             start_station_name  start_station_latitude  \
4            Frank H Ogawa Plaza               37.804562
5  4th St at Mission Bay Blvd S               37.770407
```

```
6         Palm St at Willow St             37.317298
7   Washington St at Kearny St             37.795393
8   Washington St at Kearny St             37.795393

   start_station_longitude end_station_id         end_station_name  \
4              -122.271738            222     10th Ave at E 15th St
5              -122.391198            323        Broadway at Kearny
6              -121.884995            312  San Jose Diridon Station
7              -122.404770            127    Valencia St at 21st St
8              -122.404770            127    Valencia St at 21st St

   end_station_latitude  end_station_longitude     ...     member_birth_year  \
4             37.792714            -122.248780     ...                  1974
5             37.798014            -122.405950     ...                  1959
6             37.329732            -121.901782     ...                  1983
7             37.756708            -122.421025     ...                  1989
8             37.756708            -122.421025     ...                  1988

  member_gender  bike_share_for_all_trip start_time_dayofweek  \
4          Male                     True                  Thu
5          Male                    False                  Thu
6        Female                    False                  Thu
7          Male                    False                  Thu
8         Other                    False                  Thu

   start_time_month end_time_dayofweek end_time_month duration_min  \
4          February                Fri          March    26.416667
5          February                Fri          March    29.883333
6          February                Fri          March    19.116667
7          February                Fri          March    26.916667
8          February                Fri          March    26.166667

  start_time_hour  member_age
4              23          45
5              23          60
6              23          36
7              23          30
8              23          31

[5 rows x 22 columns]
```

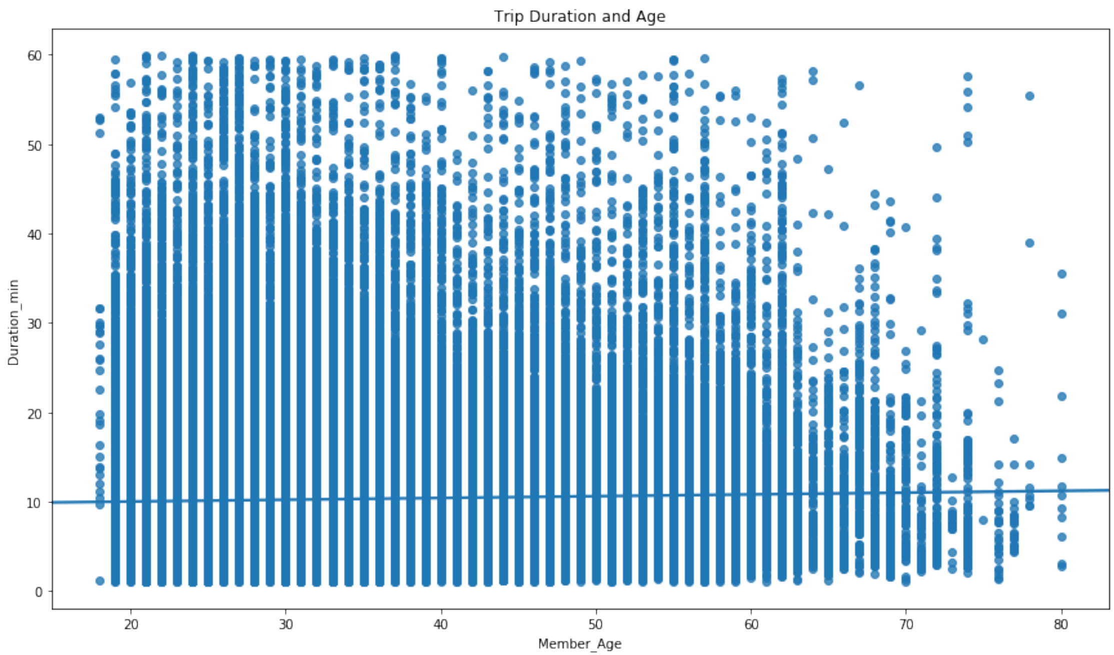
4.1 Bivariate Exploration

In this section, we'll investigate relationships between pairs of variables in the data.

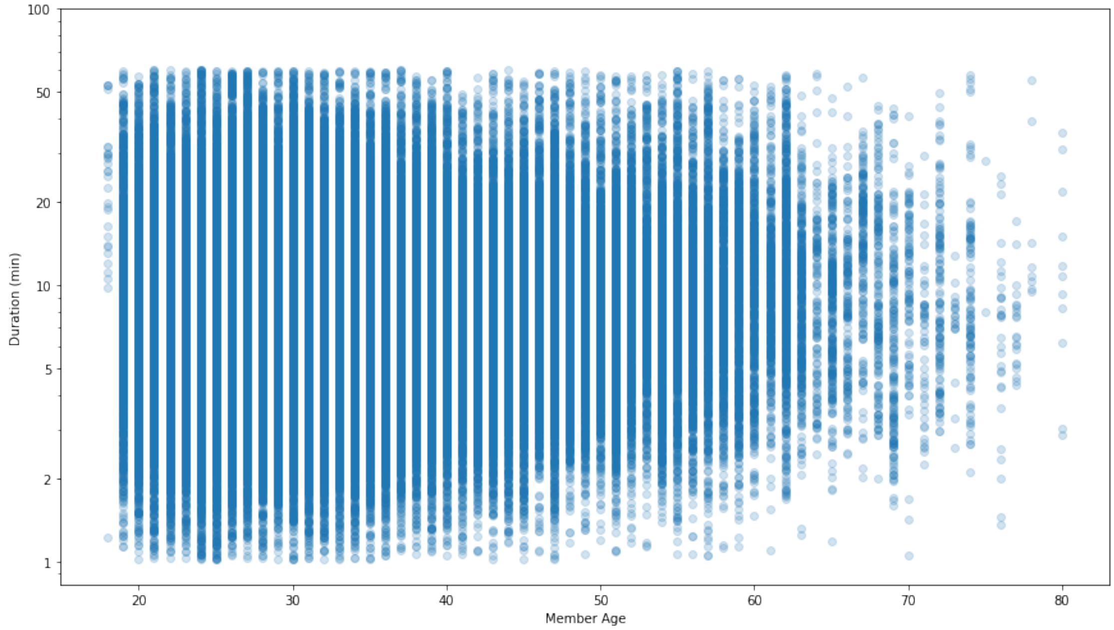
Distribution of duration by members' age

- What is the relationship between the trip duration and age?

In [77]:
```
plt.figure(figsize=[14.70, 8.27])
sns.regplot(data = df_2, x = 'member_age', y = 'duration_min');
plt.title('Trip Duration and Age')
plt.xlabel('Member_Age')
plt.ylabel('Duration_min')
plt.show()
```



In [78]:
```
# scatter plot of duration_min vs. member_age, with log transform on duration_min axis
plt.figure(figsize=[14.70, 8.27])
plt.scatter(data = df_2, x = 'member_age', y = 'duration_min', alpha = 0.2);

