Ford GoBike System Data: Exploratory Analysis

Introduction

This data set includes information about individual rides made in a bike-sharing system covering the greater San Francisco Bay area for 2017. There is a total of 519,700 entries with fifteen variables accounted for and recorded.

For this project, I will conduct an exploratory analysis on data from Ford GoBike System, a bike-sharing system provider to make discoveries about the dataset. I hope to reveal interesting stories about the average trip duration for certain bike users.

Questions to ponder on through exploration:

1. How long was the average trip in 2017?
2. Does average trip duration depend on if an user is a subscriber or customer?
3. Does average trip duration vary on the age of user?
4. Does average trip duration depend on if user is female or male?

Preliminary Data Wrangling

Part I: Gathering Data

In [1]:
```
# Import packages needed
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [2]:
```
# Load and read dataset
df= pd.read_csv('2017-bike-data.csv')
df.head()
```

Out[2]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_la
0	80110	2017-12-31 16:57:39.6540	2018-01-01 15:12:50.2450	74	Laguna St at Hayes St	37.7
1	78800	2017-12-31 15:56:34.8420	2018-01-01 13:49:55.6170	284	Yerba Buena Center for the Arts (Howard St at ...	37.7
2	45768	2017-12-31 22:45:48.4110	2018-01-01 11:28:36.8830	245	Downtown Berkeley BART	37.8
3	62172	2017-12-31 17:31:10.6360	2018-01-01 10:47:23.5310	60	8th St at Ringold St	37.7
4	43603	2017-12-31 14:23:14.0010	2018-01-01 02:29:57.5710	239	Bancroft Way at Telegraph Ave	37.8

Part II: Assessing Data

In [3]:
```
# Look at size of dataset and datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 519700 entries, 0 to 519699
Data columns (total 15 columns):
duration_sec               519700 non-null int64
start_time                 519700 non-null object
end_time                   519700 non-null object
start_station_id           519700 non-null int64
start_station_name         519700 non-null object
start_station_latitude     519700 non-null float64
start_station_longitude    519700 non-null float64
end_station_id             519700 non-null int64
end_station_name           519700 non-null object
end_station_latitude       519700 non-null float64
end_station_longitude      519700 non-null float64
bike_id                    519700 non-null int64
user_type                  519700 non-null object
member_birth_year          453159 non-null float64
member_gender              453238 non-null object
dtypes: float64(5), int64(4), object(6)
memory usage: 59.5+ MB
```

In [4]:
```
# Look at some descriptive statistics of dataset
df.describe()
```

Out[4]:

	duration_sec	start_station_id	start_station_latitude	start_station_longitude	end_station_i
count	519700.000000	519700.000000	519700.000000	519700.000000	519700.00000
mean	1099.009521	95.034245	37.771653	-122.363927	92.18404
std	3444.146451	86.083078	0.086305	0.105573	84.96949
min	61.000000	3.000000	37.317298	-122.444293	3.00000
25%	382.000000	24.000000	37.773492	-122.411726	23.00000
50%	596.000000	67.000000	37.783521	-122.398870	66.00000
75%	938.000000	139.000000	37.795392	-122.391034	134.00000
max	86369.000000	340.000000	37.880222	-121.874119	340.00000

Quality and Tidiness Issues

1. Calculate age of users with birth year
2. Remove null rows for columns member_birth_year and member_gender
3. Remove member ages that are greater than 60
4. Convert bike ride duration in seconds to minutes
5. Remove member genders listed as "Other"

What is the structure of your dataset?

There are 519,700 bike rides in the dataset with 15 features (duration, 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, and member gender).

Most variables are numeric in nature, but the variables user type and member gender are categorical and nominal . The variables with id contains numbers that are nominal as well.

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

I am most interested in discovering what features may determine the average trip duration of bike rides among riders with consideration to their age, gender, and if they are a customer or subscriber of the bike-sharing system.

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

I think the user type will have the strongest effect on the average trip duration: I predict customers will have a longer average trip duration as they would want to make the most of their one-time ride purchase. As for subscribers, I expect that they will have a shorter average trip duration as they are not being charged extra for additional rides, they are simply making use of their subscription. I also think age and gender will have effects on the average trip duration, though to a smaller degree than the main effect of user type.

Part III: Cleaning Data

In [5]:
```
# Create copies of original dataset
df_clean = df.copy()
```

In [6]:
```
# Check for duplicates
df_clean.duplicated().sum()
```

Out[6]: 0

Define

Calculate age of users with birth year

Code

In [7]:
```
# Calculate age by subtracting from the year data was taken from, 2017
df_clean['member_age'] = 2017-df_clean['member_birth_year']
```

Test

In [8]:
```
# Check dataset
df_clean.head()
```

Out[8]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_la
0	80110	2017-12-31 16:57:39.6540	2018-01-01 15:12:50.2450	74	Laguna St at Hayes St	37.7
1	78800	2017-12-31 15:56:34.8420	2018-01-01 13:49:55.6170	284	Yerba Buena Center for the Arts (Howard St at ...	37.7
2	45768	2017-12-31 22:45:48.4110	2018-01-01 11:28:36.8830	245	Downtown Berkeley BART	37.8
3	62172	2017-12-31 17:31:10.6360	2018-01-01 10:47:23.5310	60	8th St at Ringold St	37.7
4	43603	2017-12-31 14:23:14.0010	2018-01-01 02:29:57.5710	239	Bancroft Way at Telegraph Ave	37.8

In [9]:
```
# Remove unnecessary columns for analysis
df_clean.drop(columns= ['start_time', 'end_time', 'start_station_id', 'start_s
tation_name', 'start_station_latitude', 'start_station_longitude', 'end_statio
n_id', 'end_station_name', 'end_station_latitude', 'end_station_longitude', 'b
ike_id', 'member_birth_year'], inplace = True)
```

In [10]:
```
# Check removal of columns
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 519700 entries, 0 to 519699
Data columns (total 4 columns):
duration_sec     519700 non-null int64
user_type        519700 non-null object
member_gender    453238 non-null object
member_age       453159 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 15.9+ MB
```

In [11]:
```
# Review columns
df_clean
```

Out[11]:

	duration_sec	user_type	member_gender	member_age
0	80110	Customer	Male	30.0
1	78800	Customer	Female	52.0
2	45768	Customer	NaN	NaN
3	62172	Customer	NaN	NaN
4	43603	Subscriber	Female	20.0
5	9226	Customer	NaN	NaN
6	4507	Customer	Female	26.0
7	4334	Customer	NaN	NaN
8	4150	Customer	NaN	NaN
9	4238	Customer	NaN	NaN
10	3292	Customer	NaN	NaN
11	3177	Customer	NaN	NaN
12	2183	Subscriber	Male	27.0
13	2170	Subscriber	Male	27.0
14	2697	Customer	NaN	NaN
15	1544	Subscriber	Female	37.0
16	1474	Subscriber	Male	38.0
17	1397	Customer	NaN	NaN
18	1532	Subscriber	Other	29.0
19	1216	Subscriber	Male	46.0
20	386	Subscriber	Male	25.0
21	4174	Customer	NaN	NaN
22	422	Subscriber	Male	32.0
23	1165	Customer	NaN	NaN
24	1149	Customer	NaN	NaN
25	1130	Customer	NaN	NaN
26	1003	Customer	NaN	NaN
27	862	Customer	NaN	NaN
28	871	Subscriber	Male	38.0
29	784	Customer	NaN	NaN
...	...	...	...	...
519670	123	Subscriber	Female	40.0
519671	73	Subscriber	Male	35.0
519672	1909	Subscriber	Male	33.0
519673	1908	Subscriber	Male	28.0

	duration_sec	user_type	member_gender	member_age
519674	672	Subscriber	Male	38.0
519675	602	Subscriber	Male	48.0
519676	893	Subscriber	Male	46.0
519677	1136	Subscriber	Male	33.0
519678	268	Subscriber	Female	33.0
519679	321	Subscriber	Male	30.0
519680	797	Subscriber	Male	44.0
519681	720	Subscriber	Male	30.0
519682	484	Subscriber	Male	30.0
519683	889	Subscriber	Female	33.0
519684	510	Subscriber	Male	51.0
519685	486	Subscriber	Male	31.0
519686	379	Subscriber	Female	61.0
519687	640	Subscriber	Male	39.0
519688	410	Subscriber	Male	38.0
519689	278	Subscriber	Male	65.0
519690	553	Subscriber	Male	44.0
519691	1086	Subscriber	Male	59.0
519692	1201	Subscriber	Male	32.0
519693	590	Subscriber	Male	34.0
519694	730	Subscriber	Male	37.0
519695	435	Subscriber	Male	26.0
519696	431	Subscriber	Male	44.0
519697	424	Subscriber	Female	32.0
519698	366	Subscriber	Male	36.0
519699	188	Subscriber	Male	33.0

519700 rows × 4 columns

Define

Remove null rows for columns member_birth_year and member_gender

Code

In [12]:
```
# Remove null values from member_gender and member_age columns
df_clean.dropna(inplace = True)
```

Test

In [13]:
```
# Check for null values
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 453159 entries, 0 to 519699
Data columns (total 4 columns):
duration_sec     453159 non-null int64
user_type        453159 non-null object
member_gender    453159 non-null object
member_age       453159 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 17.3+ MB
```

In [14]:
```
# Look at dataset
df_clean.head()
```

Out[14]:

	duration_sec	user_type	member_gender	member_age
0	80110	Customer	Male	30.0
1	78800	Customer	Female	52.0
4	43603	Subscriber	Female	20.0
6	4507	Customer	Female	26.0
12	2183	Subscriber	Male	27.0

In [15]:
```
# Check statistics of dataset
df_clean.describe()
```

Out[15]:

	duration_sec	member_age
count	453159.000000	453159.000000
mean	832.934014	36.595213
std	2525.280717	10.513488
min	61.000000	18.000000
25%	364.000000	29.000000
50%	556.000000	34.000000
75%	838.000000	43.000000
max	86252.000000	131.000000

Define

Remove member ages that are greater than 60

Code

In [16]:
```
# Look for the 95th percentile to remove outliers
df_clean.member_age.describe(percentiles = [ .95])
```

Out[16]:
```
count    453159.000000
mean         36.595213
std          10.513488
min          18.000000
50%          34.000000
95%          56.000000
max         131.000000
Name: member_age, dtype: float64
```

For the 95th percentile, the age is 54, I will remove records of ages greater than 60. This will help with relevancy of data.

In [17]:
```
# Remove member_age that is greater than 60
df_clean = df_clean.query('member_age <=60')
```

Test

In [18]:
```
# Check code
check_60 = df_clean.loc[(df_clean['member_age'] > 60)]
len(check_60)
```

Out[18]:
```
0
```

In [19]:
```
# Look at dataset info
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 441267 entries, 0 to 519699
Data columns (total 4 columns):
duration_sec     441267 non-null int64
user_type        441267 non-null object
member_gender    441267 non-null object
member_age       441267 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 16.8+ MB
```

In [20]:
```
# View dataset
df_clean
```

Out[20]:

	duration_sec	user_type	member_gender	member_age
0	80110	Customer	Male	30.0
1	78800	Customer	Female	52.0
4	43603	Subscriber	Female	20.0
6	4507	Customer	Female	26.0
12	2183	Subscriber	Male	27.0
13	2170	Subscriber	Male	27.0
15	1544	Subscriber	Female	37.0
16	1474	Subscriber	Male	38.0
18	1532	Subscriber	Other	29.0
19	1216	Subscriber	Male	46.0
20	386	Subscriber	Male	25.0
22	422	Subscriber	Male	32.0
28	871	Subscriber	Male	38.0
32	733	Subscriber	Female	37.0
33	781	Customer	Female	26.0
34	475	Subscriber	Male	39.0
35	152	Subscriber	Male	37.0
36	249	Subscriber	Male	24.0
39	243	Subscriber	Male	40.0
40	833	Subscriber	Male	33.0
41	820	Subscriber	Female	34.0
46	538	Customer	Male	26.0
47	577	Subscriber	Male	39.0
48	418	Subscriber	Male	50.0
52	707	Customer	Male	23.0
54	1240	Subscriber	Male	43.0
58	552	Subscriber	Female	49.0
59	546	Subscriber	Male	55.0
60	196	Subscriber	Male	28.0
62	323	Subscriber	Male	30.0
...	...	...	...	...
519668	124	Subscriber	Male	45.0
519669	662	Subscriber	Other	37.0
519670	123	Subscriber	Female	40.0
519671	73	Subscriber	Male	35.0

	duration_sec	user_type	member_gender	member_age
519672	1909	Subscriber	Male	33.0
519673	1908	Subscriber	Male	28.0
519674	672	Subscriber	Male	38.0
519675	602	Subscriber	Male	48.0
519676	893	Subscriber	Male	46.0
519677	1136	Subscriber	Male	33.0
519678	268	Subscriber	Female	33.0
519679	321	Subscriber	Male	30.0
519680	797	Subscriber	Male	44.0
519681	720	Subscriber	Male	30.0
519682	484	Subscriber	Male	30.0
519683	889	Subscriber	Female	33.0
519684	510	Subscriber	Male	51.0
519685	486	Subscriber	Male	31.0
519687	640	Subscriber	Male	39.0
519688	410	Subscriber	Male	38.0
519690	553	Subscriber	Male	44.0
519691	1086	Subscriber	Male	59.0
519692	1201	Subscriber	Male	32.0
519693	590	Subscriber	Male	34.0
519694	730	Subscriber	Male	37.0
519695	435	Subscriber	Male	26.0
519696	431	Subscriber	Male	44.0
519697	424	Subscriber	Female	32.0
519698	366	Subscriber	Male	36.0
519699	188	Subscriber	Male	33.0

441267 rows × 4 columns

In [21]:
```
# Check descriptive statistics
df_clean.describe()
```

Out[21]:

	duration_sec	member_age
count	441267.000000	441267.000000
mean	831.684946	35.775186
std	2522.180893	9.225110
min	61.000000	18.000000
25%	364.000000	29.000000
50%	554.000000	34.000000
75%	836.000000	42.000000
max	86252.000000	60.000000

Define

Convert bike ride duration in seconds to minutes

Code

In [22]:
```
# Covert the seconds of duration to minutes of duration for better understandi
ng
df_clean['duration_min'] = df_clean['duration_sec']/60
```

