Part_I_notebook

November 15, 2022

1 Part I - Ford-Go-Bike-Feb-2019 : Communicate Data Findings

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1.1.1 Quick link Shortcuts

Introduction Preliminary Wrangling Univariate Exploration Bivariate Exploration Multivariate Exploration Conclusions

Introduction > The Ford Go Bike 2019 dataset is about individual bike rides in the bike sharing system covering the greater San Francisco Bay Area

Preliminary Wrangling

1.1.2 a. Gathering

1. Import all relevant libraries, packages and modules

```
In [2]: # importing relevant libraries and modules
        import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        import seaborn as sns
        import calendar as cal
        import math
        import time as tm
```

```
In [3]: # setting plots to be embedded inline
        %matplotlib inline
```

```
In [4]: # importing warnings module to ignore warnings
        import warnings
        warnings.filterwarnings('ignore')
```

2. Load the 2019 ford bike dataset into a pandas dataframe and describe its properties

```
In [5]: # loading the 'fordgobike' csv file dataset into a pandas dataframe
        ford_bike_2019 = pd.read_csv('201902-fordgobike-tripdata.csv')
```

1.1.3 b. Assessing

1.1.4 What is the structure of your dataset?

The dataset has 183412 data rows and 16 data columns, that is, 183412 trips and 16 features(related details).7 features have the float data type, 2 features have the integer data type, and the other 7 have the integer data type

3. Define a simple function that will display short summaries of the ford-bike dataset structure and invoke it later on

```
In [6]: # defining a function to explore the dataset structure

        def structure_insights(a):
            a.info()
            print('*'* 75)
            print(' ')
            print('(rows, columns): ', a.shape)
            print('*'* 75)
            print(' ')
            print('column label list: ')
            print(a.columns)
            print('*'* 75)
            print(' ')
            print('The dataset has {} trips and {} indicators.'.format(a.shape[0], a.shape[1]))
```

```
In [7]: # invoking the structure_insights(a) function to understand the entire dataset structure

        structure_insights(ford_bike_2019)
```

```
<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
***************************************************************************

(rows, columns):  (183412, 16)
***************************************************************************

column label list:
Index(['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'],
      dtype='object')
***************************************************************************

The dataset has 183412 trips and 16 indicators.
```

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

The main feature of interest is 'duration-sec' because it is used as a unit of measurement to charge both the subscribers and customers alike for the enterprise.

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

The 'member_birth_year' feature will be crucial when determining the age of the riders, the 'duration-sec' will be crucial when converting the units to smaller time units like minutes, the 'start_time' feature will also come in handy with generating start hours, and dates for each bike ride.

4. Check for missing values, duplicate values, wrong data types

- ***issue#1****: some features have missing values*
- ***issue#2****: wrong data types for some features*
- ***issue#3****: some features may need to be split further*

In [8]:
```python
# checking for the datatypes of the columns in the bike dataset
ford_bike_2019.dtypes
```

Out[8]:
```
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 [9]:
```
# returning the number of duplicated rows in the ford_bike_2019 dataset
ford_bike_2019.duplicated().sum()
```

Out[9]:
```
0
```

In [10]:
```
# returning the number of missing values per data column
columns = ['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']

for i in columns:
    print(('missing values in '+i+' are '), ford_bike_2019[i].isna().sum())
    print('*'*30)
    print(' ')
```

```
missing values in duration_sec are  0
******************************

missing values in start_time are  0
******************************

missing values in end_time are  0
******************************

missing values in start_station_id are  197
******************************

missing values in start_station_name are  197
******************************

missing values in start_station_latitude are  0
******************************

missing values in start_station_longitude are  0
******************************

missing values in end_station_id are  197
******************************
```

```
missing values in end_station_name are  197
******************************

missing values in end_station_latitude are  0
******************************

missing values in end_station_longitude are  0
******************************

missing values in bike_id are  0
******************************

missing values in user_type are  0
******************************

missing values in member_birth_year are  8265
******************************

missing values in member_gender are  8265
******************************

missing values in bike_share_for_all_trip are  0
******************************
```

1.1.7 Cleaning

- ***issue#1***: *some features have missing values*

Define:

- start_station_id, start_station_name has 197 missing values
- end_station_id, end_station_name has 197 missing values
- member_birth_year, member_gender have 8265 missing values
- since the replcement values are absent, the data rows with the missing values will have to be dropped

Code:

```
In [11]: # deleting all data rows with missing values
         ford_bike_2019.dropna(axis=0, inplace=True)
```

Test:

```
In [12]: # checking to confirm new changes
         ford_bike_2019.isnull().sum()
```

```
Out[12]: 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
```

- ***issue#2**: wrong data types for some features*

Define:

- start-time and end-time data columns have the string data type
- start-station-id and end-sation-id have the float data type
- bike-id has the integer data type, user-type has the string data type
- member-gender has the string data type, bike-share-for-all-trip has the string data type
- member-birth-year has the float data type

Code:

```
In [13]: # converting the data type of the time variables from object to datetime
         ford_bike_2019[['start_time', 'end_time']] = ford_bike_2019[['start_time', 'end_time']]
```

```
In [14]: # converting the data type of the station and bike ids from float to string
         ford_bike_2019[['start_station_id', 'end_station_id', 'bike_id']] = ford_bike_2019[['st
```

```
In [15]: # converting the data types of member_gender, bike_share_for_all, and user_type from st
         ford_bike_2019[['user_type', 'member_gender', 'bike_share_for_all_trip']] = ford_bike_2
```

```
In [16]: ford_bike_2019['member_birth_year'] = ford_bike_2019['member_birth_year'].astype(int)
```

Test:

```
In [17]: # returning a customized pandas dataframe of the affected features to check for the neu
         ford_bike_2019[['start_time', 'end_time', 'start_station_id', 'end_station_id', 'bike_i
```

```
Out[17]: start_time                 datetime64[ns]
         end_time                   datetime64[ns]
         start_station_id                   object
```

```
end_station_id                          object
bike_id                                 object
member_birth_year                        int64
user_type                             category
member_gender                         category
bike_share_for_all_trip               category
dtype: object
```

- ***issue#3****: some features may need to be split further*

Define:

Code: 1. Create another column that will categorize the start-hours into morning, afternoon, evening and night.

```
In [18]: # splitting the day time into morning, afternoon, evening and night

         # extracting the hour from the start time
         ford_bike_2019['start_hour'] = ford_bike_2019['start_time'].dt.hour
         ford_bike_2019['part_of_the_day'] = ' '
```

```
In [19]: # defining a function to help assign the different parts of the day to their respective
         def assign_day_periods(a, b, c):
             ford_bike_2019['part_of_the_day'][(ford_bike_2019['start_hour'] >= a) & (ford_bike_
```

```
In [20]: # assigning 'morning' to an hour range of midnight to 4 a.m.
         assign_day_periods(0, 4, 'night')
```

```
In [21]: # assigning 'morning' to an hour range of 5 a.m. to 11 a.m.
         assign_day_periods(5, 11, 'morning')
```

```
In [22]: # assigning 'afternoon' to an hour range of 12 p.m. to 5 p.m.
         assign_day_periods(12, 17, 'afternoon')
```

```
In [23]: # assigning 'evening' an hour range of 6 p.m. to 9 p.m.
         assign_day_periods(18, 21, 'evening')
```

```
In [24]: # assigning 'night' an hour range of
         assign_day_periods(22, 23, 'night')
```

2. Create another column that will categorize the month of February into the days of the week.

```
In [25]: # extracting the day of the week from the start time
         ford_bike_2019['start_weekday_no'] = ford_bike_2019['start_time'].apply(lambda time: ti
```

```
In [26]: # assigning the day of the week to their respective day number
         dmap = {0:'Mon', 1:'Tue', 2:'Wed', 3:'Thu', 4:'Fri', 5:'Sat', 6:'Sun'}
```

In [27]:
```python
# mapping the day number to the day of the week
ford_bike_2019['start_weekday_name'] = ford_bike_2019['start_weekday_no'].map(dmap)
```

3. Convert the data type of period_day and start_weekday_name to a categorical data type

In [28]:
```python
ford_bike_2019.iloc[:, 16:20].dtypes
```

Out[28]:
```
start_hour             int64
part_of_the_day       object
start_weekday_no       int64
start_weekday_name    object
dtype: object
```

In [29]:
```python
# creating an ordinal variable dictionary for the day of the week and the different par

# the dictionary is categorical in nature and the order of the variables is important
ordinal_var_dict = {'part_of_the_day': ['morning', 'afternoon', 'evening', 'night'], 's
```

In [30]:
```python
# iterating through the ordinal variable dictionary using a for loop to convert the var

for var in ordinal_var_dict:
    ordered_var = pd.api.types.CategoricalDtype(ordered = True, categories = ordinal_va
    ford_bike_2019[var] = ford_bike_2019[var].astype(ordered_var)
```

4. Create an age data column that will depend on the member_birth_age data column to determine the ages of all he bike riders respectively.

In [31]:
```python
# creating an age data column and filling it with the age of the riders

# the age of the riders is calculated by subtracting the year of birth from the year 20
ford_bike_2019['age'] = 2019 - ford_bike_2019['member_birth_year']
```

5. Create a 'duration-min' to convert all the duration seconds into minutes for all the specific bike rides

In [32]:
```python
# filling the duration-min data column with results of the division of the duration-sec
ford_bike_2019['duration_min'] = (ford_bike_2019['duration_sec']/60).astype(int)
```

Test:

In [33]:
```python
ford_bike_2019['part_of_the_day'].value_counts()
```

Out[33]:
```
afternoon    67018
morning      65252
evening      36153
night         6529
Name: part_of_the_day, dtype: int64
```

In [34]:
```python
ford_bike_2019.iloc[:, 16:22].dtypes
```

```
Out[34]: start_hour                int64
         part_of_the_day        category
         start_weekday_no          int64
         start_weekday_name     category
         age                       int64
         duration_min              int64
         dtype: object
```

```
In [35]: # returning a random sample of the ford_bike_2019 dataset with 5 rows in sight plus the
         ford_bike_2019.iloc[:, 16:22].sample(5)
```