# plt.xlim([0, 3.5])
plt.xlabel('Member Age');
plt.yscale('log');
plt.yticks([1, 2, 5, 10, 20, 50, 100], [1, 2, 5, 10, 20, 50, 100]);
plt.ylabel('Duration (min)');
```

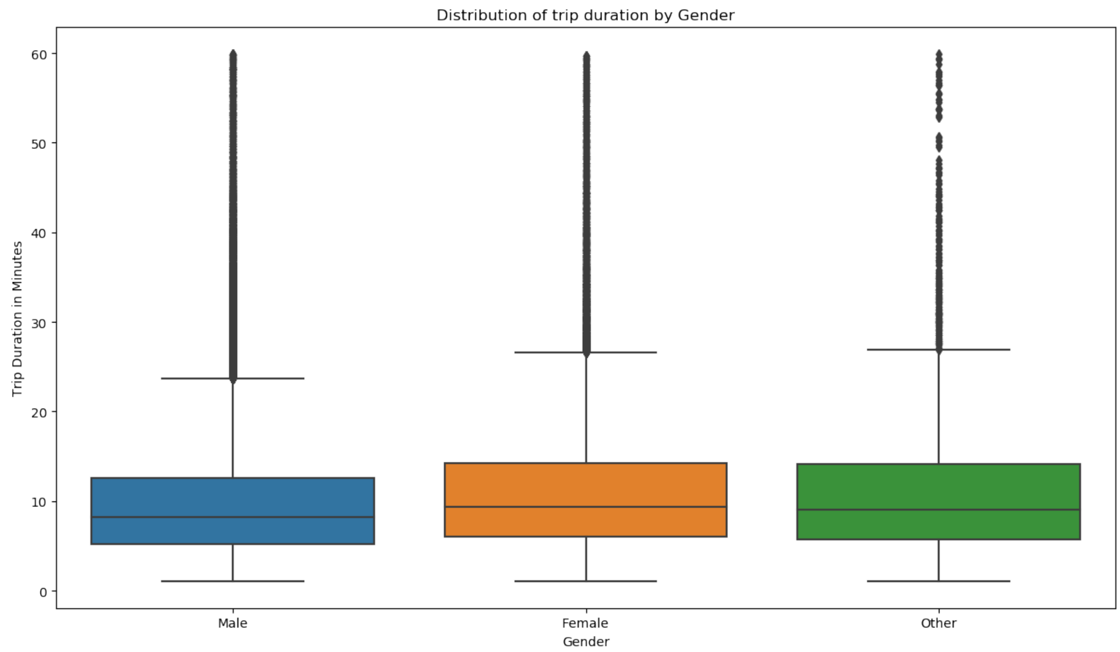


A negative correlation occurred between trip duration and age

Distribution by members' gender

- What is the relationship between the trip duration and gender?

In [79]:
```
plt.figure(figsize=[14.70, 8.27], dpi = 100)

sns.boxplot(data = df_2, x = "member_gender", y = "duration_min")
plt.xlabel('Gender');
plt.ylabel('Trip Duration in Minutes')

plt.title("Distribution of trip duration by Gender")