```
C:\Users\Cathy Moy\Anaconda3\New folder (2)\lib\site-packages\ipykernel_launc
her.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
```

Test

In [23]:
```
# Check dataset
df_clean
```

Out[23]:

	duration_sec	user_type	member_gender	member_age	duration_min
0	80110	Customer	Male	30.0	1335.166667
1	78800	Customer	Female	52.0	1313.333333
4	43603	Subscriber	Female	20.0	726.716667
6	4507	Customer	Female	26.0	75.116667
12	2183	Subscriber	Male	27.0	36.383333
13	2170	Subscriber	Male	27.0	36.166667
15	1544	Subscriber	Female	37.0	25.733333
16	1474	Subscriber	Male	38.0	24.566667
18	1532	Subscriber	Other	29.0	25.533333
19	1216	Subscriber	Male	46.0	20.266667
20	386	Subscriber	Male	25.0	6.433333
22	422	Subscriber	Male	32.0	7.033333
28	871	Subscriber	Male	38.0	14.516667
32	733	Subscriber	Female	37.0	12.216667
33	781	Customer	Female	26.0	13.016667
34	475	Subscriber	Male	39.0	7.916667
35	152	Subscriber	Male	37.0	2.533333
36	249	Subscriber	Male	24.0	4.150000
39	243	Subscriber	Male	40.0	4.050000
40	833	Subscriber	Male	33.0	13.883333
41	820	Subscriber	Female	34.0	13.666667
46	538	Customer	Male	26.0	8.966667
47	577	Subscriber	Male	39.0	9.616667
48	418	Subscriber	Male	50.0	6.966667
52	707	Customer	Male	23.0	11.783333
54	1240	Subscriber	Male	43.0	20.666667
58	552	Subscriber	Female	49.0	9.200000
59	546	Subscriber	Male	55.0	9.100000
60	196	Subscriber	Male	28.0	3.266667
62	323	Subscriber	Male	30.0	5.383333
...	...	...	...	...	...
519668	124	Subscriber	Male	45.0	2.066667
519669	662	Subscriber	Other	37.0	11.033333
519670	123	Subscriber	Female	40.0	2.050000
519671	73	Subscriber	Male	35.0	1.216667

	duration_sec	user_type	member_gender	member_age	duration_min
519672	1909	Subscriber	Male	33.0	31.816667
519673	1908	Subscriber	Male	28.0	31.800000
519674	672	Subscriber	Male	38.0	11.200000
519675	602	Subscriber	Male	48.0	10.033333
519676	893	Subscriber	Male	46.0	14.883333
519677	1136	Subscriber	Male	33.0	18.933333
519678	268	Subscriber	Female	33.0	4.466667
519679	321	Subscriber	Male	30.0	5.350000
519680	797	Subscriber	Male	44.0	13.283333
519681	720	Subscriber	Male	30.0	12.000000
519682	484	Subscriber	Male	30.0	8.066667
519683	889	Subscriber	Female	33.0	14.816667
519684	510	Subscriber	Male	51.0	8.500000
519685	486	Subscriber	Male	31.0	8.100000
519687	640	Subscriber	Male	39.0	10.666667
519688	410	Subscriber	Male	38.0	6.833333
519690	553	Subscriber	Male	44.0	9.216667
519691	1086	Subscriber	Male	59.0	18.100000
519692	1201	Subscriber	Male	32.0	20.016667
519693	590	Subscriber	Male	34.0	9.833333
519694	730	Subscriber	Male	37.0	12.166667
519695	435	Subscriber	Male	26.0	7.250000
519696	431	Subscriber	Male	44.0	7.183333
519697	424	Subscriber	Female	32.0	7.066667
519698	366	Subscriber	Male	36.0	6.100000
519699	188	Subscriber	Male	33.0	3.133333

441267 rows × 5 columns

In [24]:

```
# Remove duration_sec column and check
df_clean.drop(columns = ['duration_sec'], inplace = True)
```