```
Out[35]:         start_hour part_of_the_day  start_weekday_no start_weekday_name  age  \
         101549          17       afternoon                 3                Thu   57
         18687           18         evening                 1                Tue   36
         104940           8         morning                 3                Thu   49
         2498            17       afternoon                 3                Thu   29
         103572          12       afternoon                 3                Thu   54

                 duration_min
         101549             8
         18687              3
         104940             2
         2498              19
         103572            10
```

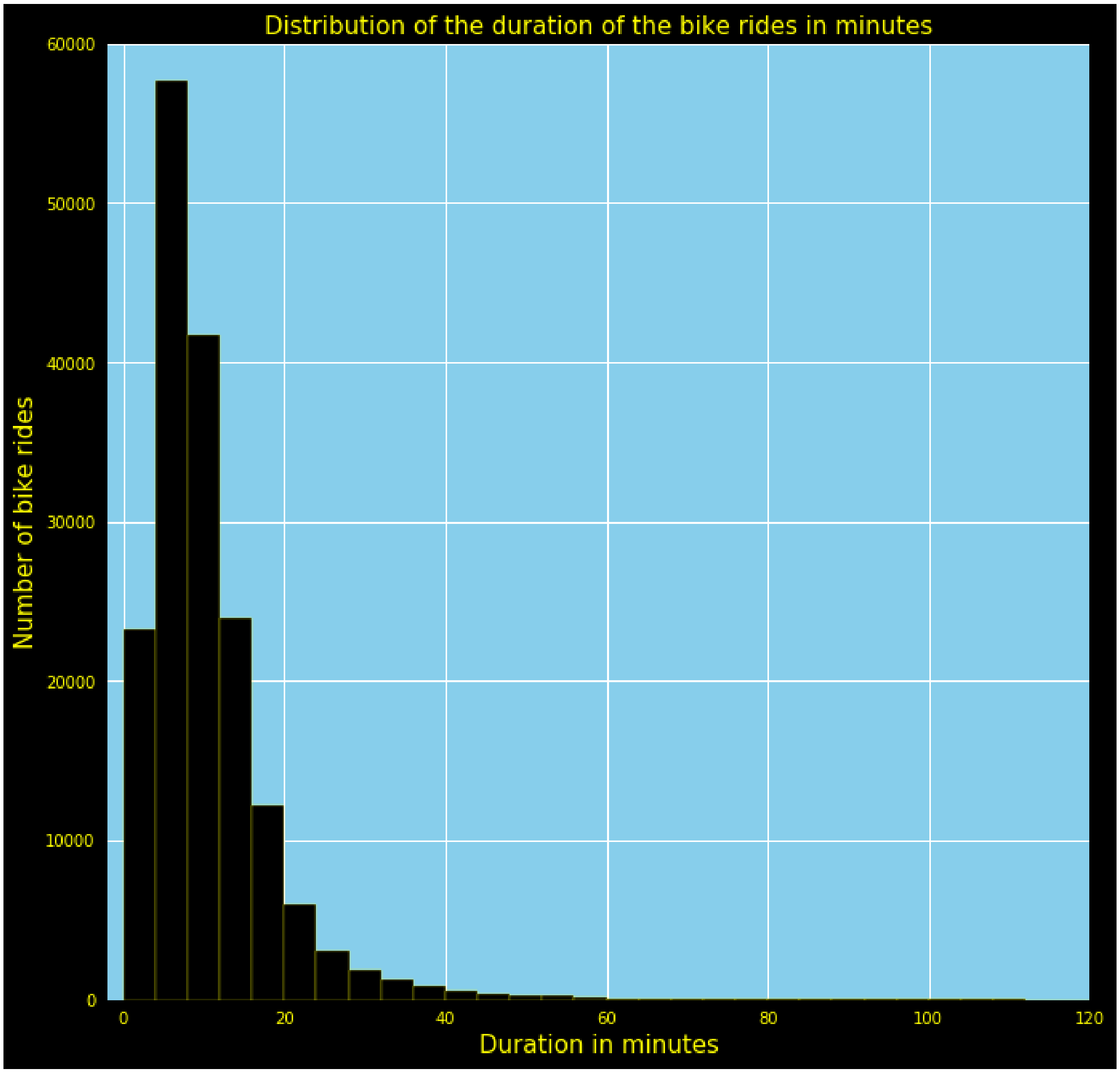
Univariate Exploration

1.1.8 Question#1:

What are the commonly used minutes when all bike trips are considered?

1.1.9 Visualization(s) #1:

```
In [88]: # plotting the distribution of the duration of the bike rides in minutes
         binsize = 4
         bins = np.arange(0, ford_bike_2019['duration_min'].max()+ binsize, binsize)
         plt.figure(figsize=[11, 11])
         plt.hist(data = ford_bike_2019, x = 'duration_min', bins = bins, color = 'black', edgec
         plt.title('Distribution of the duration of the bike rides in minutes', fontsize = 15)
         plt.xlabel('Duration in minutes', fontsize = 15)
         plt.ylabel('Number of bike rides', fontsize = 15)
         plt.axis([-2, 120, 0, 60000])
         sns.set(rc={'figure.facecolor':'black', 'axes.facecolor':'skyblue', 'axes.labelcolor':'
         plt.show()
```



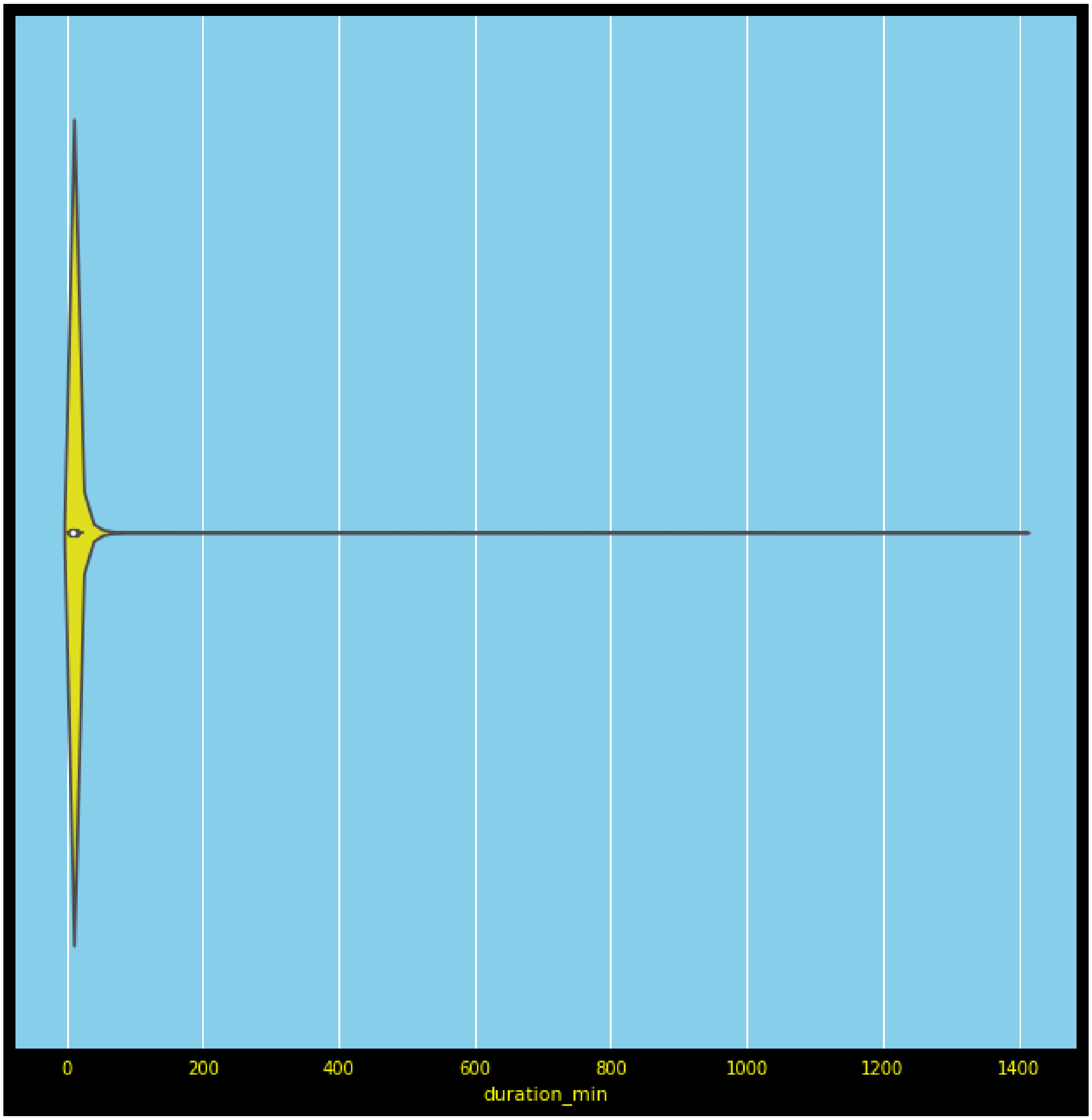

```
In [37]: ford_bike_2019['duration_min'].value_counts()
```

```
Out[37]: 5       15073
         4       14675
         6       14357
         7       13578
         8       12433
         3       12196
         9       10946
         10       9840
         11       8545
         2        8074
         12       7470
         13       6343
```

14	5430
15	4712
16	3934
17	3260
1	2979
18	2741
19	2263
20	1893
21	1580
22	1344
23	1149
24	954
25	799
26	728
27	592
28	548
29	492
30	457
	...
597	1
979	1
467	1
211	1
1234	1
722	1
466	1
721	1
1232	1
1359	1
1103	1
335	1
207	1
1101	1
960	1
333	1
204	1
714	1
329	1
201	1
328	1
582	1
325	1
324	1
323	1
1090	1
194	1
449	1
321	1

```
826          1
Name: duration_min, Length: 426, dtype: int64
```

In [89]:
```
# using the violin plot to have a second look at the distribution of the duration of th
sns.violinplot(data=ford_bike_2019, x='duration_min', color = 'yellow',  width = 0.8);
```



In [39]:
```
ford_bike_2019['duration_min'].value_counts()
```

Out[39]:
```
5        15073
4        14675
6        14357
7        13578
8        12433
```

3	12196
9	10946
10	9840
11	8545
2	8074
12	7470
13	6343
14	5430
15	4712
16	3934
17	3260
1	2979
18	2741
19	2263
20	1893
21	1580
22	1344
23	1149
24	954
25	799
26	728
27	592
28	548
29	492
30	457
	...
597	1
979	1
467	1
211	1
1234	1
722	1
466	1
721	1
1232	1
1359	1
1103	1
335	1
207	1
1101	1
960	1
333	1
204	1
714	1
329	1
201	1
328	1
582	1