plt.show()
```

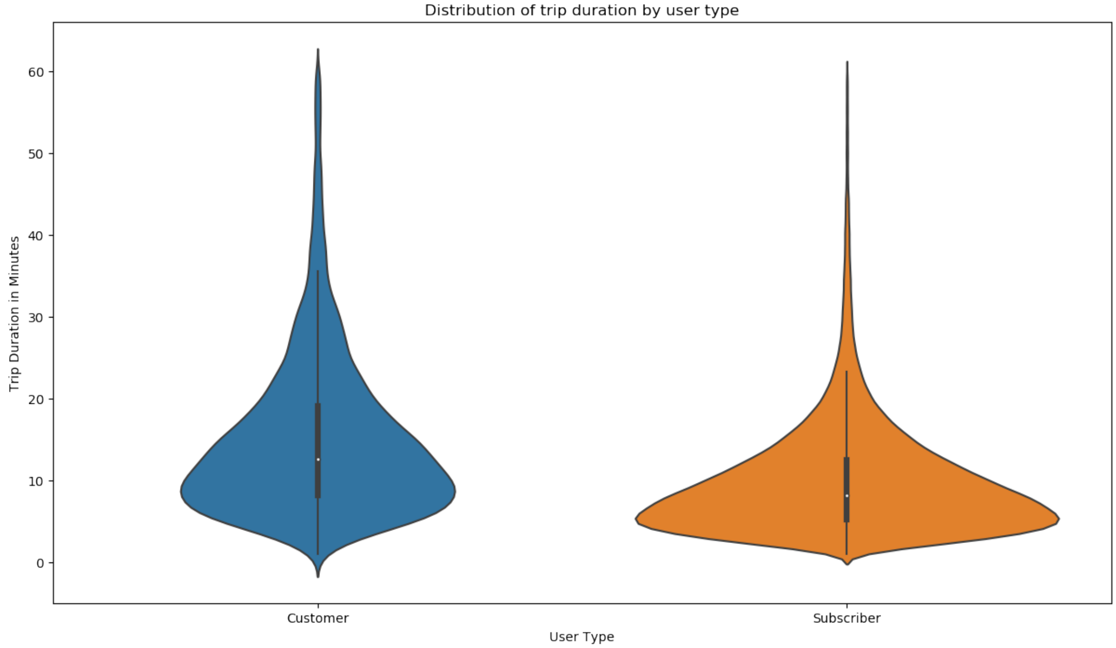


Male riders have shorter trips compared to female riders and other gender types.

Distribution by user type

- What is the relationship between trip durations and user type?

In [80]:
```
# using a violin plot to show the relationship
plt.figure(figsize=[14.70, 8.27], dpi = 100)

sns.violinplot(data = df_2, x = "user_type", y = "duration_min")
plt.xlabel('User Type');
plt.ylabel('Trip Duration in Minutes')

plt.title("Distribution of trip duration by user type")

plt.show()
```



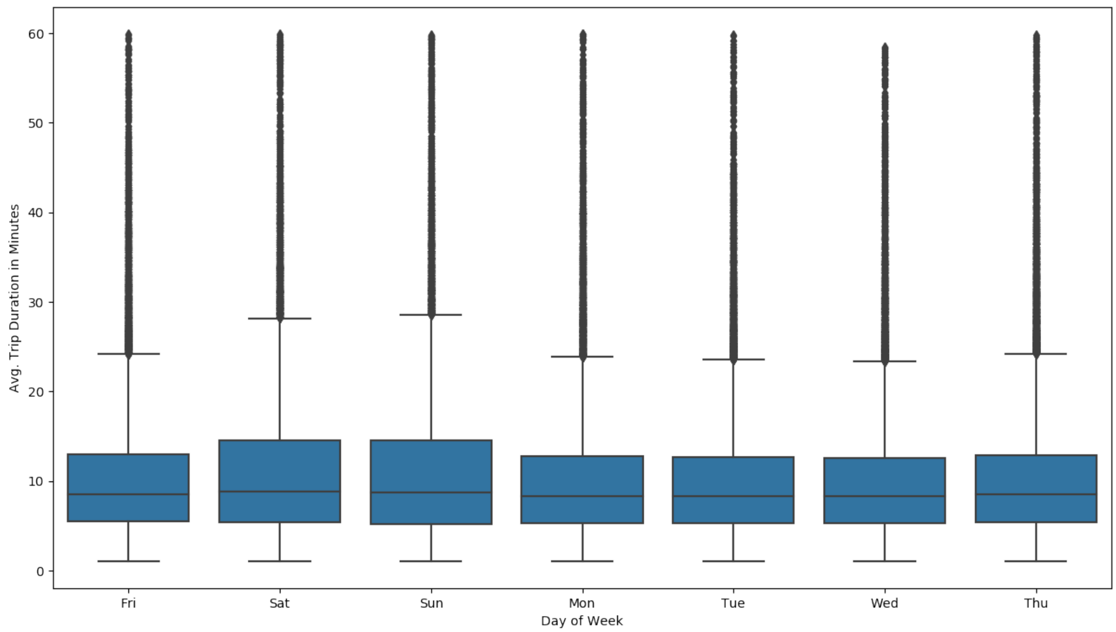
From the above graph customers have longer trips while subscribers have shorter trips.

Distribution by start time day of the week

- How do different days of the week affect the duration of the trips?

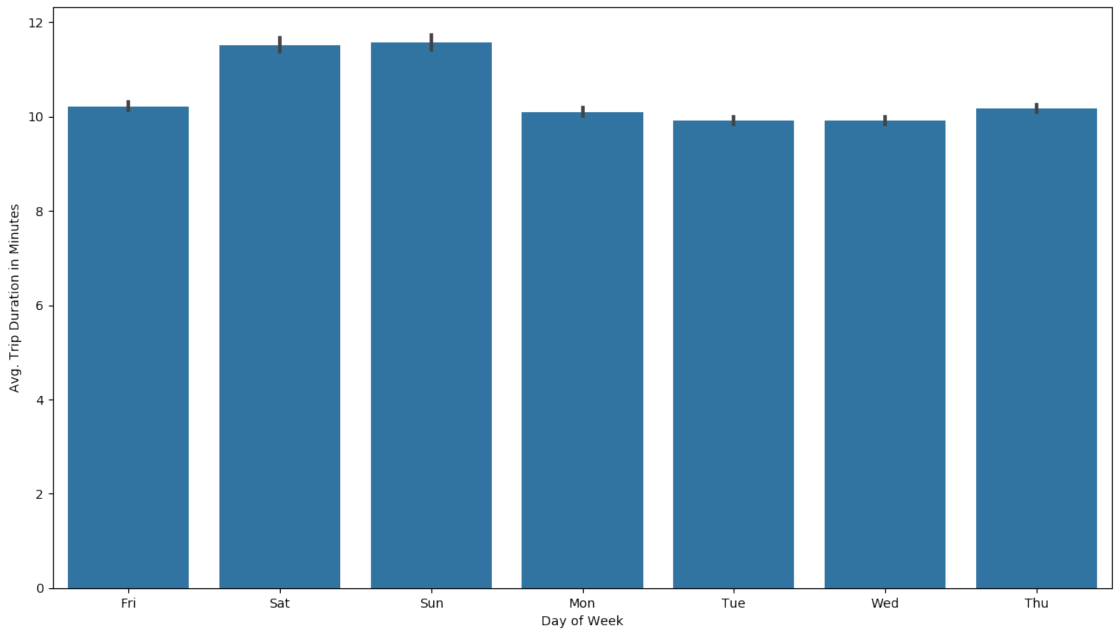
```
In [81]: # using a barplot
         plt.tight_layout()
         plt.figure(figsize=[14.70, 8.27], dpi = 100)