```
C:\Users\Cathy Moy\Anaconda3\New folder (2)\lib\site-packages\pandas\core\fra
me.py:3697: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  errors=errors)
```

In [25]:
```
# Check descriptive statistics
df_clean.describe()
```

Out[25]:

	member_age	duration_min
count	441267.000000	441267.000000
mean	35.775186	13.861416
std	9.225110	42.036348
min	18.000000	1.016667
25%	29.000000	6.066667
50%	34.000000	9.233333
75%	42.000000	13.933333
max	60.000000	1437.533333

Define

Remove member genders listed as "Other"

Code

In [26]:
```
# Look for rows with member_gender = Other to remove
df_clean[df_clean['member_gender']== 'Other']
```

Out[26]:

	user_type	member_gender	member_age	duration_min
18	Subscriber	Other	29.0	25.533333
78	Subscriber	Other	29.0	66.016667
136	Subscriber	Other	29.0	13.650000
218	Customer	Other	30.0	19.766667
313	Subscriber	Other	29.0	10.550000
362	Subscriber	Other	24.0	3.250000
401	Subscriber	Other	49.0	28.033333
414	Customer	Other	25.0	7.416667
491	Subscriber	Other	30.0	15.516667
656	Subscriber	Other	20.0	7.800000
668	Subscriber	Other	20.0	6.050000
683	Subscriber	Other	43.0	10.316667
736	Subscriber	Other	24.0	4.066667
752	Subscriber	Other	20.0	7.516667
762	Customer	Other	25.0	8.633333
799	Customer	Other	25.0	11.950000
803	Customer	Other	51.0	14.433333
878	Customer	Other	25.0	29.700000
904	Customer	Other	47.0	9.183333
935	Subscriber	Other	50.0	43.100000
951	Subscriber	Other	49.0	18.083333
1037	Customer	Other	51.0	19.316667
1046	Customer	Other	25.0	42.600000
1073	Subscriber	Other	43.0	16.416667
1084	Subscriber	Other	50.0	40.250000
1253	Subscriber	Other	49.0	18.600000
1330	Subscriber	Other	29.0	11.016667
1348	Subscriber	Other	24.0	10.683333
1492	Customer	Other	24.0	28.516667
1514	Customer	Other	24.0	28.033333
...	...	...	...	...
514705	Subscriber	Other	42.0	15.300000
514863	Subscriber	Other	35.0	6.250000
515250	Subscriber	Other	41.0	9.200000
515284	Customer	Other	52.0	36.066667

	user_type	member_gender	member_age	duration_min
515285	Customer	Other	43.0	36.650000
515346	Customer	Other	52.0	16.850000
515370	Customer	Other	52.0	28.550000
515371	Customer	Other	43.0	28.450000
515924	Subscriber	Other	41.0	7.183333
516541	Customer	Other	43.0	14.133333
516551	Customer	Other	29.0	13.533333
516607	Subscriber	Other	35.0	23.750000
516611	Customer	Other	29.0	26.966667
516642	Customer	Other	43.0	13.683333
516760	Customer	Other	29.0	11.566667
516776	Customer	Other	29.0	32.283333
516802	Customer	Other	29.0	21.066667
517154	Subscriber	Other	47.0	12.633333
517593	Subscriber	Other	35.0	7.183333
517649	Subscriber	Other	35.0	4.383333
517905	Subscriber	Other	35.0	7.216667
518208	Subscriber	Other	37.0	12.283333
518581	Subscriber	Other	47.0	4.633333
518629	Subscriber	Other	35.0	13.516667
518677	Subscriber	Other	35.0	12.050000
518699	Subscriber	Other	37.0	9.366667
518830	Subscriber	Other	35.0	6.033333
519080	Subscriber	Other	35.0	4.783333
519129	Subscriber	Other	37.0	12.833333
519669	Subscriber	Other	37.0	11.033333

6169 rows × 4 columns

In [27]:
```
# Remove the 6169 entries where member_gender is "Other"
df_clean = df_clean.drop(df_clean[df_clean["member_gender"] == 'Other'].index)
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 435098 entries, 0 to 519699
Data columns (total 4 columns):
user_type        435098 non-null object
member_gender    435098 non-null object
member_age       435098 non-null float64
duration_min     435098 non-null float64
dtypes: float64(2), object(2)
memory usage: 16.6+ MB
```

Test

In [28]:
```
# Check dataset
df_clean
```

Out[28]:

	user_type	member_gender	member_age	duration_min
0	Customer	Male	30.0	1335.166667
1	Customer	Female	52.0	1313.333333
4	Subscriber	Female	20.0	726.716667
6	Customer	Female	26.0	75.116667
12	Subscriber	Male	27.0	36.383333
13	Subscriber	Male	27.0	36.166667
15	Subscriber	Female	37.0	25.733333
16	Subscriber	Male	38.0	24.566667
19	Subscriber	Male	46.0	20.266667
20	Subscriber	Male	25.0	6.433333
22	Subscriber	Male	32.0	7.033333
28	Subscriber	Male	38.0	14.516667
32	Subscriber	Female	37.0	12.216667
33	Customer	Female	26.0	13.016667
34	Subscriber	Male	39.0	7.916667
35	Subscriber	Male	37.0	2.533333
36	Subscriber	Male	24.0	4.150000
39	Subscriber	Male	40.0	4.050000
40	Subscriber	Male	33.0	13.883333
41	Subscriber	Female	34.0	13.666667
46	Customer	Male	26.0	8.966667
47	Subscriber	Male	39.0	9.616667
48	Subscriber	Male	50.0	6.966667
52	Customer	Male	23.0	11.783333
54	Subscriber	Male	43.0	20.666667
58	Subscriber	Female	49.0	9.200000
59	Subscriber	Male	55.0	9.100000
60	Subscriber	Male	28.0	3.266667
62	Subscriber	Male	30.0	5.383333
63	Subscriber	Male	31.0	10.466667
...	...	...	...	...
519667	Subscriber	Female	38.0	40.516667
519668	Subscriber	Male	45.0	2.066667
519670	Subscriber	Female	40.0	2.050000
519671	Subscriber	Male	35.0	1.216667

	user_type	member_gender	member_age	duration_min
519672	Subscriber	Male	33.0	31.816667
519673	Subscriber	Male	28.0	31.800000
519674	Subscriber	Male	38.0	11.200000
519675	Subscriber	Male	48.0	10.033333
519676	Subscriber	Male	46.0	14.883333
519677	Subscriber	Male	33.0	18.933333
519678	Subscriber	Female	33.0	4.466667
519679	Subscriber	Male	30.0	5.350000
519680	Subscriber	Male	44.0	13.283333
519681	Subscriber	Male	30.0	12.000000
519682	Subscriber	Male	30.0	8.066667
519683	Subscriber	Female	33.0	14.816667
519684	Subscriber	Male	51.0	8.500000
519685	Subscriber	Male	31.0	8.100000
519687	Subscriber	Male	39.0	10.666667
519688	Subscriber	Male	38.0	6.833333
519690	Subscriber	Male	44.0	9.216667
519691	Subscriber	Male	59.0	18.100000
519692	Subscriber	Male	32.0	20.016667
519693	Subscriber	Male	34.0	9.833333
519694	Subscriber	Male	37.0	12.166667
519695	Subscriber	Male	26.0	7.250000
519696	Subscriber	Male	44.0	7.183333
519697	Subscriber	Female	32.0	7.066667
519698	Subscriber	Male	36.0	6.100000
519699	Subscriber	Male	33.0	3.133333

435098 rows × 4 columns

In [29]:
```
# Check that these were removed
df_clean['member_gender'].str.contains('Other').value_counts()
```

Out[29]:
```
False    435098
Name: member_gender, dtype: int64
```

In [30]:
```
# Look at breakdown of member gender
df_clean['member_gender'].str.contains('Female').value_counts()
```

Out[30]:
```
False    338224
True      96874
Name: member_gender, dtype: int64
```

In [31]:
```
# Look at breakdown of member gender
df_clean['member_gender'].str.contains('Male').value_counts()
```

Out[31]:
```
True     338224
False     96874
Name: member_gender, dtype: int64
```

In [32]:
```
# Check sum of genders to ensure correct
338224 + 96874
```

Out[32]:
```
435098
```

From these 435,098 entries: the gender of users are 338,224 males and 96,874 females.

In [33]:
```
# Look at descriptive statistics
df_clean.describe()
```

Out[33]:

	member_age	duration_min
count	435098.000000	435098.000000
mean	35.771431	13.820759
std	9.221190	41.840967
min	18.000000	1.016667
25%	29.000000	6.050000
50%	34.000000	9.233333
75%	42.000000	13.916667
max	60.000000	1437.533333

Store cleaned data

In [34]:
```
# Save cleaned data
df_clean.to_csv('clean-2017-bike-data.csv', index = False)
```

Visualization

Focus on the average trip duration between different characteristics of users such as gender, age group, and user type.

The average trip duration in minutes for the whole data set is 13.82 minutes.

We have a total of 435,098 entries to account in this data analysis.

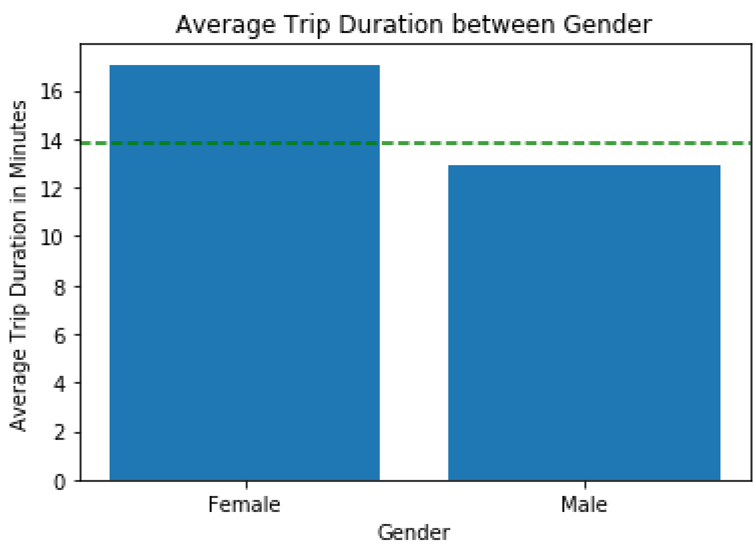
Univariate Exploration

I will begin to explore the dataset by checking the average duration of bike rides in minutes by gender, between females and males.

In [35]:
```
# Find average trip durations for female and male
df_clean_gender_mean = df_clean.groupby('member_gender').duration_min.mean()
df_clean_gender_mean
```

Out[35]:
```
member_gender
Female    17.063716
Male      12.891912
Name: duration_min, dtype: float64
```

In [36]:
```
# Create a bar chart
labels = ['Female', 'Male']
heights = df_clean_gender_mean
labels = df_clean_gender_mean.index.str.replace('_', ' ').str.title()