```
325         1
324         1
323         1
1090        1
194         1
449         1
321         1
826         1
Name: duration_min, Length: 426, dtype: int64
```

1.1.10 Observation(s) #1:

- 5 minutes are the most preferred bike trip duration time interval
- the histogram is unimodal and positively skewed. It has a right skewed distribution
- 3 to 9 minutes all have a total bike trip tally that is greater than 10,000

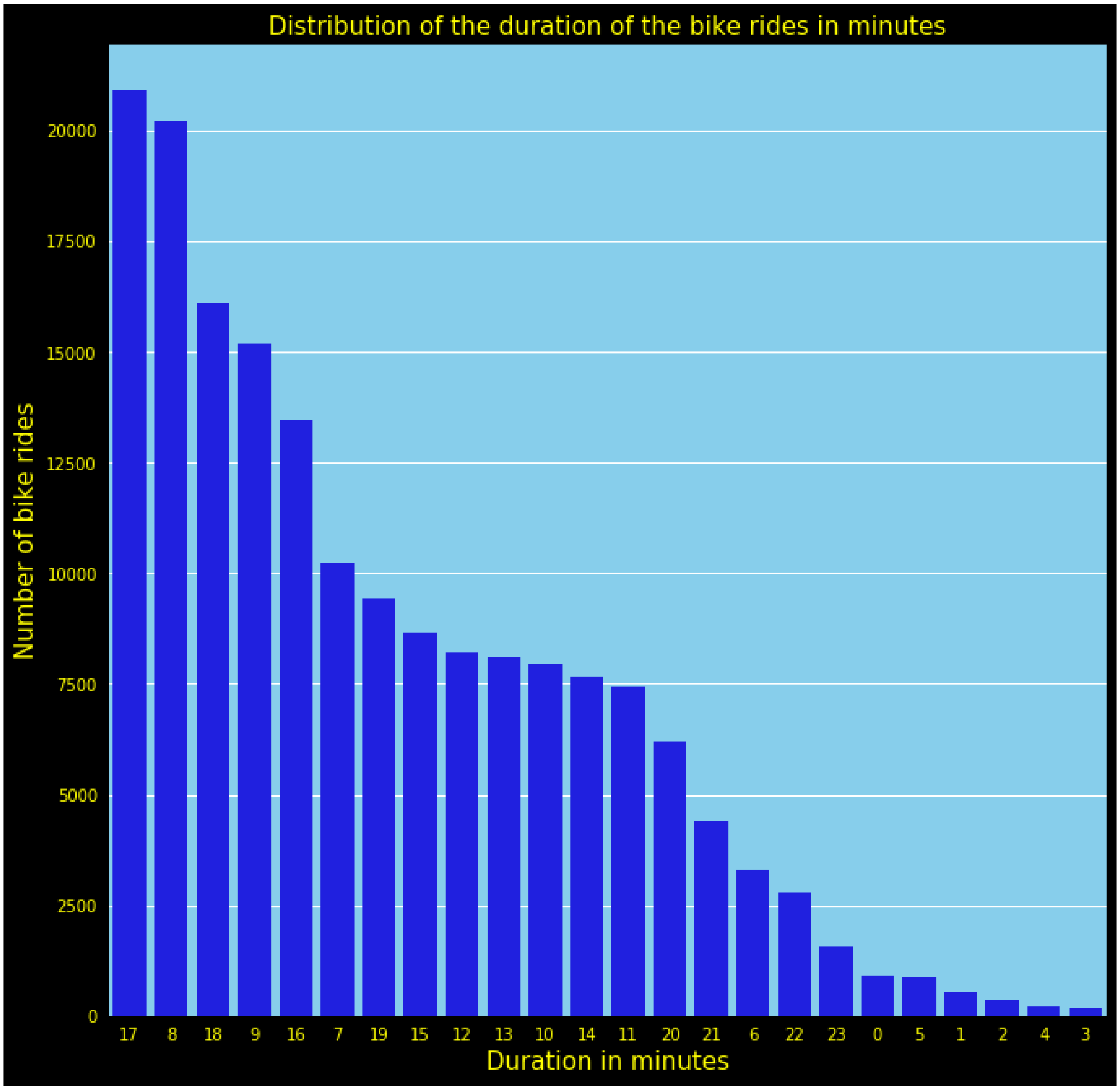
1.1.11 Question #2:

What are the busiest and most relaxed hours of the day within a week in February?

1.1.12 Visualization(s) #2:

```
In [40]: ordered_hours = ford_bike_2019['start_hour'].value_counts().index
```

```
In [91]: sns.countplot(data = ford_bike_2019, x = 'start_hour', color = 'blue', order = ordered_
         sns.set(rc={'figure.facecolor':'black', 'axes.facecolor':'skyblue', 'figure.figsize':(1
         plt.title('Distribution of the duration of the bike rides in minutes', fontsize = 15)
         sns.set(rc={'figure.facecolor':'black', 'axes.facecolor':'skyblue', 'axes.labelcolor':'
         plt.xlabel('Duration in minutes', fontsize = 15);
         plt.ylabel('Number of bike rides', fontsize = 15);
```



1.1.13 Observation(s) #2:

- the 17th hour is the busiest hour of the day in February, about 5 p.m.
- the 3rd hour is the least busy in February

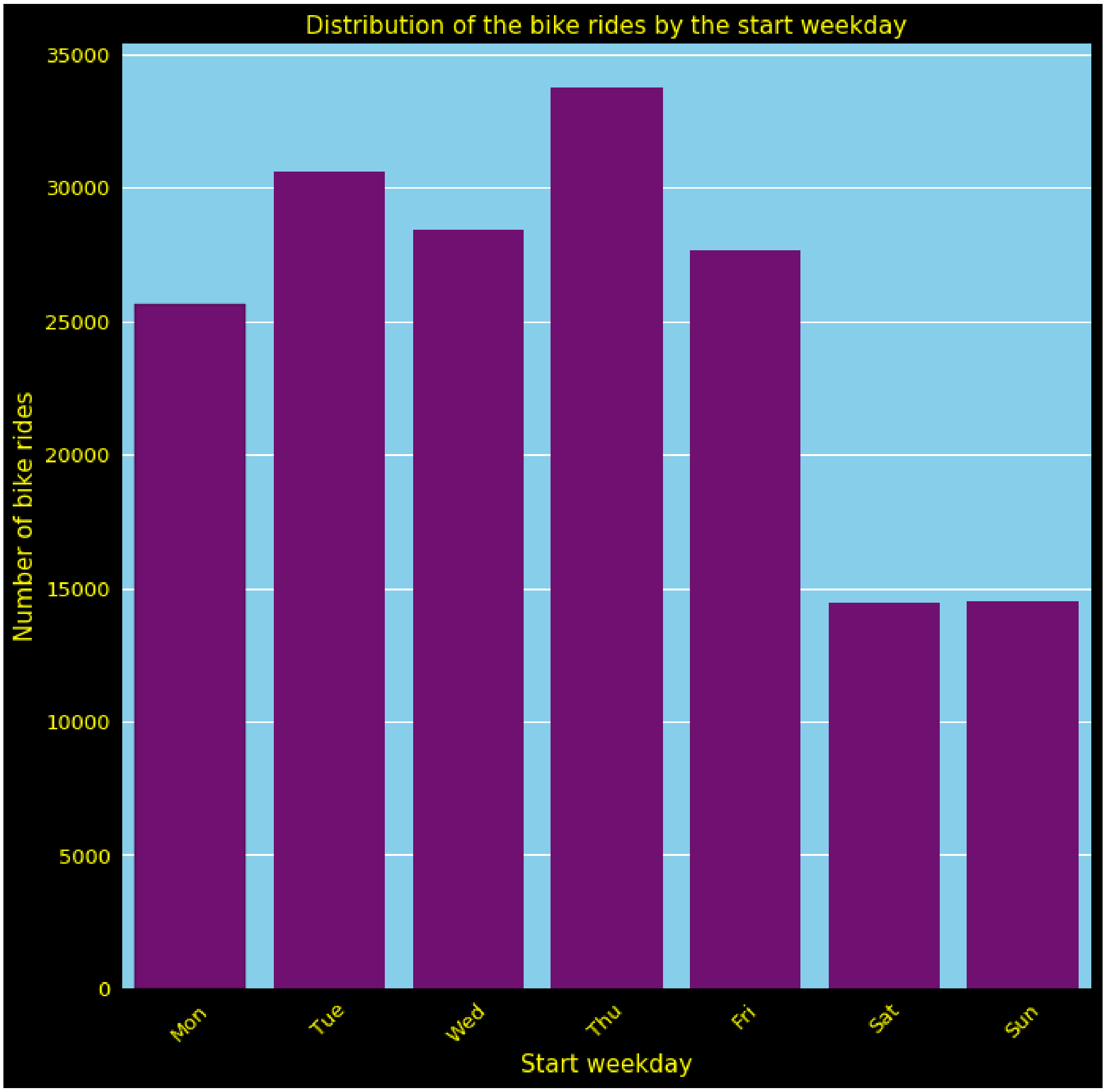
1.1.14 Question #3:

What is the busiest day of the week in February?

1.1.15 Visualization(s) #3:

```
In [93]: sns.countplot(data = ford_bike_2019, x = 'start_weekday_name', color = 'purple', edgeco
         plt.xlabel('Start weekday', fontsize = 15);
         plt.ylabel('Number of bike rides', fontsize = 15);
```