         sns.boxplot(data = df_2, x = "start_time_dayofweek", y = "duration_min", color=base_col
         plt.xlabel('Day of Week');
         plt.ylabel('Avg. Trip Duration in Minutes')

         plt.show();
```

```
<matplotlib.figure.Figure at 0x7f8da22ce748>
```

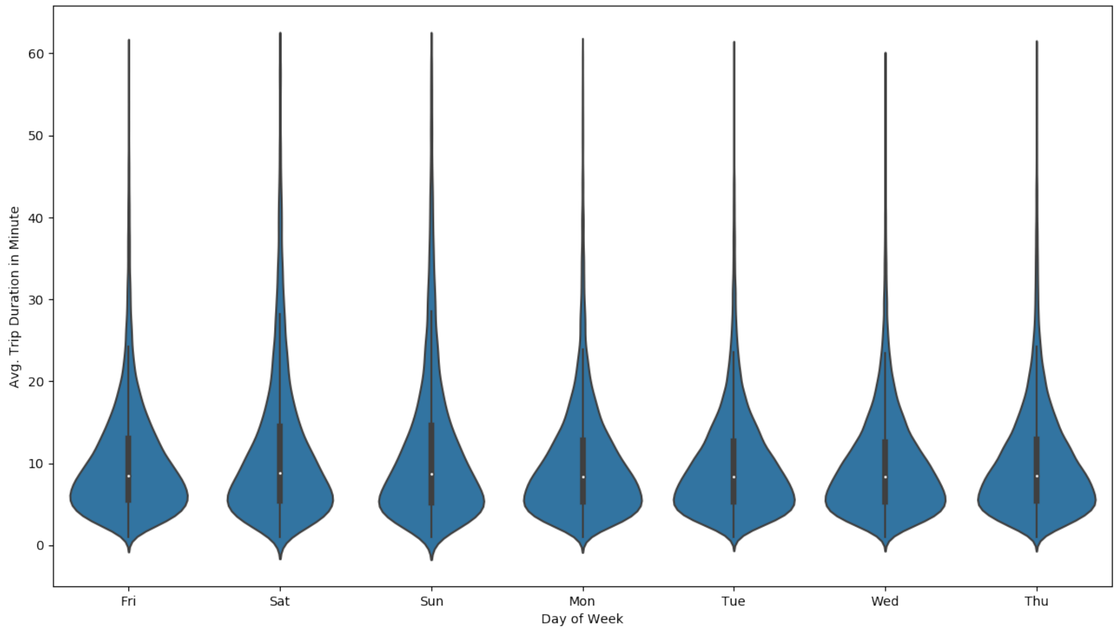


In [82]:
```
# using a barplot
plt.tight_layout()
plt.figure(figsize=[14.70, 8.27], dpi = 100)

sns.barplot(data = df_2, x = "start_time_dayofweek", y = "duration_min", color=base_col
plt.xlabel('Day of Week');
plt.ylabel('Avg. Trip Duration in Minutes')

plt.show();
```

```
<matplotlib.figure.Figure at 0x7f8da230f6d8>
```



In [83]:
```
# using a violinplot
plt.figure(figsize=[14.70, 8.27], dpi = 100)

sns.violinplot(data = df_2, x = "start_time_dayofweek", y = "duration_min", color=base_
plt.xlabel('Day of Week');
plt.ylabel('Avg. Trip Duration in Minute')