plt.bar(labels, heights, tick_label = labels)
plt.title('Average Trip Duration between Gender')
plt.xlabel('Gender')
plt.ylabel('Average Trip Duration in Minutes')

mean = df_clean['duration_min'].mean()
plt.axhline(mean, color='green', linestyle='--')
plt.savefig('Avg Trip between Gender');
```



The dotted line in the bar plot represents its relation to the overall average trip duration for all bike riders.

In [37]:
```
# Record average time duration for all
mean
```

Out[37]:
```
13.820758541754026
```

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

Most of my points were as expected, nothing was unusual to make any major transformations.

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?

When investigating the member_gender variables, there were entries of 'Other'. With this, I decided to remove these 'Other' entries to be consistent with my data analysis. In doing so, I can focus on how gender may play a role in the average trip duration between females and males.

Bivariate Exploration

I will further explore the dataset by user type (customer or subscriber) to the gender and check the average duration of bike rides in minutes between subscribers who are female to male and customers who are female to male. I will also continue to compare the two alternatives for those variables.

In [38]:
```
# Check counts of Subscribers and Customers
df_clean['user_type'].str.contains('Subscriber').value_counts()
```

Out[38]:
```
True     387763
False     47335
Name: user_type, dtype: int64
```

In [39]:
```
# Check counts of Subscribers and Customers
df_clean['user_type'].str.contains('Customer').value_counts()
```

Out[39]:
```
False    387763
True      47335
Name: user_type, dtype: int64
```

In [40]:
```
# Check sum of Subscribers and Customers
387763 + 47335
```

Out[40]:
```
435098
```

In [41]:
```
# Find means by user type
df_clean_user_mean = df_clean.groupby('user_type').duration_min.mean()
df_clean_user_mean
```

Out[41]:
```
user_type
Customer      31.471878
Subscriber    11.666051
Name: duration_min, dtype: float64
```

In [42]:
```
# Find customers who are females
cond1 = df_clean["user_type"] == 'Customer'
cond2 = df_clean["member_gender"] == 'Female'

cust_fem = df_clean[cond1 & cond2]
cust_fem
```

Out[42]:

	user_type	member_gender	member_age	duration_min
1	Customer	Female	52.0	1313.333333
6	Customer	Female	26.0	75.116667
33	Customer	Female	26.0	13.016667
97	Customer	Female	24.0	18.883333
99	Customer	Female	28.0	3.733333
151	Customer	Female	33.0	16.883333
154	Customer	Female	27.0	16.816667
159	Customer	Female	28.0	3.133333
181	Customer	Female	39.0	10.800000
205	Customer	Female	28.0	10.516667
223	Customer	Female	33.0	26.016667
237	Customer	Female	33.0	15.366667
254	Customer	Female	39.0	11.200000
263	Customer	Female	39.0	19.066667
298	Customer	Female	36.0	56.450000
320	Customer	Female	21.0	462.716667
323	Customer	Female	27.0	398.500000
324	Customer	Female	39.0	21.183333
335	Customer	Female	32.0	4.816667
336	Customer	Female	29.0	5.250000
357	Customer	Female	23.0	35.966667
371	Customer	Female	23.0	80.950000
395	Customer	Female	23.0	13.983333
418	Customer	Female	40.0	10.083333
437	Customer	Female	27.0	12.483333
440	Customer	Female	40.0	14.450000
450	Customer	Female	28.0	18.883333
475	Customer	Female	40.0	9.700000
484	Customer	Female	18.0	6.316667
485	Customer	Female	46.0	6.666667
...	...	...	...	...
517512	Customer	Female	27.0	27.250000
517525	Customer	Female	36.0	44.066667
517526	Customer	Female	33.0	51.900000
517569	Customer	Female	34.0	20.050000

	user_type	member_gender	member_age	duration_min
517571	Customer	Female	31.0	20.333333
517573	Customer	Female	36.0	47.283333
517665	Customer	Female	48.0	95.633333
517670	Customer	Female	33.0	29.383333
517719	Customer	Female	36.0	19.733333
517720	Customer	Female	27.0	26.050000
517724	Customer	Female	23.0	12.983333
517906	Customer	Female	37.0	6.183333
518145	Customer	Female	24.0	9.633333
518157	Customer	Female	27.0	7.700000
518158	Customer	Female	24.0	17.883333
518233	Customer	Female	24.0	11.933333
518389	Customer	Female	32.0	13.433333
518414	Customer	Female	37.0	19.866667
518680	Customer	Female	37.0	18.650000
518689	Customer	Female	29.0	17.500000
518710	Customer	Female	27.0	15.883333
518717	Customer	Female	32.0	135.333333
519077	Customer	Female	29.0	422.733333
519121	Customer	Female	27.0	12.966667
519235	Customer	Female	27.0	21.366667
519246	Customer	Female	30.0	8.716667
519374	Customer	Female	30.0	11.583333
519471	Customer	Female	30.0	19.600000
519473	Customer	Female	25.0	23.366667
519484	Customer	Female	43.0	150.466667

14612 rows × 4 columns

In [43]:
```
# Find statistics for females customers to obtain mean
cust_fem.describe()
```

Out[43]:

	member_age	duration_min
count	14612.000000	14612.000000
mean	31.590953	37.016251
std	8.362354	102.442378
min	18.000000	1.016667
25%	26.000000	11.583333
50%	30.000000	17.516667
75%	35.000000	26.416667
max	60.000000	1437.533333

In [44]:
```
# Find customers who are males
cond3 = df_clean["user_type"] == 'Customer'
cond4 = df_clean["member_gender"] == 'Male'

cust_male = df_clean[cond3 & cond4]
cust_male
```

Out[44]:

	user_type	member_gender	member_age	duration_min
0	Customer	Male	30.0	1335.166667
46	Customer	Male	26.0	8.966667
52	Customer	Male	23.0	11.783333
98	Customer	Male	30.0	24.166667
100	Customer	Male	29.0	3.416667
123	Customer	Male	25.0	20.233333
141	Customer	Male	24.0	10.750000
155	Customer	Male	27.0	16.600000
160	Customer	Male	29.0	3.150000
173	Customer	Male	25.0	15.416667
182	Customer	Male	38.0	11.300000
206	Customer	Male	29.0	10.950000
225	Customer	Male	35.0	9.600000
253	Customer	Male	38.0	9.650000
264	Customer	Male	38.0	17.716667
292	Customer	Male	23.0	7.533333
294	Customer	Male	23.0	8.800000
300	Customer	Male	31.0	7.966667
310	Customer	Male	23.0	26.600000
314	Customer	Male	31.0	10.683333
318	Customer	Male	27.0	35.833333
319	Customer	Male	30.0	35.700000
321	Customer	Male	31.0	7.800000
325	Customer	Male	38.0	21.400000
337	Customer	Male	31.0	75.350000
345	Customer	Male	37.0	27.933333
367	Customer	Male	23.0	13.233333
389	Customer	Male	31.0	6.300000
396	Customer	Male	26.0	13.466667
416	Customer	Male	23.0	18.616667
...	...	...	...	...
518702	Customer	Male	49.0	10.683333
518738	Customer	Male	50.0	6.866667
518783	Customer	Male	29.0	8.316667
518786	Customer	Male	29.0	23.033333

	user_type	member_gender	member_age	duration_min
518810	Customer	Male	23.0	54.700000
518938	Customer	Male	47.0	9.900000
518947	Customer	Male	37.0	13.866667
518973	Customer	Male	38.0	18.166667
519062	Customer	Male	43.0	8.633333
519089	Customer	Male	36.0	85.683333
519094	Customer	Male	40.0	7.750000
519107	Customer	Male	40.0	62.833333
519112	Customer	Male	54.0	84.200000
519115	Customer	Male	58.0	17.400000
519117	Customer	Male	19.0	55.216667
519164	Customer	Male	28.0	22.283333
519179	Customer	Male	51.0	7.266667
519186	Customer	Male	27.0	10.633333
519212	Customer	Male	32.0	5.866667
519230	Customer	Male	40.0	8.783333
519242	Customer	Male	53.0	61.816667
519265	Customer	Male	54.0	17.033333
519370	Customer	Male	23.0	15.666667
519373	Customer	Male	23.0	14.566667
519472	Customer	Male	31.0	21.466667
519476	Customer	Male	28.0	157.016667
519482	Customer	Male	40.0	14.016667
519519	Customer	Male	45.0	1.766667
519574	Customer	Male	28.0	29.966667
519636	Customer	Male	43.0	90.683333

32723 rows × 4 columns

In [45]:
```
# Find statistics for males customers to obtain mean
cust_male.describe()
```

Out[45]:

	member_age	duration_min
count	32723.000000	32723.000000
mean	33.596645	28.996115
std	8.873089	84.136201
min	18.000000	1.016667
25%	27.000000	9.316667
50%	32.000000	14.533333
75%	39.000000	22.633333
max	60.000000	1432.916667

In [46]:
```
# Find subscribers who are females
cond5 = df_clean["user_type"] == 'Subscriber'
cond6 = df_clean["member_gender"] == 'Female'