```
plt.xticks(rotation = 45, fontsize = 13);
plt.yticks(fontsize = 13);
sns.set(rc={'figure.facecolor':'black', 'axes.facecolor':'skyblue', 'axes.labelcolor':'
plt.title('Distribution of the bike rides by the start weekday', fontsize = 15);
```



1.1.16 Observation(s) #3:

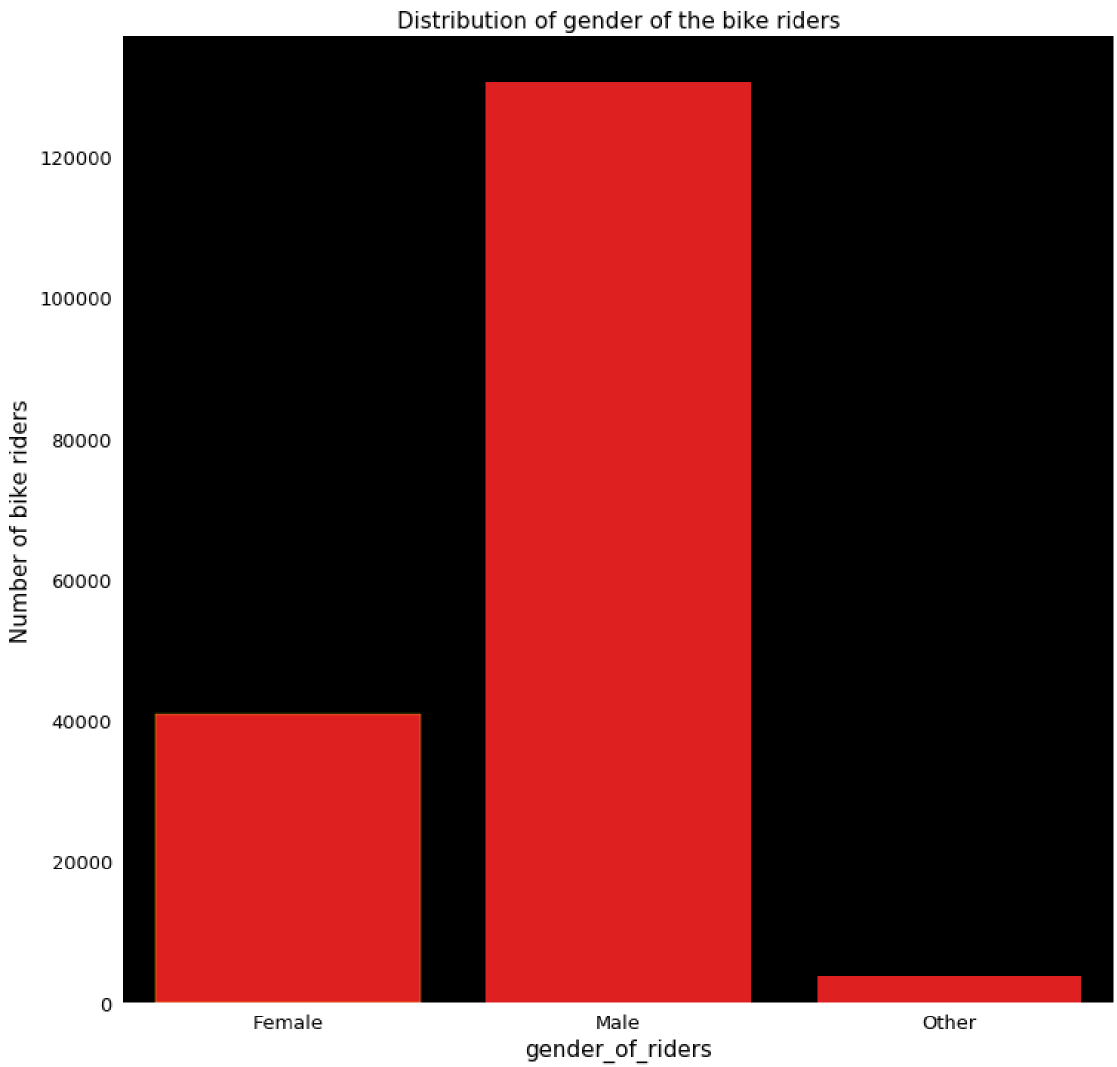
- thursday is the busiest day of the week
- Saturday is the least busy day of the week

1.1.17 Question #4:

What is the composition of the bike riders in the month of February?

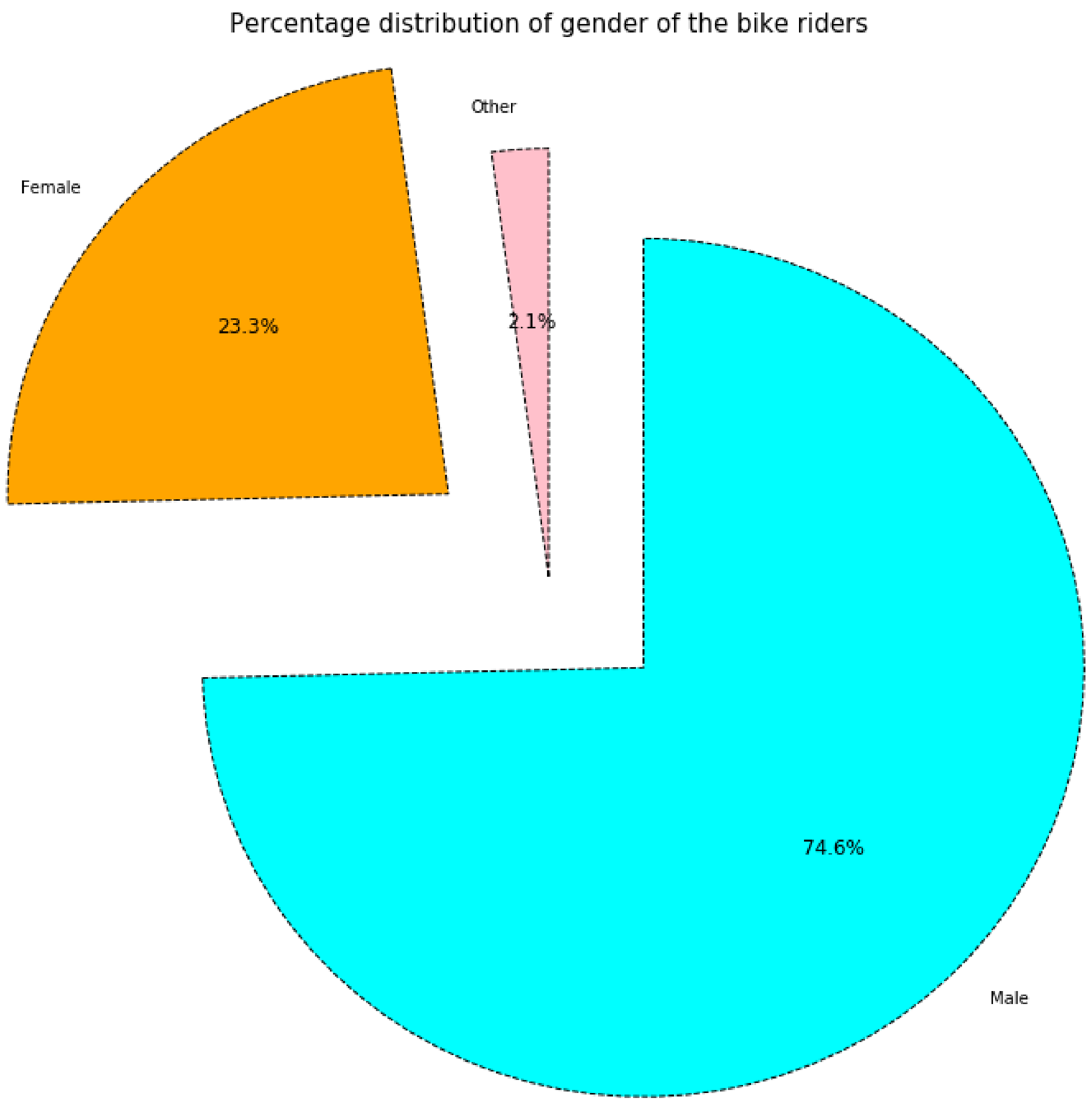
1.1.18 Visualization(s) #4:

In [96]:
```
sns.countplot(x='member_gender', data=ford_bike_2019, color='red', edgecolor='yellow');
sns.set(rc={'axes.facecolor':'black', 'figure.facecolor':'white', 'figure.figsize':(12,
plt.title('Distribution of gender of the bike riders', fontsize = 15);
plt.xlabel('gender_of_riders', fontsize = 15);
plt.ylabel('Number of bike riders', fontsize = 15);
plt.xticks(fontsize = 13);
plt.yticks(fontsize = 13);
plt.grid(False);
```



In [101]:
```
gender_name = ['Male', 'Female', 'Other']
gender_num = [130151, 40646, 3617]
colors = ('cyan', 'orange', 'pink')
plt.title('Percentage distribution of gender of the bike riders', fontsize = 15);
```

```
plt.pie(gender_num, labels=gender_name, autopct='%1.1f%%', startangle=90, counterclock
plt.show()
```



1.1.19 Observation(s) #4:

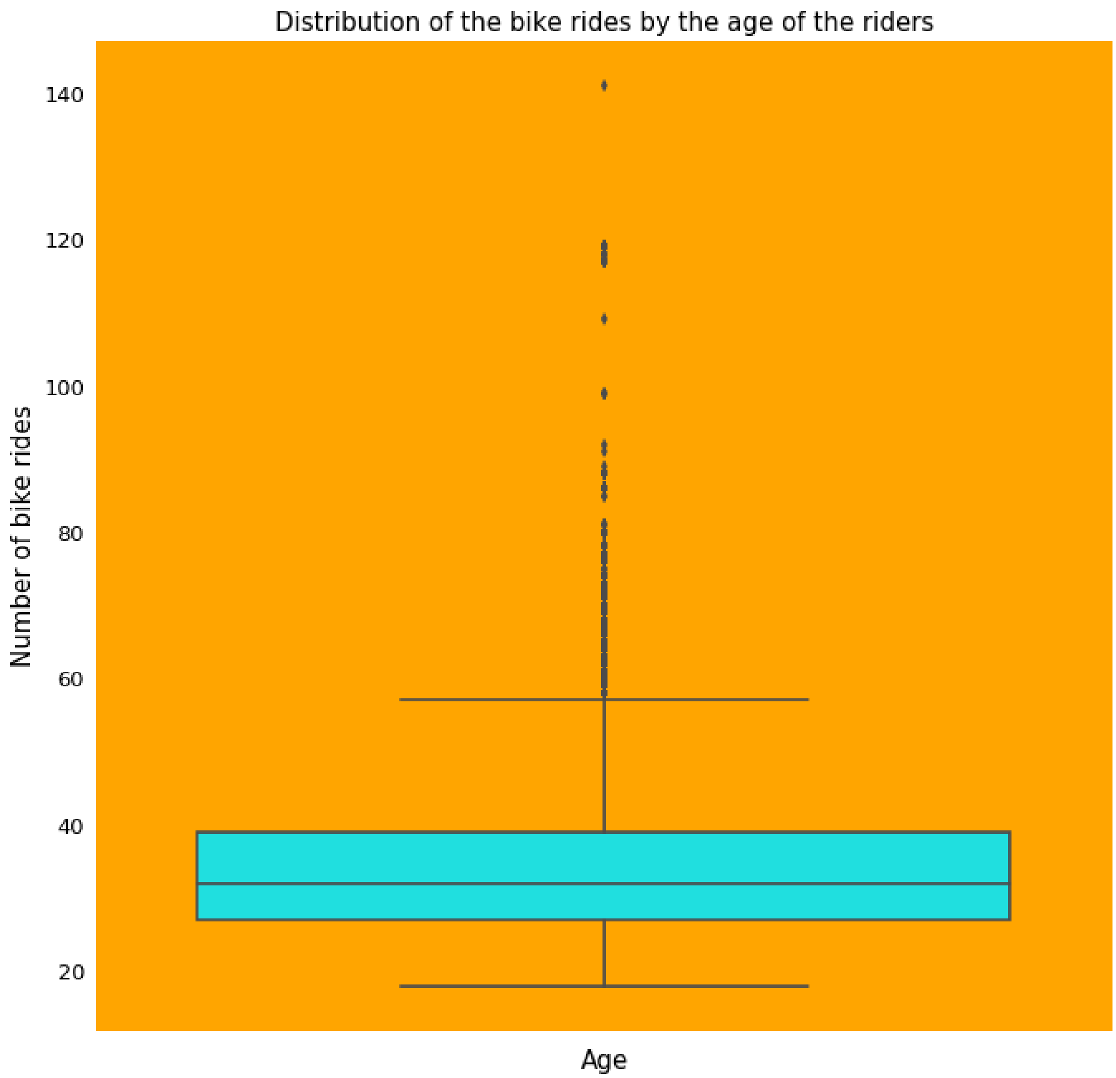
- the male gender has the highesst number of bike riders turning up for the event
- the male gender is 74.6% of the total population
- the female gender is 23.3% of the total population
- the other gender is only 2.1% of the total population
- the histogram is unimodal
- it has a non-symmetrical unimodal distribution
- the distribution is normal

1.1.20 Question #5:

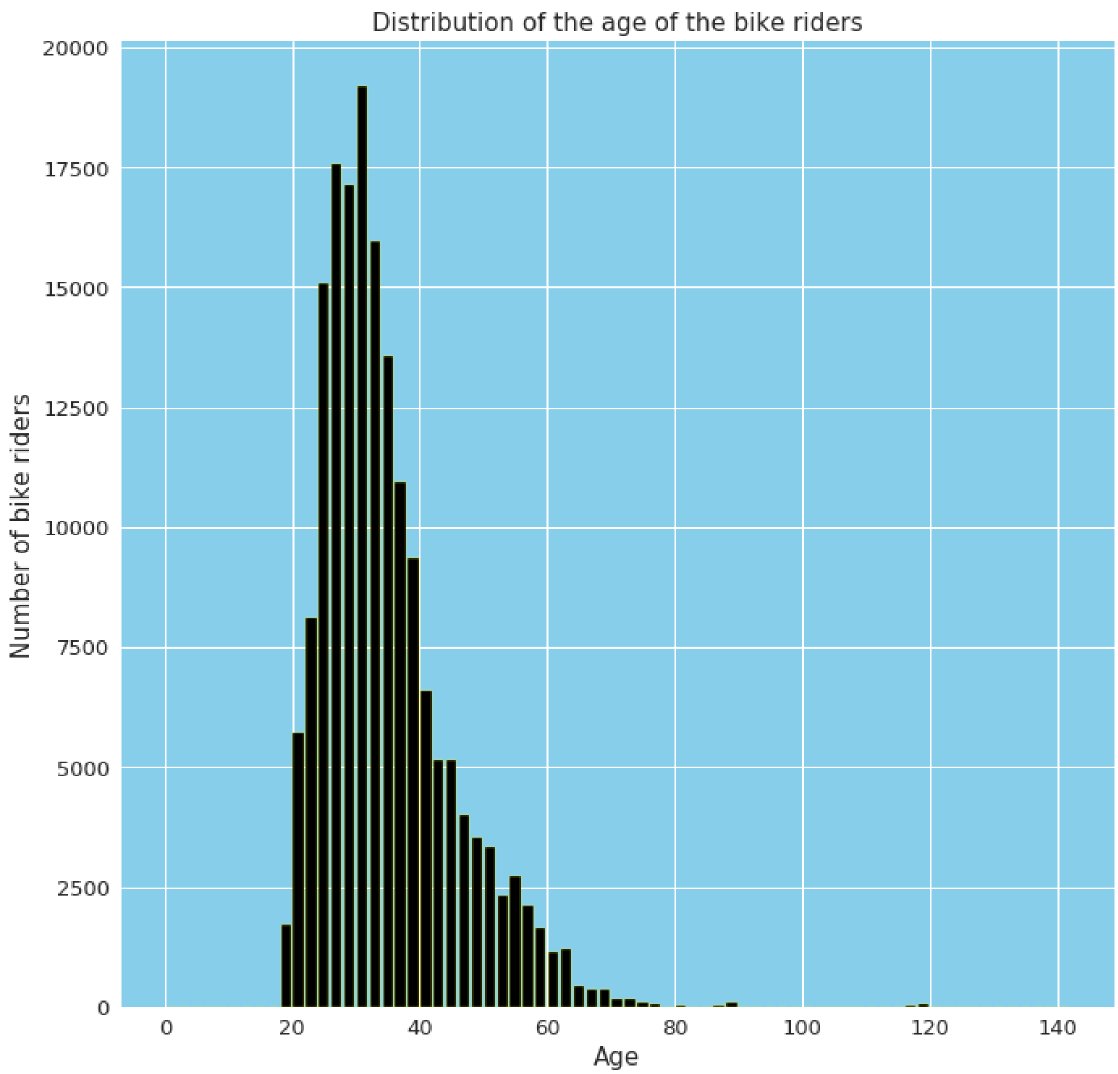
Describe the distribution of age in the month of February

1.1.21 Visualization(s) #5:

```
In [104]: sns.boxplot(data = ford_bike_2019, y ='age', color = 'cyan');
          plt.xlabel('Age', fontsize = 15);
          plt.ylabel('Number of bike rides', fontsize = 15);
          plt.title('Distribution of the bike rides by the age of the riders', fontsize = 15);
          plt.xticks(fontsize = 13);
          plt.yticks(fontsize = 13);
          plt.grid(False);
          sns.set(rc={'axes.facecolor':'orange', 'figure.facecolor':'white', 'figure.figsize':(1
```



In [106]:
```
binsize=2
bins=np.arange(0, ford_bike_2019['age'].max()+binsize, binsize)
plt.hist(data = ford_bike_2019, x = 'age', bins = bins, rwidth=0.8, color='black', edg
sns.set(rc={'axes.facecolor':'skyblue', 'figure.facecolor':'white', 'figure.figsize':(
plt.title('Distribution of the age of the bike riders', fontsize = 15);
plt.xlabel('Age', fontsize = 15);
plt.ylabel('Number of bike riders', fontsize = 15);
plt.xticks(fontsize = 13);
plt.yticks(fontsize = 13);
plt.gca().set_facecolor('skyblue');
plt.show()
```



In [48]:
```
ford_bike_2019['age'].value_counts()
```

```
Out[48]: 31      10214
         26       9323
         30       8967
         29       8640
         28       8484
         27       8245
         32       8010
         33       7953
         25       7654
         24       7420
         34       7023
         35       6557
         36       5953
         39       5011
         37       4987
         23       4637
         38       4344
         40       3756
         22       3476
         21       3208
         41       2830
         42       2706
         45       2633
         20       2504
         44       2503
         43       2435
         46       2080
         51       1927
         48       1924
         47       1909
                 ...
         65        301
         67        189
         68        180
         69        178
         66        158
         72        135
         64        134
         74        105
         70         99
         88         89
         119        53
         71         51
         18         34
         76         30
         77         21
         86         20
         73         19
```

```
80        11
117       11
78         9
118        6
99         3
81         3
85         2
75         2
92         1
91         1
109        1
89         1
141        1
Name: age, Length: 75, dtype: int64
```

1.1.22 Observation(s) #5:

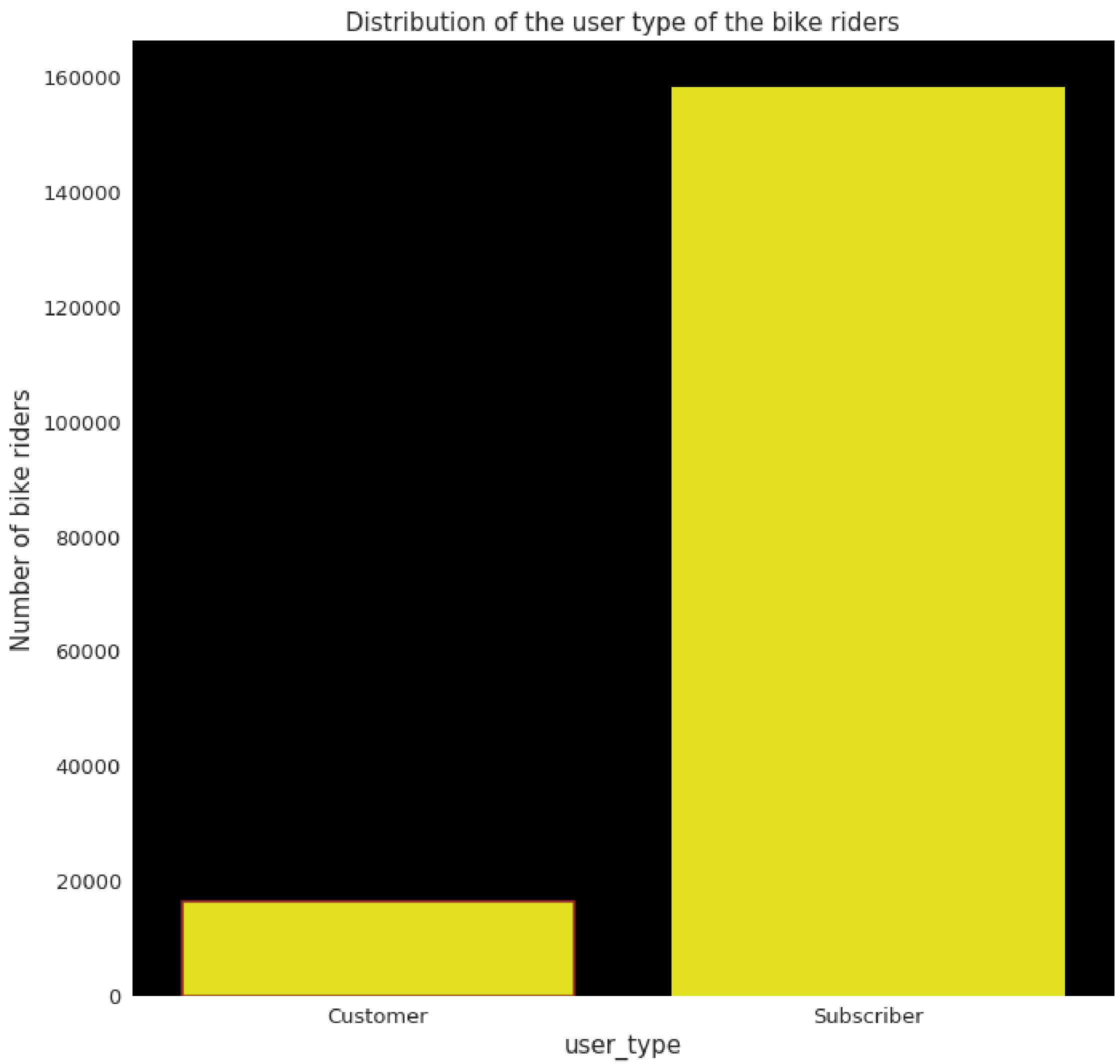
- the histogram has a non-symmetrical unimodal right skewed distribution of the age of the age of the riders across the entire dataset.
- bike riders aged 31 have the highest number turn up of 10214 at the riding event.

1.1.23 Question #6:

Describe the composition of the user type of all the bike riders in the month of February

1.1.24 Visualization(s) #6:

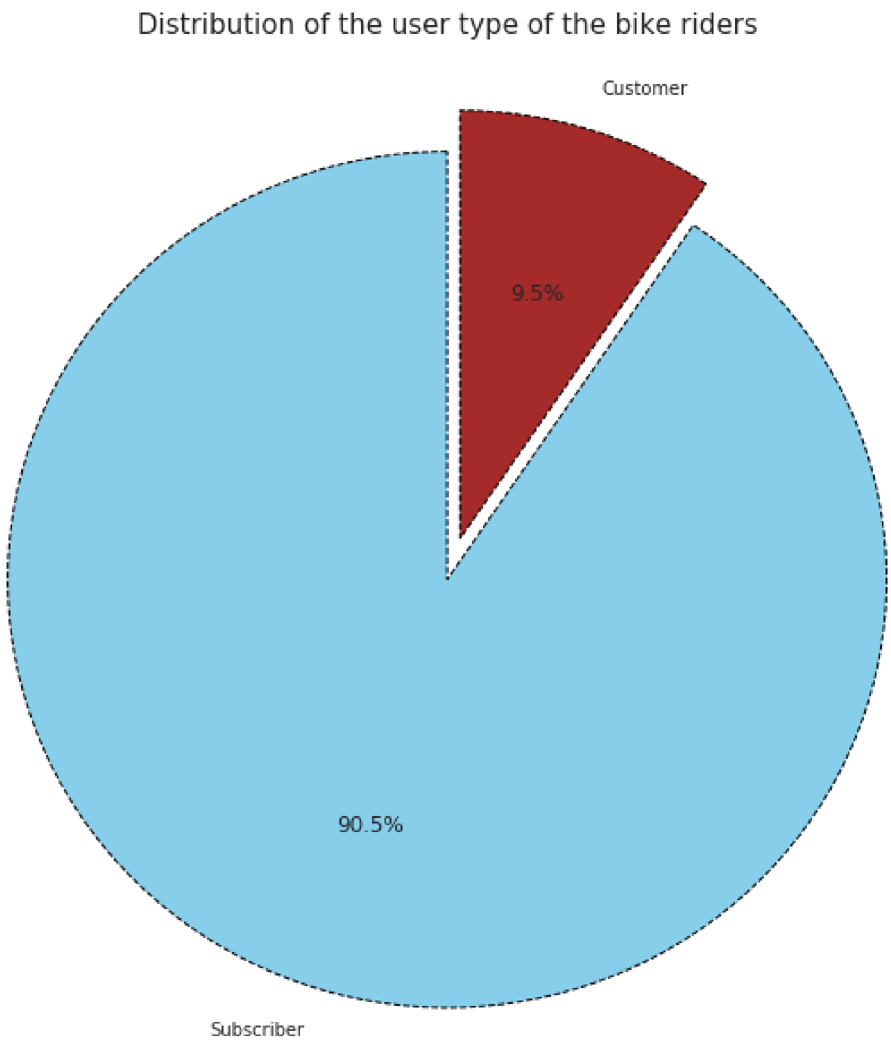
In [109]:
```
sns.countplot(data = ford_bike_2019, x = 'user_type', color = 'yellow', edgecolor = 'b
sns.set(rc={'axes.facecolor':'black', 'figure.facecolor':'white'});
plt.title("Distribution of the user type of the bike riders", fontsize = 15);
plt.xlabel('user_type', fontsize = 15);
plt.ylabel('Number of bike riders', fontsize = 15);
plt.grid(False);
plt.xticks(fontsize = 13);
plt.yticks(fontsize = 13);
plt.show()
```



In [50]:
```
ford_bike_2019['user_type'].value_counts()
```

Out[50]:
```
Subscriber    158386
Customer       16566
Name: user_type, dtype: int64
```

In [114]:
```
user_name = ['Customer', 'Subscriber']
user_num = [16566, 158386]
colors = ('brown', 'skyblue')
plt.title("Distribution of the user type of the bike riders", fontsize = 15)
plt.pie(user_num, labels=user_name, autopct='%1.1f%%', startangle=90, counterclock=Fal
plt.rcParams['font.size'] = 12
plt.show()
```