plt.show()
```

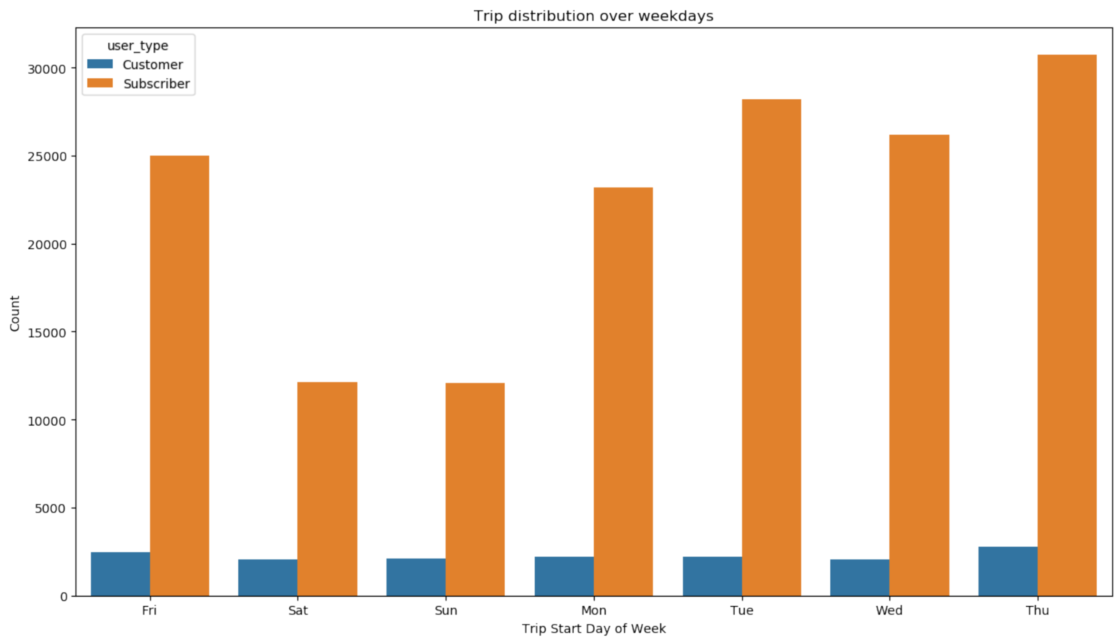


Trips are longer during weekends (Saturdays and Sundays). One can say the trips are mostly taken for fun during weekends.

Distribution by user type over weekdays

- How do the different user types use the bike system during weeekdays?

In [84]:
```
plt.figure(figsize=[14.70, 8.27], dpi = 100)

sns.countplot(data=df_2, x='start_time_dayofweek', hue='user_type')
plt.xlabel('Trip Start Day of Week')
plt.ylabel('Count')
plt.title("Trip distribution over weekdays")

plt.show()
```

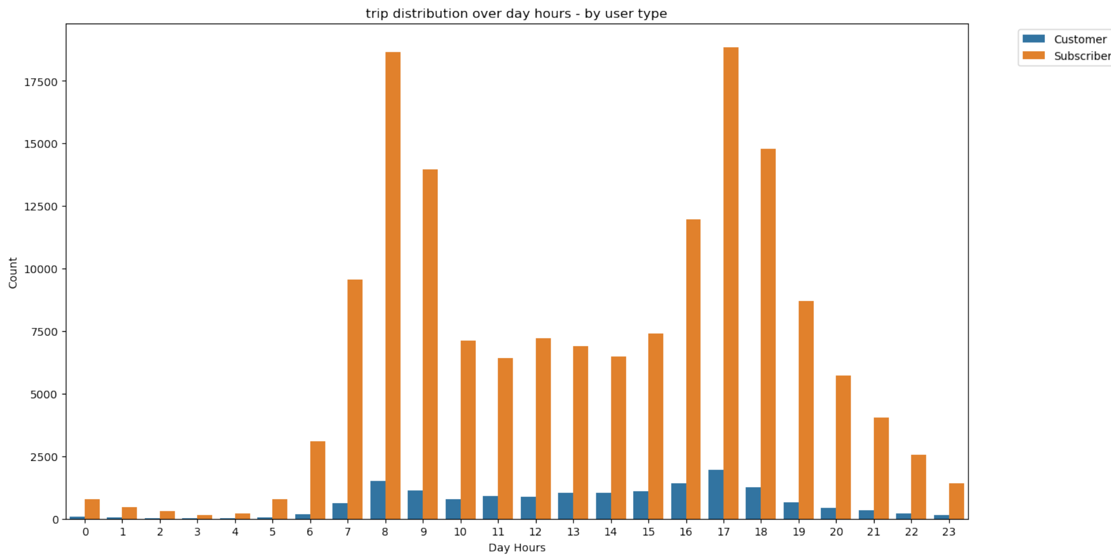


Subscribers tend to have consistent usage for a specific purpose every day, mainly: work and study. As a result the number of their rides declines the most at weekends

Distribution by user type over hours of the day

- How do user types use the bike system at different hours of each day?

```
In [85]: plt.figure(figsize=[14.70, 8.27], dpi = 100)

         sns.countplot(data = df_2, x = "start_time_hour", hue='user_type')
         plt.title("trip distribution over day hours - by user type")
         plt.xlabel('Day Hours')
         plt.ylabel('Count')
         plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