sub_female = df_clean[cond5 & cond6]
sub_female
```

Out[46]:

	user_type	member_gender	member_age	duration_min
4	Subscriber	Female	20.0	726.716667
15	Subscriber	Female	37.0	25.733333
32	Subscriber	Female	37.0	12.216667
41	Subscriber	Female	34.0	13.666667
58	Subscriber	Female	49.0	9.200000
64	Subscriber	Female	23.0	9.116667
70	Subscriber	Female	34.0	13.283333
103	Subscriber	Female	39.0	15.783333
137	Subscriber	Female	29.0	11.933333
140	Subscriber	Female	28.0	14.966667
153	Subscriber	Female	30.0	10.633333
156	Subscriber	Female	37.0	9.866667
163	Subscriber	Female	49.0	6.866667
166	Subscriber	Female	41.0	6.450000
172	Subscriber	Female	25.0	15.683333
176	Subscriber	Female	40.0	15.166667
192	Subscriber	Female	24.0	28.283333
193	Subscriber	Female	37.0	3.600000
198	Subscriber	Female	23.0	12.916667
201	Subscriber	Female	23.0	10.983333
202	Subscriber	Female	21.0	4.233333
207	Subscriber	Female	21.0	4.066667
245	Subscriber	Female	31.0	21.316667
256	Subscriber	Female	29.0	17.733333
257	Subscriber	Female	37.0	2.683333
258	Subscriber	Female	31.0	3.250000
260	Subscriber	Female	49.0	4.216667
272	Subscriber	Female	41.0	7.816667
273	Subscriber	Female	23.0	4.800000
278	Subscriber	Female	32.0	12.700000
...	...	...	...	...
519395	Subscriber	Female	37.0	9.100000
519397	Subscriber	Female	37.0	8.833333
519401	Subscriber	Female	28.0	13.566667
519407	Subscriber	Female	37.0	2.166667

	user_type	member_gender	member_age	duration_min
519413	Subscriber	Female	48.0	34.850000
519450	Subscriber	Female	40.0	13.250000
519455	Subscriber	Female	30.0	14.916667
519457	Subscriber	Female	34.0	18.750000
519459	Subscriber	Female	43.0	19.333333
519463	Subscriber	Female	40.0	2.116667
519478	Subscriber	Female	21.0	10.533333
519491	Subscriber	Female	29.0	9.866667
519531	Subscriber	Female	52.0	13.083333
519537	Subscriber	Female	43.0	4.550000
519550	Subscriber	Female	32.0	5.400000
519556	Subscriber	Female	32.0	24.716667
519565	Subscriber	Female	45.0	6.416667
519571	Subscriber	Female	30.0	6.350000
519579	Subscriber	Female	42.0	44.450000
519590	Subscriber	Female	29.0	23.850000
519599	Subscriber	Female	28.0	13.050000
519628	Subscriber	Female	45.0	15.100000
519638	Subscriber	Female	21.0	11.850000
519641	Subscriber	Female	29.0	7.333333
519654	Subscriber	Female	55.0	12.900000
519667	Subscriber	Female	38.0	40.516667
519670	Subscriber	Female	40.0	2.050000
519678	Subscriber	Female	33.0	4.466667
519683	Subscriber	Female	33.0	14.816667
519697	Subscriber	Female	32.0	7.066667

82262 rows × 4 columns

In [47]:
```
# Find statistics for females subscribers to obtain mean
sub_female.describe()
```

Out[47]:

	member_age	duration_min
count	82262.000000	82262.000000
mean	35.159016	13.519596
std	9.014801	35.750348
min	18.000000	1.016667
25%	29.000000	6.616667
50%	33.000000	9.983333
75%	40.000000	14.766667
max	60.000000	1434.583333

In [48]:
```
# Find subscribers who are males
cond7 = df_clean["user_type"] == 'Subscriber'
cond8 = df_clean["member_gender"] == 'Male'

sub_male = df_clean[cond7 & cond8]
sub_male
```

Out[48]:

	user_type	member_gender	member_age	duration_min
12	Subscriber	Male	27.0	36.383333
13	Subscriber	Male	27.0	36.166667
16	Subscriber	Male	38.0	24.566667
19	Subscriber	Male	46.0	20.266667
20	Subscriber	Male	25.0	6.433333
22	Subscriber	Male	32.0	7.033333
28	Subscriber	Male	38.0	14.516667
34	Subscriber	Male	39.0	7.916667
35	Subscriber	Male	37.0	2.533333
36	Subscriber	Male	24.0	4.150000
39	Subscriber	Male	40.0	4.050000
40	Subscriber	Male	33.0	13.883333
47	Subscriber	Male	39.0	9.616667
48	Subscriber	Male	50.0	6.966667
54	Subscriber	Male	43.0	20.666667
59	Subscriber	Male	55.0	9.100000
60	Subscriber	Male	28.0	3.266667
62	Subscriber	Male	30.0	5.383333
63	Subscriber	Male	31.0	10.466667
65	Subscriber	Male	53.0	18.766667
66	Subscriber	Male	33.0	6.866667
69	Subscriber	Male	33.0	12.266667
71	Subscriber	Male	39.0	25.866667
72	Subscriber	Male	26.0	26.416667
75	Subscriber	Male	34.0	6.800000
76	Subscriber	Male	37.0	44.100000
77	Subscriber	Male	31.0	5.633333
86	Subscriber	Male	59.0	32.683333
91	Subscriber	Male	38.0	3.533333
95	Subscriber	Male	38.0	15.283333
...	...	...	...	...
519659	Subscriber	Male	29.0	3.766667
519661	Subscriber	Male	28.0	10.683333
519662	Subscriber	Male	33.0	10.250000
519664	Subscriber	Male	46.0	1.200000

	user_type	member_gender	member_age	duration_min
519665	Subscriber	Male	33.0	6.233333
519668	Subscriber	Male	45.0	2.066667
519671	Subscriber	Male	35.0	1.216667
519672	Subscriber	Male	33.0	31.816667
519673	Subscriber	Male	28.0	31.800000
519674	Subscriber	Male	38.0	11.200000
519675	Subscriber	Male	48.0	10.033333
519676	Subscriber	Male	46.0	14.883333
519677	Subscriber	Male	33.0	18.933333
519679	Subscriber	Male	30.0	5.350000
519680	Subscriber	Male	44.0	13.283333
519681	Subscriber	Male	30.0	12.000000
519682	Subscriber	Male	30.0	8.066667
519684	Subscriber	Male	51.0	8.500000
519685	Subscriber	Male	31.0	8.100000
519687	Subscriber	Male	39.0	10.666667
519688	Subscriber	Male	38.0	6.833333
519690	Subscriber	Male	44.0	9.216667
519691	Subscriber	Male	59.0	18.100000
519692	Subscriber	Male	32.0	20.016667
519693	Subscriber	Male	34.0	9.833333
519694	Subscriber	Male	37.0	12.166667
519695	Subscriber	Male	26.0	7.250000
519696	Subscriber	Male	44.0	7.183333
519698	Subscriber	Male	36.0	6.100000
519699	Subscriber	Male	33.0	3.133333

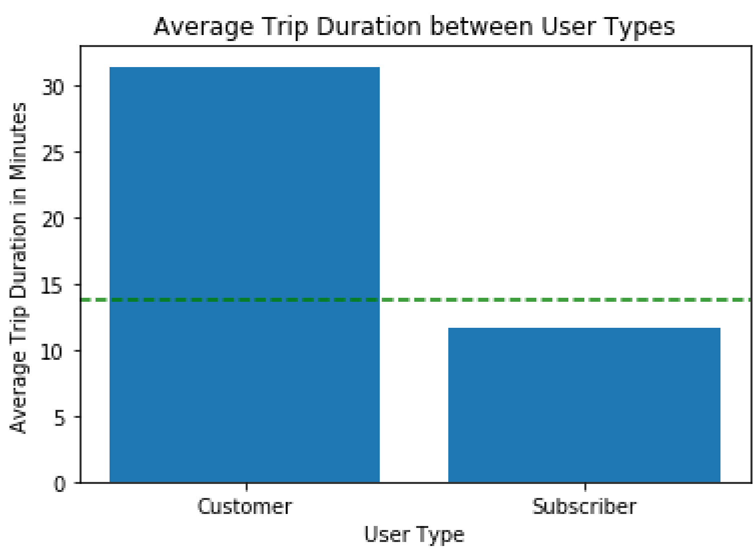
305501 rows × 4 columns

In [49]:
```
# Find statistics for males subscribers to obtain mean
sub_male.describe()
```

Out[49]:

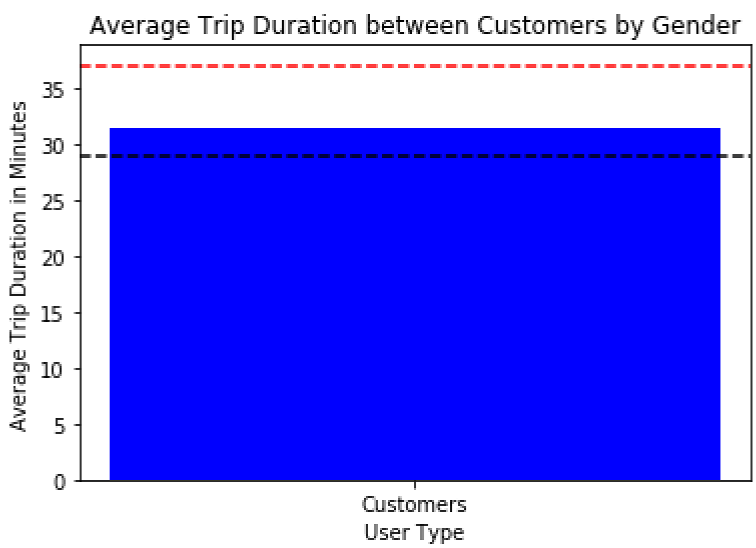
	member_age	duration_min
count	305501.000000	305501.000000
mean	36.369233	11.166949
std	9.254223	28.837056
min	18.000000	1.016667
25%	29.000000	5.650000
50%	35.000000	8.483333
75%	43.000000	12.466667
max	60.000000	1428.050000

In [50]:
```
# Create a bar chart for User Types