```
In [52]: ford_bike_2019['user_type'].value_counts()
```

```
Out[52]: Subscriber    158386
         Customer       16566
         Name: user_type, dtype: int64
```

1.1.25 Observation(s) #6:

- Subscribers use 90.5% of the total bike trip population, that is, 158386
- Customers only use 9.5% of the total bike trip population, that is, 16566

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

The bike trip duration feature was the center of focus. The users used the bike riding system extensively. The first five days of the week are used actively by the riders. The peak hours for the bike riders are 8 a.m. and 5 p.m. Males persons dominate the bike trip population. Bike riders aged 25 to 35 are the most engaged unlike other age groups. Over 90% of the bike riding trips are dominate by subscriber bike riders.

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

I simply cleaned the data set initially by dropping all the missing values before visual exploration. The bike trip duration was only in seconds at first. This had to be converted to minutes and given a new data column which is 'duration_min' data column.

The start hour of the day was extracted from the 'start_time' details, the same applies to determining the day of the week. The age of the users had to be determined using the member birth year against the year of the dataset

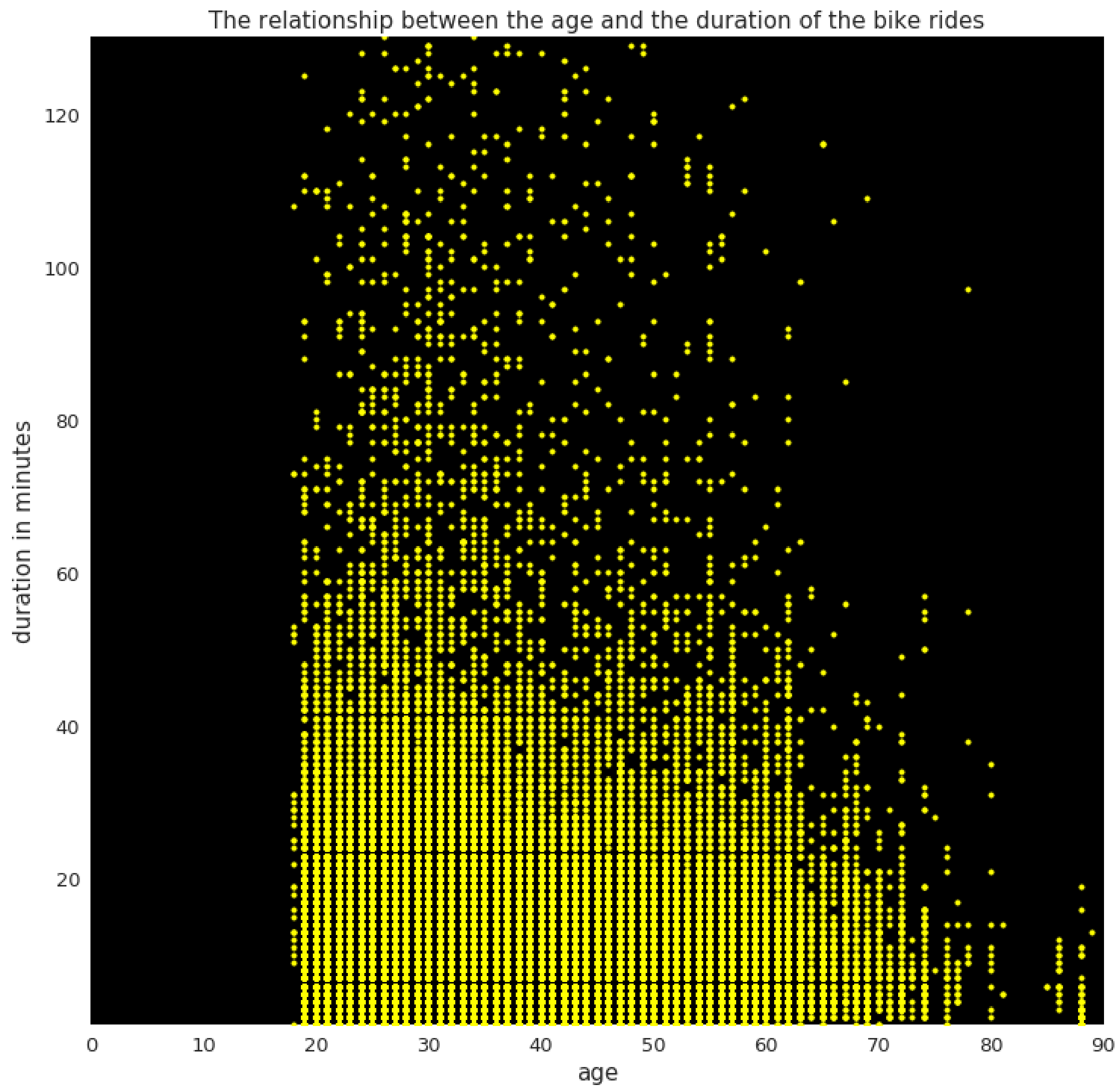
Bivariate Exploration

1.1.28 Question #8:

What s the relationship between the age of the bike riders and the duration of the bike trips in minutes ?

1.1.29 Visualization(s) #8:

```
In [53]: plt.figure(figsize=[12,12]);
         plt.scatter(ford_bike_2019['age'], ford_bike_2019['duration_min'], alpha = 1, marker =
         plt.grid(False);
         plt.axis([0, 90, 1, 130]);
         plt.title('The relationship between the age and the duration of the bike rides', fontsi
         plt.xlabel('age', fontsize = 15);
         plt.ylabel('duration in minutes', fontsize = 15);
         plt.xticks(fontsize = 13);
         plt.yticks(fontsize = 13);
         sns.set(rc={'axes.facecolor':'black', 'axes.labelcolor':'black', 'xtick.color':'black',
         plt.show();
```



1.1.30 Observation(s) #8:

- there is a moderate negative correlation betweeen the age of the bikers and the duration of the bkie trips in minutes
- there is an indirect proporptionality between the age and duration in minutes variables
- therefore, increase in the age of the bike riders will gradually lead to a decrease in the number of bike trips

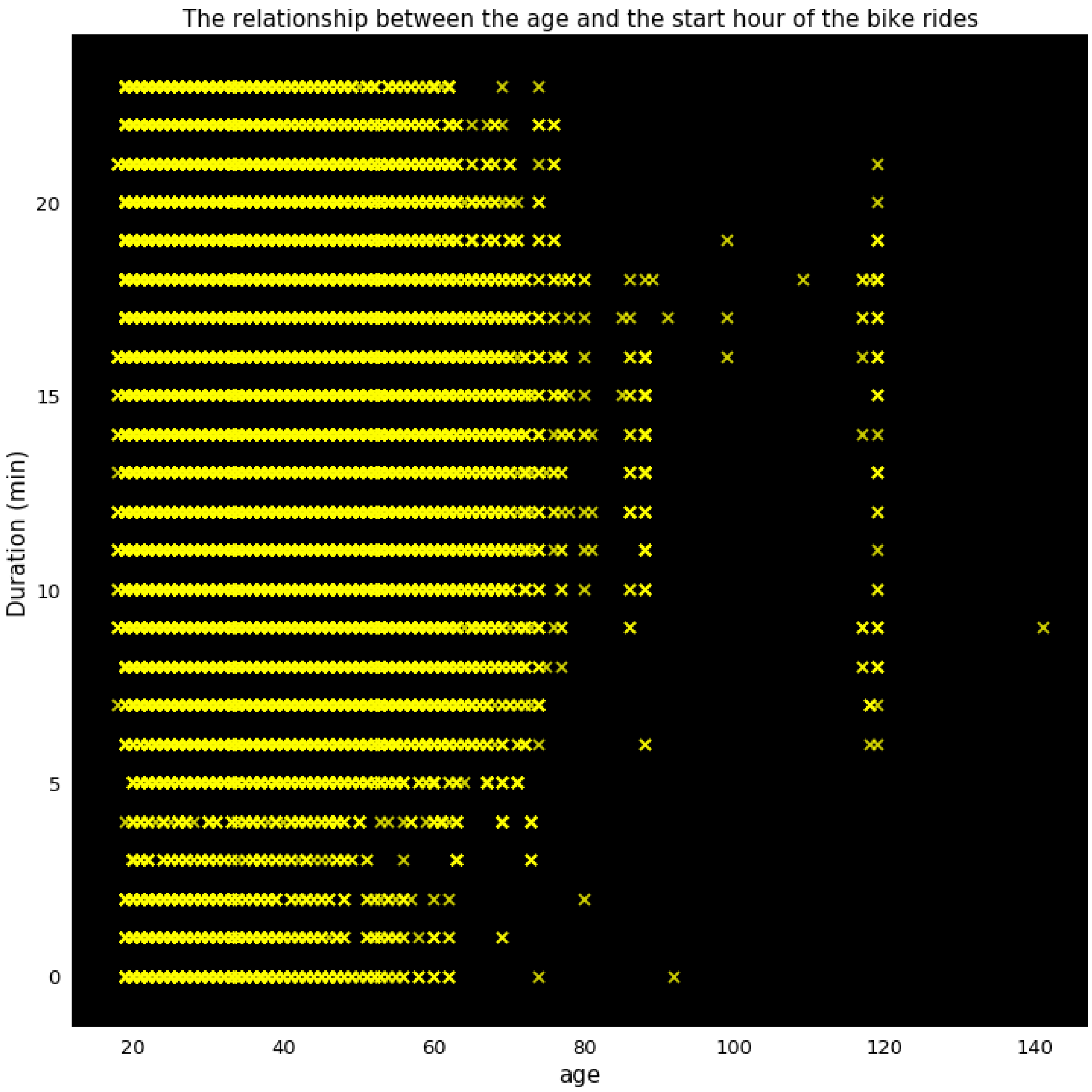
1.1.31 Question #9:

What is the relationship between age and the start hours of the bike rides?

1.1.32 Visualization(s) #9:

In [54]:
```
# scatter plot showing the relationship between age and the start hours of the bike rid