         plt.show()
```



We can notice that peak hours for both user types are those from 7 - 9 am which might be when workers and students go to work/school and from 4 - 6 pm when they leave work/school.

4.1.1 How did the feature(s) of interest vary with other features in the dataset?

- As mentioned earlier, the main focus of interest of this study is the trip timing, so I have studied the trip duration with the member age, and also I have studied the the rush hour usage across the day for both user types; the subscriber and the customer.

4.1.2 Interesting relationships between other features

1. Yes I have observed interesting relationships, for the duration_min vs the member age, I have concluded that from age 20 to 40, the duration of major trips was ranging between 2 mins to 30 mins and the trip duration range is narrowing as the age increased, this is obviously described with the duration_min vs age on the log scale as it looks like a horizontal cone which tends to narrow as the age of the member increased.

2. For the rush hour of the of the day vs the user type, I have found that the rush hours for both user types are 5 P.M and 8 A.M and those two rush hours are matching with the rush hours

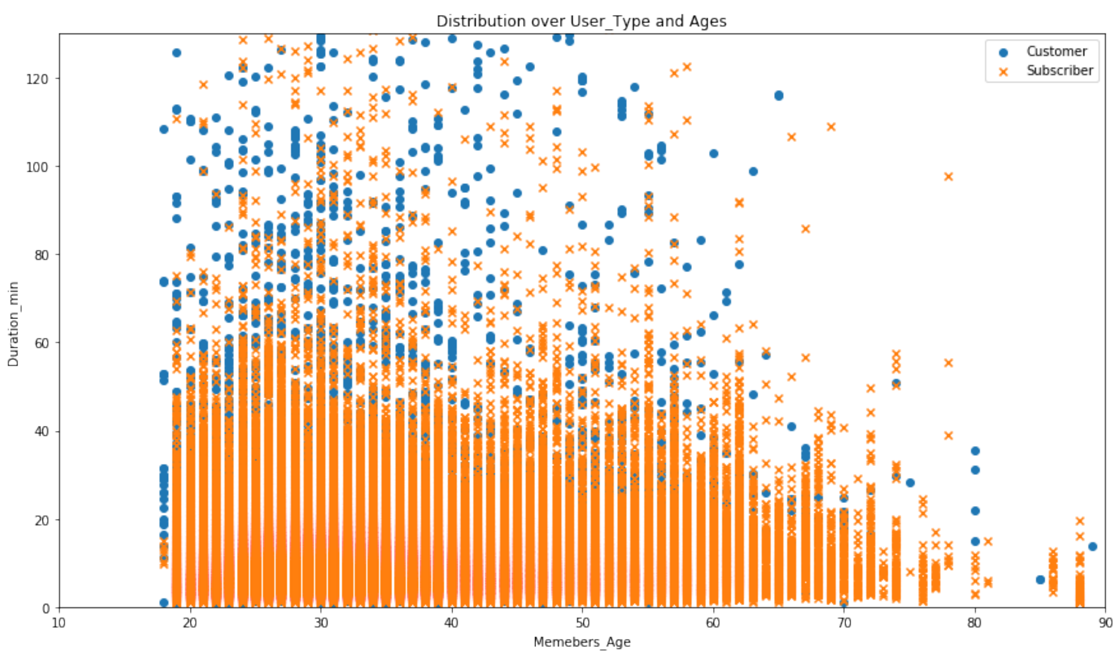
of whole dataset which was investigated at the univariate visualization earlier but obviously the number of trips for subscriber users at those two hours are larger than same two hours for the customer users.

3. There are way more subscribers than customers. Subscribers usage seem to be very consistent and standard, their usage is intended for daily routine such as work or study. Therfore subscribers usage reaches its highest levels during rush hours and work days. Customers on the other hand tend to use bikes for fun, their usage is concentrated during weekends at midnights and middays

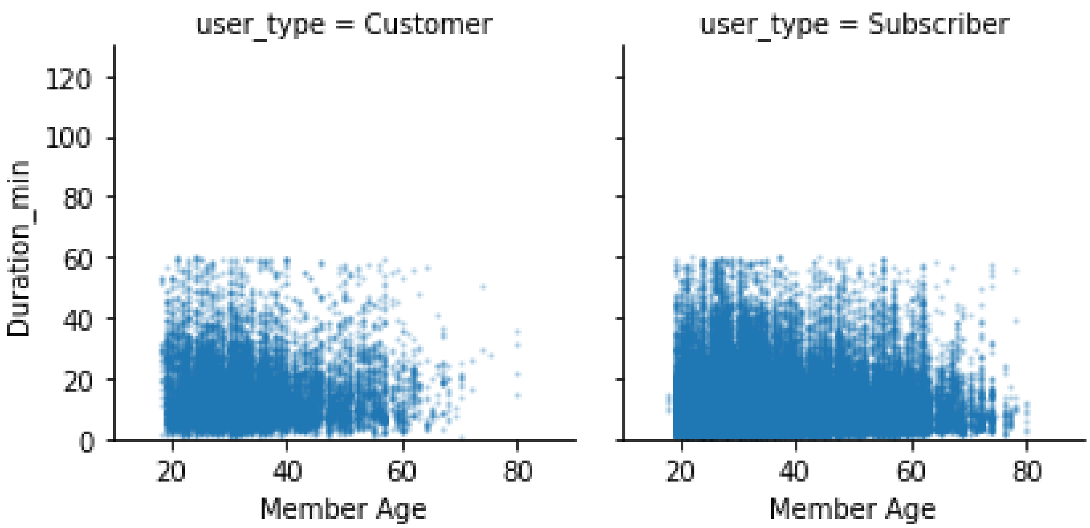
4.2 Multivariate Exploration

- What's the distribution over user type and age, trip durations, weekdays?

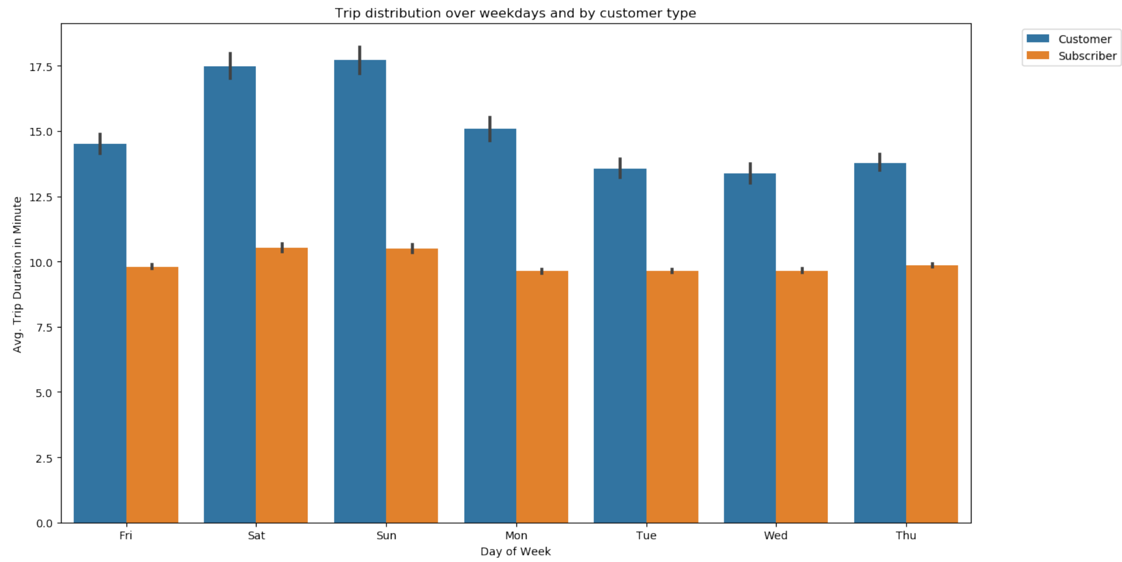
```
In [86]: # distribution over user types and age
         plt.figure(figsize=[14.70, 8.27])
         usertype_markers = [['Customer', 'o'],
                             ['Subscriber', 'x']]