labels = ['Customer', 'Subscriber']
heights = df_clean_user_mean
labels = df_clean_user_mean.index.str.replace('_', ' ').str.title()

plt.bar(labels, heights, tick_label = labels)
plt.title('Average Trip Duration between User Types')
plt.xlabel('User Type')
plt.ylabel('Average Trip Duration in Minutes')

mean = df_clean['duration_min'].mean()

plt.axhline(mean, color='green', linestyle='--')
plt.savefig('Avg Trip between Users');
```



The dotted line in the bar plot represents its relation to the overall average trip duration for all bike riders.

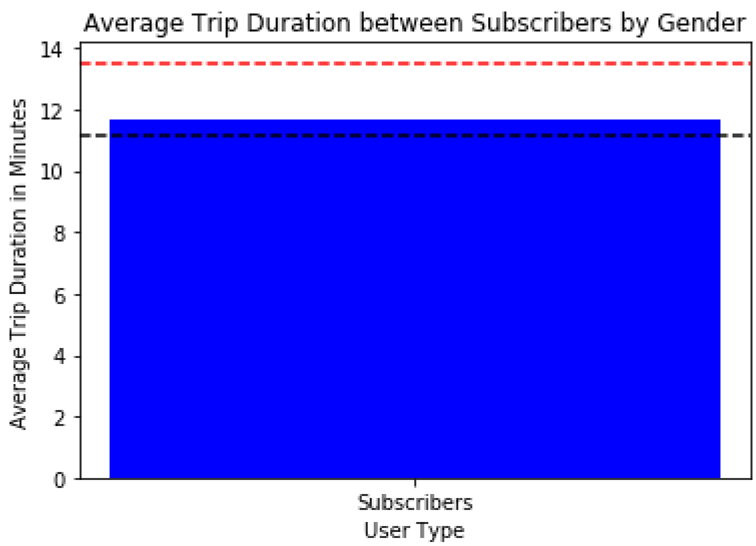
In [51]:
```
# Create a bar chart for Customers
labels = ['Customers']
customers = df_clean["user_type"] == 'Customer'
customers = df_clean[customers]
customers_mean = customers['duration_min'].mean()

heights = customers_mean

plt.bar(labels, heights, tick_label = labels, color = 'blue')
plt.title('Average Trip Duration between Customers by Gender')
plt.xlabel('User Type')
plt.ylabel('Average Trip Duration in Minutes')

# Customer Mean = 31.47
# Mean 2 = Average Duration for Customers who are Females
mean2 = 37.02

# Mean 3 = Average Duration for Customers who are Males
mean3 = 29.00

# Females in Dotted Red Line
# Males in Dotted Black Line

plt.axhline(mean2, color='red', linestyle='--')
plt.axhline(mean3, color='black', linestyle='--')
plt.savefig('Avg Trip between Customers by Gender');
```



The red dotted line in the bar plot represents female customers and their relation to the average trip duration for all customers.

The black dotted line in the bar plot represents male customers and their relation to the average trip duration for all customers.

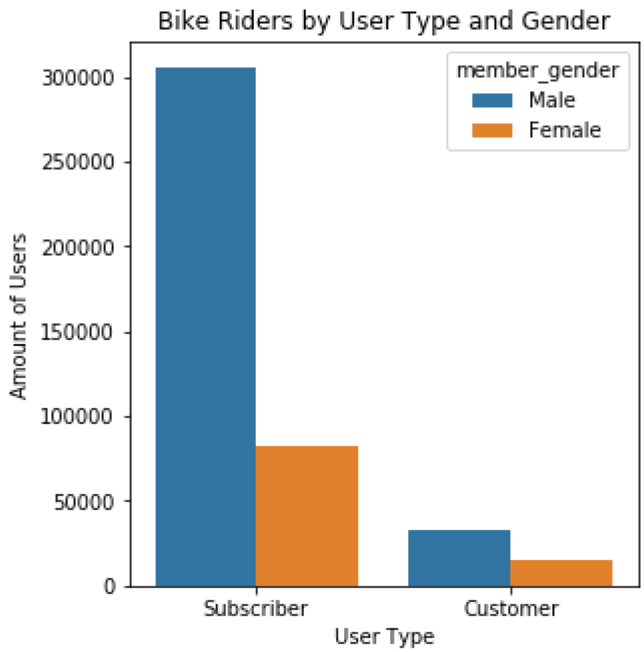
In [52]:
```
# Create a bar chart for Subscribers
labels = ['Subscribers']
subscribers = df_clean["user_type"] == 'Subscriber'
subscribers = df_clean[subscribers]
subscribers_mean = subscribers['duration_min'].mean()

heights = subscribers_mean

plt.bar(labels, heights, tick_label = labels, color = 'b')
plt.title('Average Trip Duration between Subscribers by Gender')
plt.xlabel('User Type')
plt.ylabel('Average Trip Duration in Minutes')

# Subscriber Mean = 11.67
# Mean 4 = Average Duration for Subscribers who are Females
mean4 = 13.52

# Mean 5 = Average Duration for Subscribers who are Males
mean5 = 11.17

# Femaes in Dotted Red Line
# Males in Dotted Black Line

plt.axhline(mean4, color='red', linestyle='--')
plt.axhline(mean5, color='black', linestyle='--')
plt.savefig('Avg Trip between Subscribers by Gender');
```



The red dotted line in the bar plot represents female subscribers and their relation to the average trip duration for all subscribers.

The black dotted line in the bar plot represents male subscribers and their relation to the average trip duration for all subscribers.

In [53]:
```
# Create bar chart with subplot
plt.figure(figsize = [10, 5])

plt.subplot(1, 2, 1)

g = sns.countplot(data=df_clean, x="user_type", hue="member_gender", order=df_
clean.user_type.value_counts().index)
g.set_xlabel('User Type')
g.set_ylabel('Amount of Users')
g.set_title('Bike Riders by User Type and Gender')
plt.savefig('Bike Riders by User Type and Gender');
```



This bar plot represents the breakdown of subscribers and customers by gender to obtain an idea of how they represented among bike riders for this bike-sharing system for year 2017. We can see there is significantly higher amount of subscribers than to customers and same goes for gender, there is much more males than females.

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?

The overall average trip duration for all entries was 13.82 minutes.

Looking at the divide of gender, the average for females was 17.06 minutes and for males 12.89 minutes. Females were above overall average and males were below.

Looking at the divide of user type, the average for customers was 31.47 minutes and for subscribers 11.67 minutes. Customers were above overall average and subscribers were below.

Averages

All Customers: 31.47 minutes

Female Customers: 37.02 minutes

Male Customers: 29.00 minutes

All Subscribers: 11.67 minutes

Female Subscribers: 13.52 minutes

Male Subscribers: 11.17 minutes

Interestingly, adding the factor of user type: Female Customers & Females Subscribers were also above its average while Male Customers and Male Subscribers were below average.

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

Expected relationships were found in the association between user type (customer and subscriber) to average trip duration. Customers have a significantly higher average trip duration than subscribers, their average trip duration is nearly twice as long. Even with the factor of user type, females still have a higher average than males.

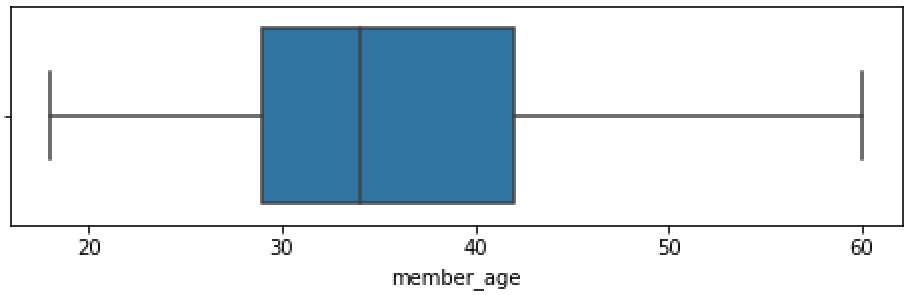
There also seems to be a correlation to gender to average trip duration. Females generally have a higher average trip duration than males even with disregard to their user type as a customer or subscriber.

To note: they are more entries of males and subscribers than we have for females and customers, so with this limited data, it may not be representative of findings. More entries of females and customers may offer new findings.

Multivariate Exploration

I will finish exploring the dataset by adding member age to further examine the average duration of bike rides in minutes among user type and gender.

In [54]:
```
# Create boxplot of member_age