plt.figure(figsize=[12, 12])
plt.yticks([0, 5, 10, 15, 20, 25], [0, 5, 10, 15, 20, 25]);
plt.scatter(data = ford_bike_2019, x = 'age', y = 'start_hour', alpha = 0.8, marker = '
plt.grid(False);
plt.title('The relationship between the age and the start hour of the bike rides', font
plt.xlabel('age', fontsize = 15);
plt.ylabel('start hour', fontsize = 15);
plt.xlabel('age');
plt.gca().set_facecolor('black');
plt.ylabel('Duration (min)');
plt.xticks(fontsize = 13);
plt.yticks(fontsize = 13);
```



1.1.33 Observation(s) #9:

- based on the shared graph information above, there is no significant correlation between the age of the bike riders and the start hours of the bike riders

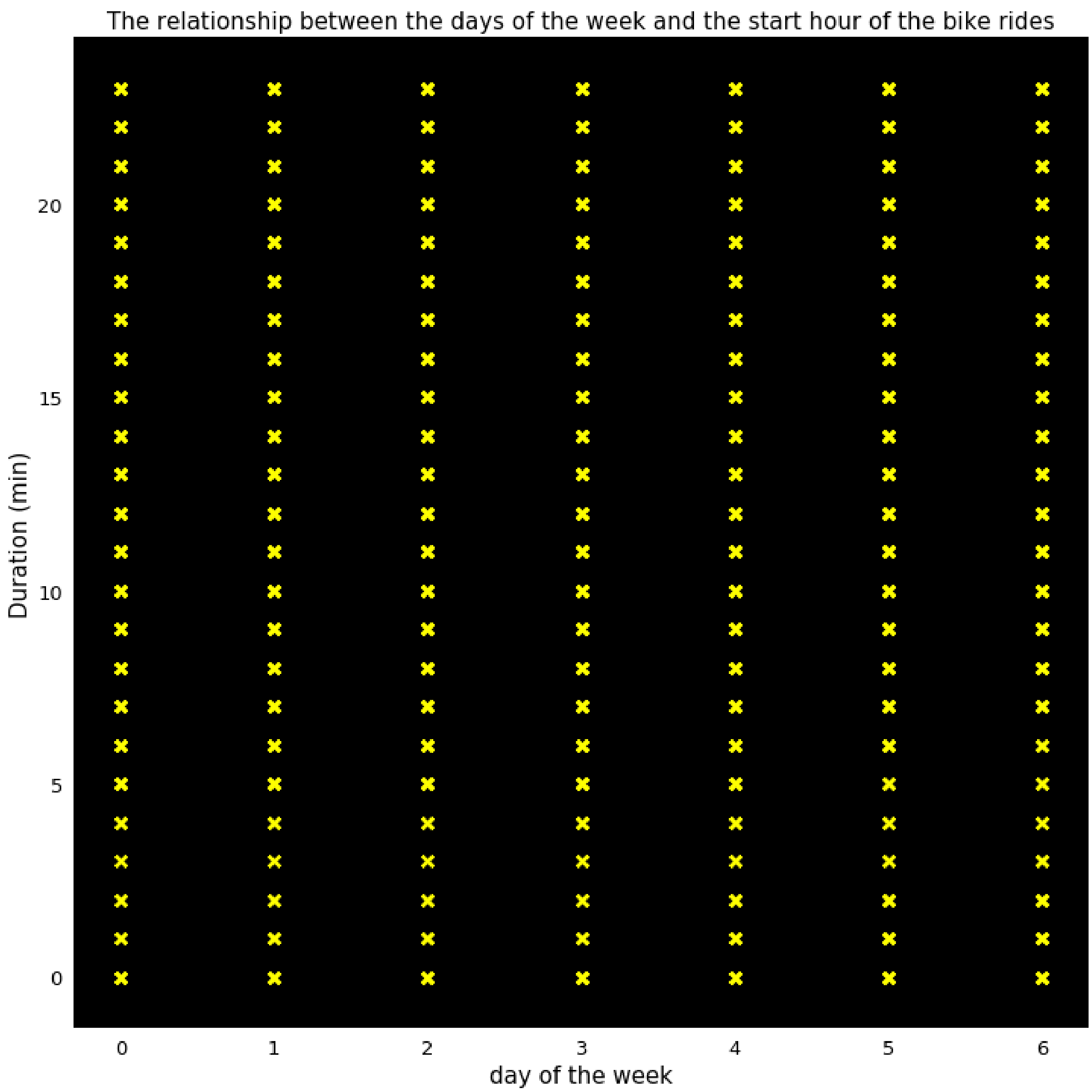
1.1.34 Question#10:

What is the relationship between the start hours and the days of the week?

1.1.35 Visualizations#10:

```
In [55]: # scatter plot showing the relationship between age and the start hours of the bike rid

         plt.figure(figsize=[12, 12])
         plt.yticks([0, 5, 10, 15, 20, 25], [0, 5, 10, 15, 20, 25]);
         plt.scatter(data = ford_bike_2019, x = 'start_weekday_no', y = 'start_hour', alpha = 0.
         plt.grid(False);
         plt.title('The relationship between the days of the week and the start hour of the bike
         plt.xlabel('day of the week', fontsize = 15);
         plt.ylabel('start hour', fontsize = 15);
         plt.gca().set_facecolor('black');
         plt.ylabel('Duration (min)');
         plt.xticks(fontsize = 13);
         plt.yticks(fontsize = 13);
```



1.1.36 Observations#10:

- there isn't any correlation at all between the days of the week and the start hours of the bike rides

1.1.37 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?

There exists a moderate negative correlation between the age and the duration in minutes for the bike rides, however, there isn't any existing correlation between the age and the start hours.

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

The other interesting relationship was that of the daya of the week against the start_hours, basically, there isn't a correlations as well. For the ages ranging from 20 to 40 years, the duration ranges from 2 to 30 minutes. Both user types have their peak hours at 5 p.m. and 8 p.m.

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.

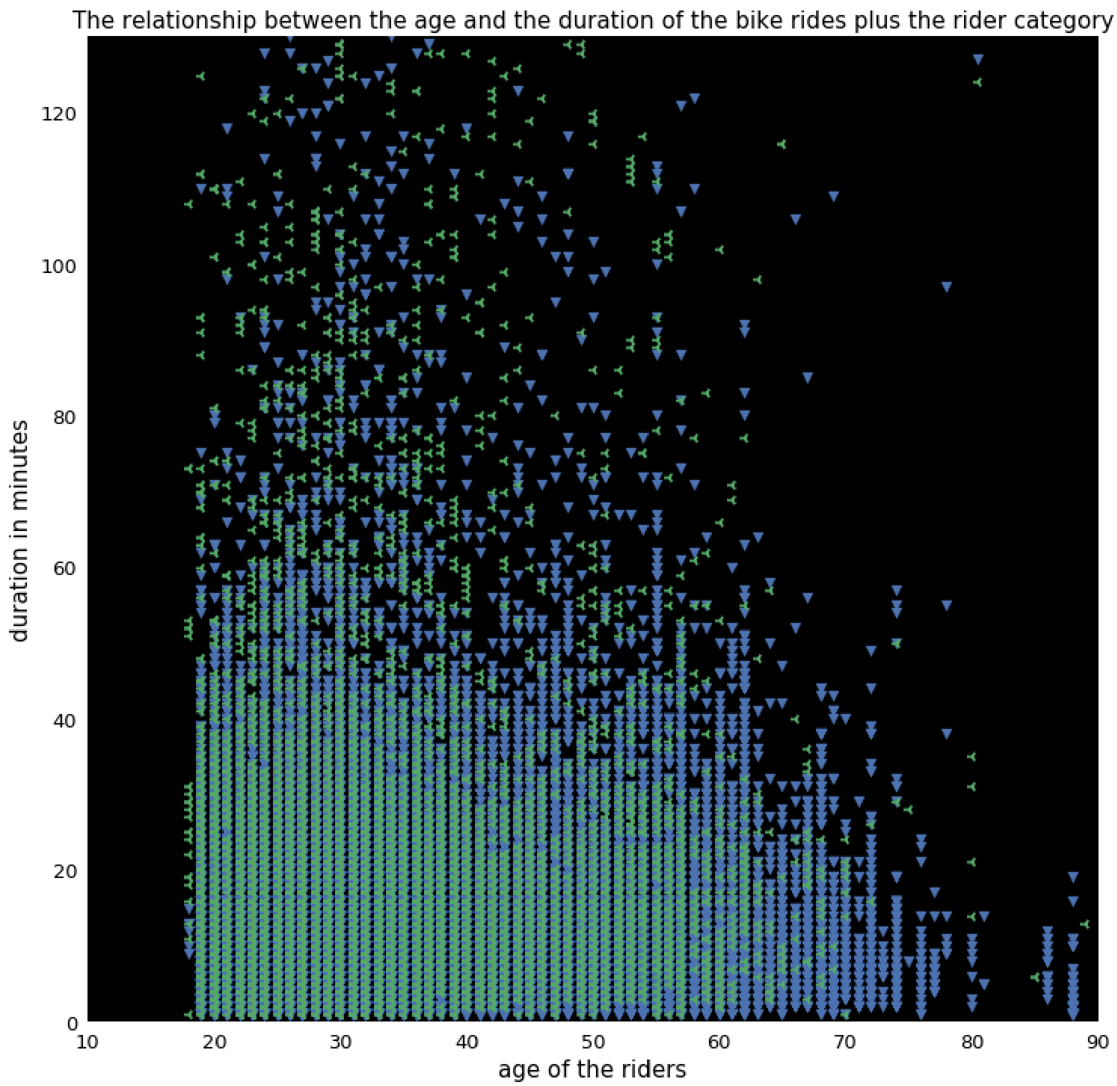
1.1.39 Question #10:

What is the contrast and comparison between the correlation of subcribers and customers to the duration in minutes?

1.1.40 Visualization(s) #10:

```
In [56]: plt.figure(figsize=[12,12])
         rider_type = [['Subscriber', 'v'],['Customer', '3']]

         for rider_type1, marker in rider_type:
             ford_bike_2019_usertype = ford_bike_2019[ford_bike_2019['user_type'] == rider_type1
             plt.scatter(ford_bike_2019_usertype['age'], ford_bike_2019_usertype['duration_min']
         plt.legend(['Subscriber','Customer'])
         plt.axis([10, 90, 0, 130 ])
         plt.title('The relationship between the age and the duration of the bike rides plus the
         plt.xlabel('age of the riders', fontsize = 15);
         plt.ylabel('duration in minutes', fontsize = 15);
         plt.xticks(fontsize = 13);
         plt.yticks(fontsize = 13);
         plt.gca().set_facecolor('black');
         plt.grid(False);
         plt.show()
```



1.1.41 Observation(s) #10:

- subscribers basically have a stronger correlation than the customer users

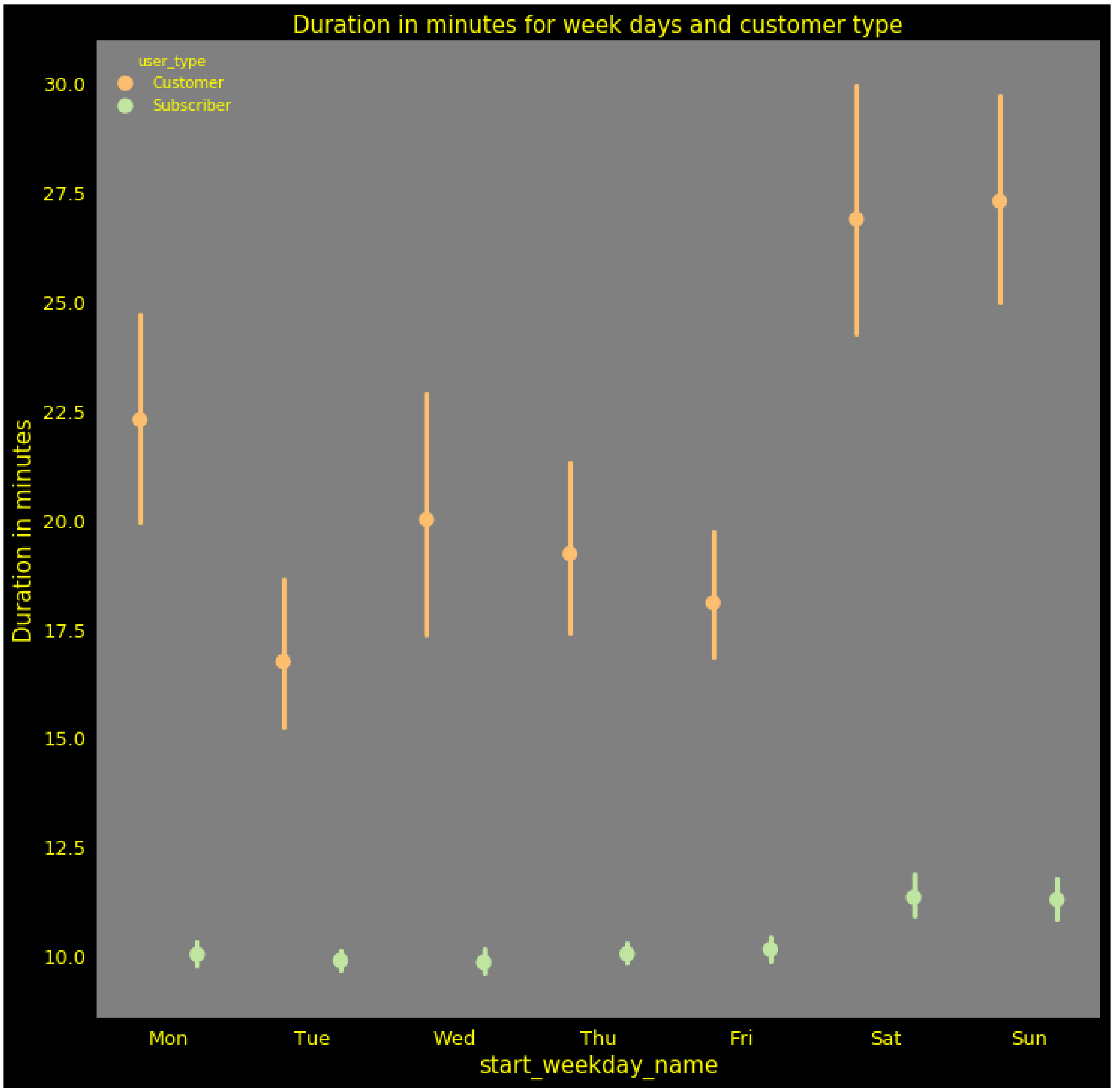
1.1.42 Question #11:

Who covers the longest distance between customers and subscribers?

1.1.43 Visualization(s) #11:

```
In [82]: plt.figure(figsize = [12,12]);
         ax = sns.pointplot(data = ford_bike_2019, x ='start_weekday_name', y = 'duration_min',
                   palette = 'Spectral', linestyles = '', dodge = 0.4, alpha=1.0);
         sns.set(rc={'figure.facecolor':'black', 'axes.facecolor':'gray', 'axes.labelcolor':'yel
```

```
plt.title('Duration in minutes for week days and customer type', fontsize=15);
plt.grid(False);
plt.ylabel('Duration in minutes', fontsize=15);
plt.xlabel('start_weekday_name', fontsize=15);
plt.xticks(fontsize=13);
plt.yticks(fontsize=13);
ax.set_yticklabels([],minor = True)
plt.show()
```



1.1.44 Observation(s) #11:

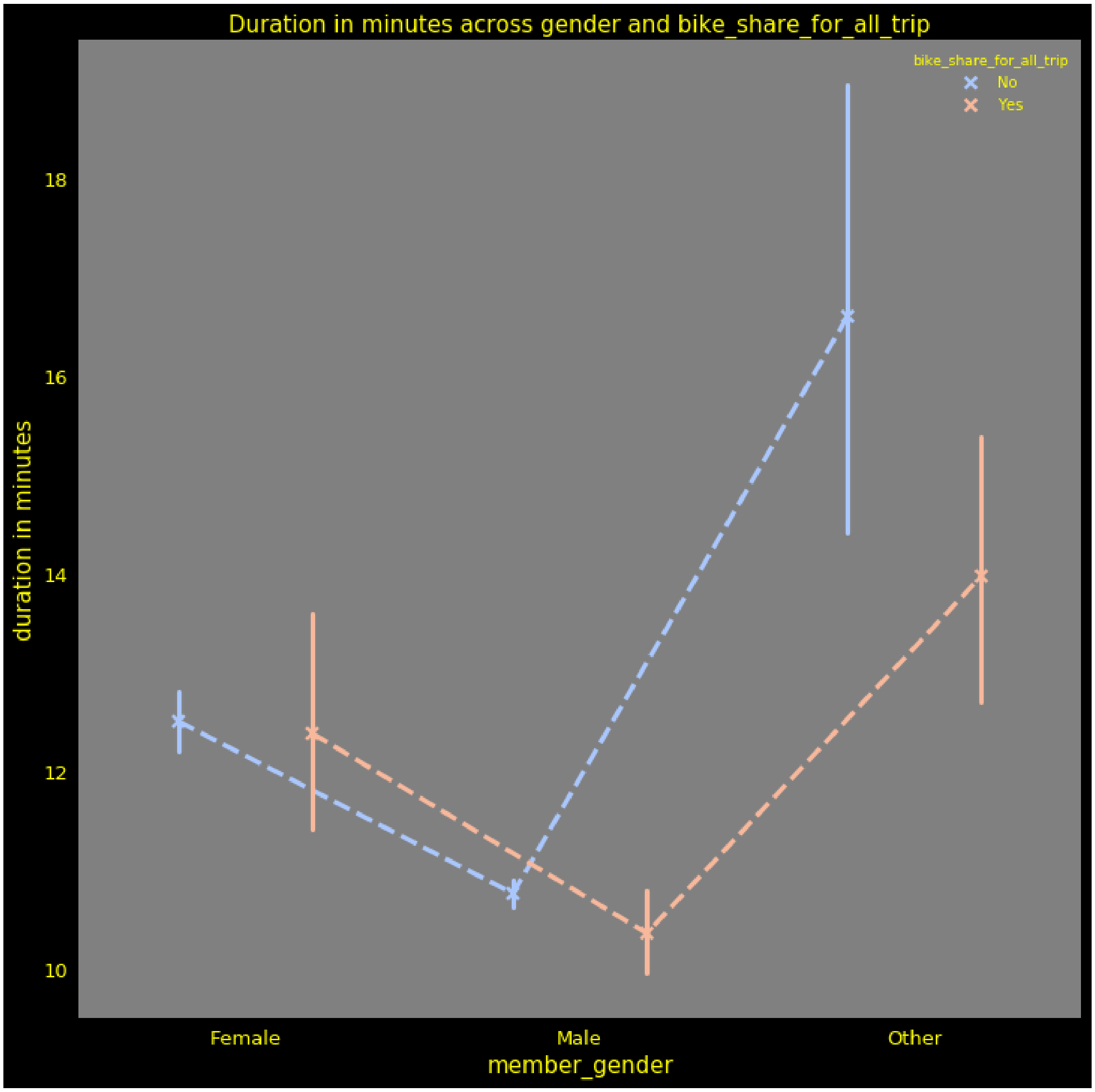
- customers travel longer distances while subscribers travel shorter distances

1.1.45 Question #12:

Who covers the longest miles among males, females and other gender type?

1.1.46 Visualization(s) #12:

In [86]:
```
plt.figure(figsize = [12,12]);
ax = sns.pointplot(data = ford_bike_2019, x ='member_gender', y = 'duration_min', hue =
sns.set(rc={'figure.facecolor':'black', 'axes.facecolor':'gray', 'axes.labelcolor':'yel
plt.title('Duration in minutes across gender and bike_share_for_all_trip', fontsize=15)
plt.grid(False);
plt.ylabel('duration in minutes', fontsize=15);
plt.xlabel('member_gender', fontsize=15)
plt.xticks(fontsize=13);
plt.yticks(fontsize=13);
ax.set_yticklabels([], minor = True);
plt.show()
```



1.1.47 Observation(s) #12:

- the other gender type covers the greatest miles

1.1.48 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?

Subscribers have a higher age range than customers

1.1.49 Were there any interesting or surprising interactions between features?

Subscribers use the bike rides for longer period of times than the customers. The subscribers have a higher age range than the customers

Conclusions > - 5 minutes are the most preferred bike trip duration time interval - the 17th hour is the busiest hour of the day in February, about 5 p.m. - thursday is the busiest day of the week - the male gender has the highest number of bike riders turning up for the event

```
In [56]: # saving the clean dataset into as a csv file that will come in handy at the nex stage
         ford_bike_2019.to_csv('ford_bike_clean.csv', index=False)
```