         for user_type, marker in usertype_markers:
             df_usertype = df[df['user_type'] == user_type]
             plt.scatter(df_usertype['member_age'], df_usertype['duration_min'], marker = marker
         plt.legend(['Customer', 'Subscriber'])
         plt.axis([10, 90, 0, 130 ])
         plt.title('Distribution over User_Type and Ages')
         plt.xlabel('Memebers_Age')
         plt.ylabel('Duration_min')
         plt.show()
```



In [87]:
```
# trip duration over different user types and members' age
user_type = sns.FacetGrid(data = df_2, col = 'user_type', col_wrap = 2, xlim = [10, 90]
user_type.map(plt.scatter, 'member_age', 'duration_min', alpha= 0.2, s=2)

user_type.set_xlabels('Member Age')
user_type.set_ylabels('Duration_min')

plt.show()
```



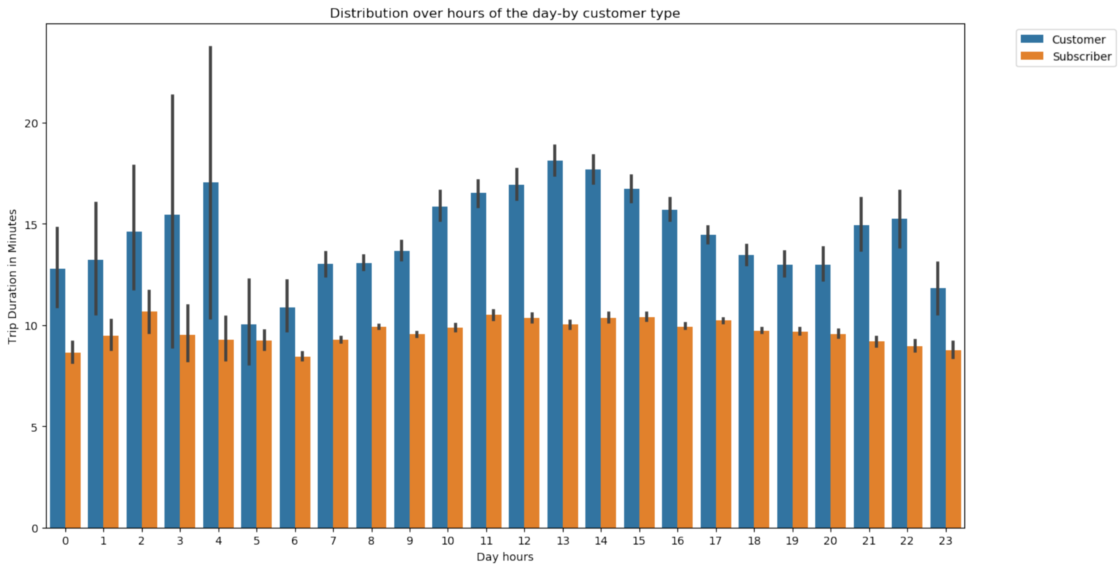
In [88]:
```
# distribution over weekdays by customer types
plt.figure(figsize = (14.70, 8.27), dpi = 100)

sns.barplot(data = df_2, x = "start_time_dayofweek", y = "duration_min", hue='user_type
plt.xlabel('Day of Week');
plt.ylabel('Avg. Trip Duration in Minute')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.title("Trip distribution over weekdays and by customer type")

plt.show()
```



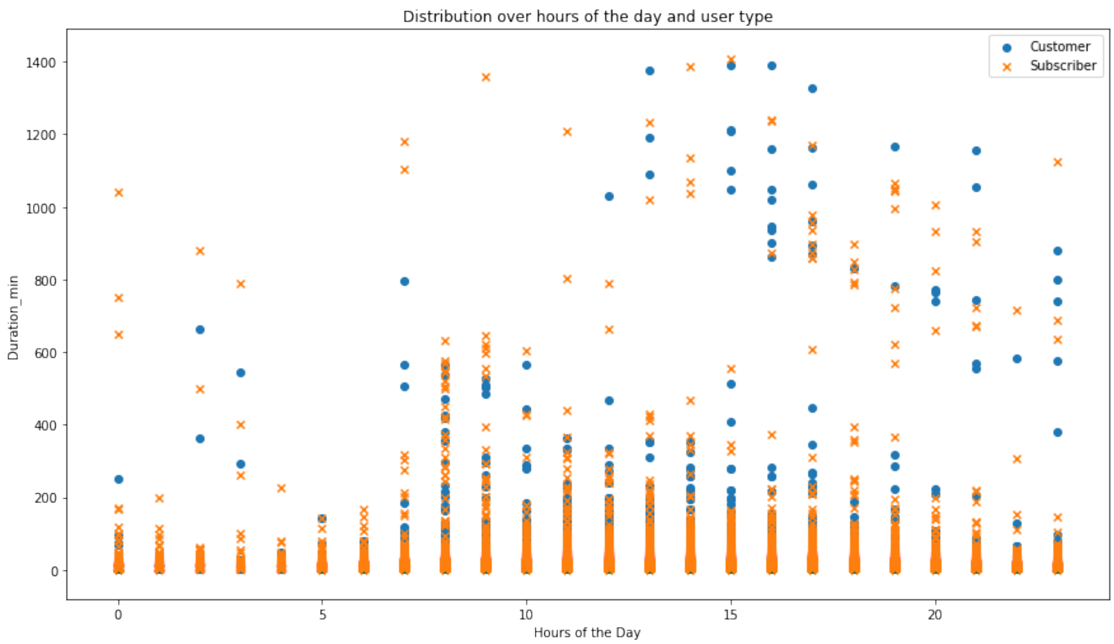
Customers have longer trips than subscribers

- What user type have longer trips and at what time of the day?

In [89]:
```
# distribution over hours of the day-by customer types
plt.figure(figsize = (14.70, 8.27), dpi = 100)