plt.figure(figsize = [8, 2])
base_color = sns.color_palette()[0]

sns.boxplot(data=df_clean, x='member_age', color=base_color)
plt.savefig('BoxPlot of Member Age');
```



Most of the data entries fall under the 30-40 age range based on this boxplot.

In [55]:
```
# Find entries for those between ages 0-20
age_20 = df_clean.loc[(df_clean['member_age'] <=20)]
```

In [56]:
```
# Find entries for those between ages 20-40
age_40 = df_clean.loc[(df_clean['member_age'] > 20) & (df_clean['member_age']
<= 40)]
```

In [57]:
```
# Find entries for those between ages 40-60
age_60 = df_clean.loc[(df_clean['member_age'] > 40) & (df_clean['member_age']
<= 60)]
```

In [58]:
```
# Find counts of each age group
len(age_20), len(age_40), len(age_60)
```

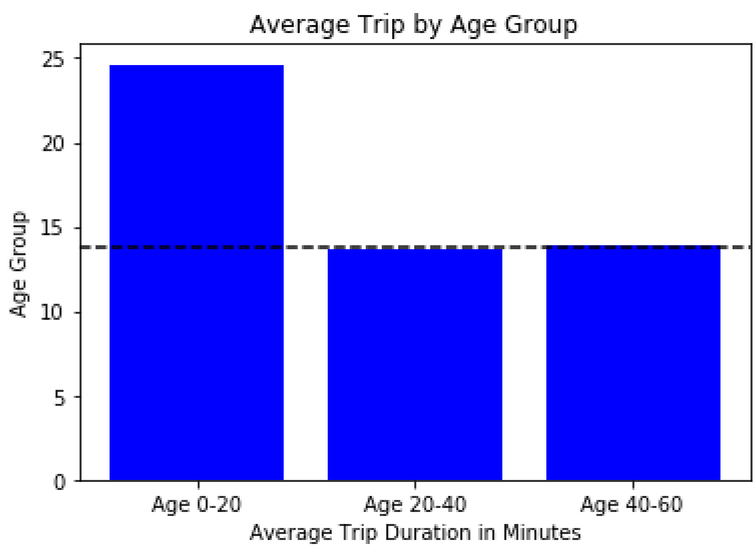
Out[58]: (4173, 310204, 120721)

In [59]:
```
# Find means of each age group
mean_20 = age_20['duration_min'].mean()
mean_40 = age_40['duration_min'].mean()
mean_60 = age_60['duration_min'].mean()

mean_20, mean_40, mean_60
```

Out[59]: (24.61149053438777, 13.662546367336992, 13.854293094545755)

In [60]:
```
# Record all means with their values rounded
mean_all = 13.82
mean_20 = 24.61
mean_40 = 13.66
mean_60 = 13.84
```

In [61]:
```
# Create plot
labels = ['Age 0-20', 'Age 20-40', 'Age 40-60']
heights = mean_20, mean_40, mean_60

plt.bar(labels, heights, tick_label = labels, color = 'b')
plt.title('Average Trip by Age Group')
plt.xlabel('Average Trip Duration in Minutes')
plt.ylabel('Age Group')

plt.axhline(mean_all, color='black', linestyle='--')
plt.savefig('Average Trip by Age Group');
```



The dotted line in the bar plot represents its relation to the overall average trip duration for all bike riders.

In [62]:
```
# Find counts for subscribers under age groups

subscribers_20 = age_20.loc[(age_20["user_type"] == 'Subscriber')]
subscribers_40 = age_40.loc[(age_40["user_type"] == 'Subscriber')]
subscribers_60 = age_60.loc[(age_60["user_type"] == 'Subscriber')]
len(subscribers_20), len(subscribers_40), len(subscribers_60)
```

Out[62]: (2424, 273481, 111858)

In [63]:
```
# Find means for subscribers under age groups

mean_sub_20 = subscribers_20['duration_min'].mean()
mean_sub_40 = subscribers_40['duration_min'].mean()
mean_sub_60 = subscribers_60['duration_min'].mean()

mean_sub_20 , mean_sub_40 , mean_sub_60
```

Out[63]: (13.578424092409211, 11.3642254854999, 12.362541794060402)

In [64]:
```
# Find counts for customers under age groups

customers_20 = age_20.loc[(age_20["user_type"] == 'Customer')]
customers_40 = age_40.loc[(age_40["user_type"] == 'Customer')]
customers_60 = age_60.loc[(age_60["user_type"] == 'Customer')]
len(customers_20), len(customers_40), len(customers_60)
```

Out[64]: (1749, 36723, 8863)

In [65]:
```
# Find means for customers under age groups

mean_cust_20 = customers_20['duration_min'].mean()
mean_cust_40 = customers_40['duration_min'].mean()
mean_cust_60 = customers_60['duration_min'].mean()

mean_cust_20 , mean_cust_40 , mean_cust_60
```

Out[65]: (39.90260148656365, 30.778443573055952, 32.68136259355377)

In [66]:
```
# Find counts for females under age groups

fem_20 = age_20.loc[(age_20["member_gender"] == 'Female')]
fem_40 = age_40.loc[(age_40["member_gender"] == 'Female')]
fem_60 = age_60.loc[(age_60["member_gender"] == 'Female')]
len(fem_20), len(fem_40), len(fem_60)
```

Out[66]: (1283, 73147, 22444)

In [67]:
```
# Find means for females under age groups

mean_fem_20 = fem_20['duration_min'].mean()
mean_fem_40 = fem_40['duration_min'].mean()
mean_fem_60 = fem_60['duration_min'].mean()

mean_fem_20 , mean_fem_40 , mean_fem_60
```

Out[67]: (29.007898155365016, 16.81219052045866, 17.20067872631126)

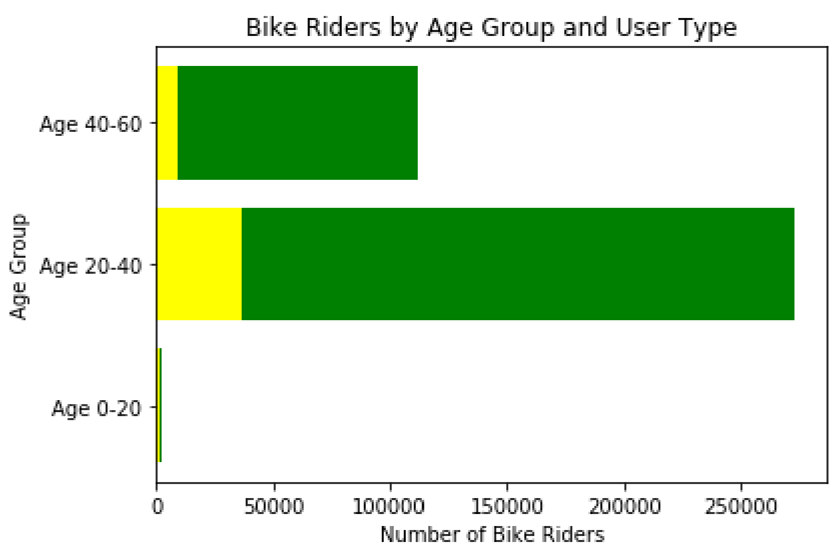
In [68]:
```
# Find counts for males under age groups

male_20 = age_20.loc[(age_20["member_gender"] == 'Male')]
male_40 = age_40.loc[(age_40["member_gender"] == 'Male')]
male_60 = age_60.loc[(age_60["member_gender"] == 'Male')]
len(male_20), len(male_40), len(male_60)
```

Out[68]:
```
(2890, 237057, 98277)
```

In [69]:
```
# Find means for males under age groups

mean_male_20 = male_20['duration_min'].mean()
mean_male_40 = male_40['duration_min'].mean()
mean_male_60 = male_60['duration_min'].mean()

mean_male_20 , mean_male_40 , mean_male_60
```

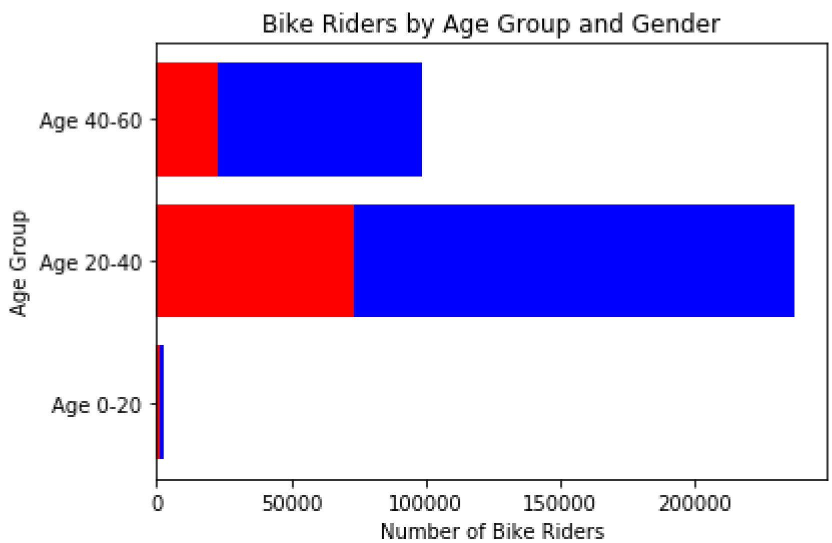
Out[69]:
```
(22.659728950403622, 12.69068297216833, 13.090062612140418)
```

In [70]:
```
# Create plot for user types by age group
labels = ['Age 0-20', 'Age 20-40', 'Age 40-60']
subscribers_20 = 2424
subscribers_40 = 273481
subscribers_60 = 111858

customers_20 = 1749
customers_40 = 36723
customers_60 = 8863

heights = subscribers_20, subscribers_40, subscribers_60
heights2 = customers_20, customers_40, customers_60

plt.barh(labels, heights, tick_label = labels, color = 'green')
plt.barh(labels, heights2, tick_label = labels, color = 'yellow')
plt.title('Bike Riders by Age Group and User Type')
plt.xlabel('Number of Bike Riders')
plt.ylabel('Age Group')

plt.savefig('Bike Riders by Age Group and User Type');
```



Subscribers are represented in green and Customers are represented in yellow.

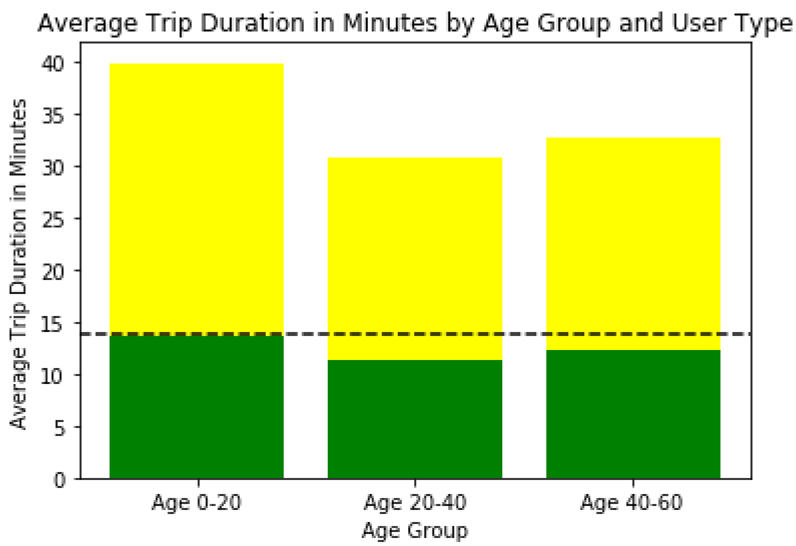
In [71]:
```
# Create plot for genders by age group

labels = ['Age 0-20', 'Age 20-40', 'Age 40-60']

fem_20 = 1283
fem_40 = 73147
fem_60 = 22444

male_20 = 2890
male_40 = 237057
male_60 = 98277

heights3 = fem_20, fem_40, fem_60
heights4 = male_20, male_40, male_60

plt.barh(labels, heights4, tick_label = labels, color = 'blue')
plt.barh(labels, heights3, tick_label = labels, color = 'red')

plt.title('Bike Riders by Age Group and Gender')
plt.xlabel('Number of Bike Riders')
plt.ylabel('Age Group')
plt.savefig('Bike Riders by Age Group and Gender');
```



Males are represented in blue and Females are represented in red.

These two bar plots above for Bike Riders provide a visual of how riders differ in age and user type, and then age and gender. To read these bar plots, the lower end of comparsion shows its proportion to the higher end. For example in the age group 20-40, there are 73,147 females to 237,057 males.

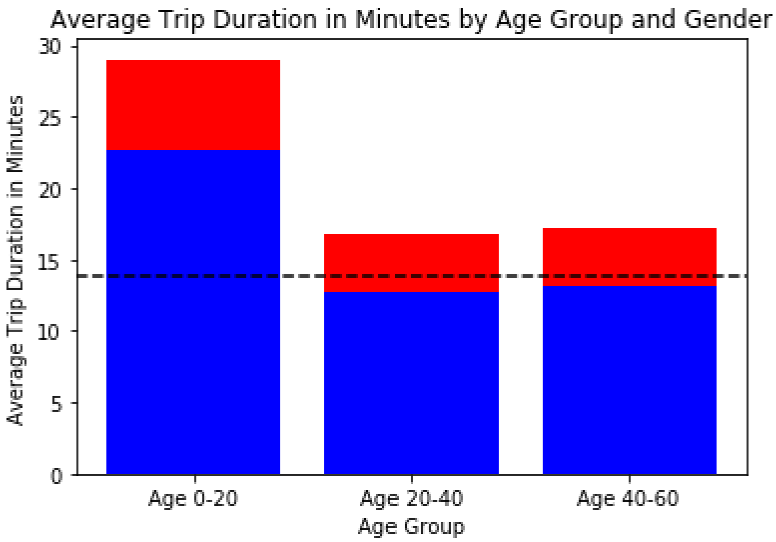
In [72]:
```
# Create a bar plot for Age Group and User Type
labels = ['Age 0-20', 'Age 20-40', 'Age 40-60']

h1 = mean_sub_20 , mean_sub_40 , mean_sub_60,
h2 = mean_cust_20 , mean_cust_40 , mean_cust_60

plt.bar(labels, h2, tick_label = labels, color = 'yellow')
plt.bar(labels, h1, tick_label = labels, color = 'green')

plt.title('Average Trip Duration in Minutes by Age Group and User Type')
plt.xlabel('Age Group')
plt.ylabel('Average Trip Duration in Minutes')
plt.axhline(mean, color='black', linestyle='--')
plt.savefig('Average Trip Duration in Minutes by Age Group and User Type');
```



The dotted line in the bar plot represents its relation to the overall average trip duration for all bike riders.

Subscribers are represented in green and Customers are represented in yellow.

In [73]:
```
labels = ['Age 0-20', 'Age 20-40', 'Age 40-60']

h3 = mean_male_20 , mean_male_40 , mean_male_60
h4 = mean_fem_20 , mean_fem_40 , mean_fem_60

plt.bar(labels, h4, tick_label = labels, color ='red')
plt.bar(labels, h3, tick_label = labels, color = 'blue')

plt.title('Average Trip Duration in Minutes by Age Group and Gender')
plt.xlabel('Age Group')
plt.ylabel('Average Trip Duration in Minutes')
plt.axhline(mean, color='black', linestyle='--')
plt.savefig('Average Trip Duration in Minutes by Age Group and Gender');
```



The dotted line in the bar plot represents its relation to the overall average trip duration for all bike riders.

Males are represented in blue and Females are represented in red.

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?

I extended my investigation of average trip duration against age in this section by looking at its impact to the other two categorical quality features of gender and user type. The multivariate exploration here showed that there is a correlation between age group with user type and gender to average trip duration. Among the three age groups, the youngest age group of Age 0-20 had the highest average trip duration as expected. However, the Age 40-60 group had a slightly higher average than Age 20-40. There is only a 0.19 of a second difference so there may be little or correlation between these age groups but interesting enough to note.

The overall average found at the start of the investigation was 13.82 minutes where the averages for the age groups of 20-40 and 40-60 are very close to. This suggest that riders from 0 to 20 in age generally have a higher average trip duration for bike rides than others of different age.

Averages among Age Group

Age 0-20: 24.61 minutes

Age 20-40: 13.66 minutes

Age 40-60: 13.85 minutes

Were there any interesting or surprising interactions between features?

Looking back on the bar plots, there seems to be some connections between the categorical features of user type, gender, age group to average trip duration. They all seem to be dependent in some sense. For more depth about age group, age 20-40 had a lower average when against user type and gender. Perhaps with life happenings, the age group for 0-20 and 40-60 may have more free time to enjoy longer bike rides. Age 20-40 may be using this bike-sharing for commute purposes rather then leisure.

Averages for Gender based on Age Group

Females 0-20: 29.01 minutes

Females 20-40: 16.81 minutes

Females 40-60: 17.20 minutes

Males 0-20: 22.66 minutes

Males 20-40: 12.69 minutes

Males 40-60: 13.09 minutes

Averages for User Type based on Age Group

Customers 0-20: 39.90 minutes

Customers 20-40: 30.78 minutes

Customers 40-60: 32.68 minutes

Subscribers 0-20: 13.58 minutes

Subscribers 20-40: 11.36 minutes

Subscribers 40-60: 12.36 minutes

Resources

1. https://stackoverflow.com/questions/17578115/pass-percentiles-to-pandas-agg-function (https://stackoverflow.com/questions/17578115/pass-percentiles-to-pandas-agg-function)
2. https://stackoverflow.com/questions/53277718/pandas-dataframe-easier-syntax-to-drop-rows-by-condition-on-values (https://stackoverflow.com/questions/53277718/pandas-dataframe-easier-syntax-to-drop-rows-by-condition-on-values)
3. https://stackoverflow.com/questions/31583151/count-number-of-rows-when-row-contains-certain-text (https://stackoverflow.com/questions/31583151/count-number-of-rows-when-row-contains-certain-text)
4. https://stackoverflow.com/questions/34828701/mean-line-on-top-of-bar-plot-with-pandas-and-matplotlib/34829398 (https://stackoverflow.com/questions/34828701/mean-line-on-top-of-bar-plot-with-pandas-and-matplotlib/34829398)
5. https://stackoverflow.com/questions/48978550/pandas-filtering-multiple-conditions (https://stackoverflow.com/questions/48978550/pandas-filtering-multiple-conditions)
6. https://stackoverflow.com/questions/18992086/save-a-pandas-series-histogram-plot-to-file (https://stackoverflow.com/questions/18992086/save-a-pandas-series-histogram-plot-to-file)
7. https://stackoverflow.com/questions/17071871/select-rows-from-a-dataframe-based-on-values-in-a-column-in-pandas (https://stackoverflow.com/questions/17071871/select-rows-from-a-dataframe-based-on-values-in-a-column-in-pandas)