sns.barplot(data = df_2, x = "start_time_hour", y = "duration_min",    hue='user_type')
plt.title("Distribution over hours of the day-by customer type")
plt.xlabel('Day hours')
plt.ylabel('Trip Duration in Minutes')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

plt.show();
```



In [90]:
```
# further insight
# distribution over hours of the day-by user types
plt.figure(figsize=[14.70, 8.27])
usertype_markers = [['Customer', 'o'],
                    ['Subscriber', 'x']]


for user_type, marker in usertype_markers:
    df_usertype = df[df['user_type'] == user_type]
    plt.scatter(df_usertype['start_time_hour'], df_usertype['duration_min'], marker = m
plt.legend(['Customer', 'Subscriber'])
plt.title('Distribution over hours of the day and user type')
plt.xlabel('Hours of the Day')
plt.ylabel('Duration_min')
plt.show()
```



Customers have consistently longer trips across all hours of the day. However, customer trips are much longer at midnight and midday

```
In [ ]: # a PairGrid
        plt.figure(figsize = (14.70, 8.27), dpi = 100)
        g = sns.PairGrid(data = df_2, vars = ['start_station_latitude', 'start_station_longitude
                                              'end_station_longitude', 'member_birth_year', 'bik
                                              'duration_min', 'start_time_hour', 'member_age'])
        g.map_diag(plt.hist)
        g.map_offdiag(plt.scatter)
```

There is a clear different usage pattern between customers and subscribers in the way we previously explained

4.2.1 Relationships observed in this part of the investigation.

- We have concluded earlier that the number of subscriber is 9-10 times the number of customers as a count but in this analysis we have found an interesting results that the subscribers users have higher age range than the customers users.
- Customers have consistently longer trips than subscribers across all hours of the day and are much longer at midnight and midday.

4.2.2 Interesting or surprising interactions between features

- The interesting result shown by the plot is that the subscribers are using the bikeshare system for longer duration and also covering higher age range which is an indication of long relationship between the clients and the bikeshare company.

- It was surprising to see that customer's rides mostly occur during midnight and midday.

4.3 Summary

DATASET

The dataset that I used was the Ford GoBike System Data. There are 183412 entries rows in the dataset with 16 columns. The features included are: trip duration(in sec), start_time, end_time, station informations(start_station_id, start_station_name, start_station_latitude, start_station_longitude, end_station_id, end_station_name, end_station_latitude and end_station_longitude), informations on members(bike_id, user_type, member_birth_year, member_gender, bike_share_for_all_trip).

FINDINGS

Univariate Analysis

- The users used the biking system for a wide range of trip duration, and after cleaning the trip duration data and removing the outliers, we have found that the major trips had a trip duration on average of 7-12 mins.
- The duration_min data were not showing a proper distribution while plotting them on a linear scale, hence the logarithmic scale in order to show proper distribution.
- The work days were the most days that the users use the bike share system especially Thursdays for this study.
- The peak hours for the users were from 7-9am and from 4-6pm and the hours are closely matching with the regular start and end working hours. This might be related to the time when employees and students go to and leave work and school. This is was also consistent with the distribution of trips over weekdays, where work days have the most demand for trips.
- The males were almost 3 times the female users, the most age range is 20-40 which belonged to the most active population either at work or studying. the subscribers are more than 9 times the customers. Customers represent 9.35% of users, whereas subscribers represents 90.65%. Males represent 74.62% of users, whereas Females represents 23.30%, the remainder is others with 2.07%

Bivariate Analysis * For the duration_min vs the member age, from age 20 to 40, the duration of major trips was ranging between 2 mins to 30 mins and the trip duration range is narrowing as the age increased, this is obviously described with the duration_min vs age on the log scale as it looks like a horizontal cone which tends to narrow as the age of the member increased.

- For the rush hour of the of the day vs the user type, the rush hours for both user types are 5 P.M and 8 A.M and those two rush hours are matching with the rush hours of whole dataset which was investigated at the univariate visualization earlier but obviously the number of trips for subscriber users at those two hours are larger than same two hours for the customer users.
- There are way more subscribers than customers. Subscribers usage seem to be very consistent and standard, their usage is intended for daily routine such as work or study. Therfore subscribers usage reaches its highest levels during rush hours and work days. Customers

on the other hand tend to use bikes for fun, their usage is concentrated during weekends at midnights and middays

Multivariate Analysis * The subscribers have been using the bikeshare system for longer duration and also covering higher age range which is an indication of long relationship between the clients and the bikeshare company.

```
In [ ]:
```