Part_I_exploration

September 3, 2022

1 Part I - Ford GoBike System Data Exploration

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1.2 Introduction

Ford GoBike System Data: This data set includes information about individual rides made in a bike-sharing system covering the greater San Francisco Bay area. .

1.3 Preliminary Wrangling

[1]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import datetime as dt
from datetime import datetime as dt
%matplotlib inline
```

[2]:
```
#load the dataset into a pandas dataframe
ford_go_bike = pd.read_csv('201902-fordgobike-tripdata.csv')
ford_go_bike.sample(15)
```

[2]:
```
        duration_sec               start_time                 end_time  \
12847            415 2019-02-27 17:12:36.9520 2019-02-27 17:19:32.8970
181506           867 2019-02-01 09:01:34.1620 2019-02-01 09:16:01.8750
90577            783 2019-02-16 12:04:13.0790 2019-02-16 12:17:16.2600
55846            463 2019-02-21 09:32:56.0270 2019-02-21 09:40:39.3280
94733            890 2019-02-15 15:48:17.0750 2019-02-15 16:03:08.0570
95428            972 2019-02-15 13:39:34.9770 2019-02-15 13:55:47.0640
62167            799 2019-02-20 17:04:06.0900 2019-02-20 17:17:25.2810
129421          1164 2019-02-10 10:15:28.6390 2019-02-10 10:34:53.2290
22742            690 2019-02-26 06:54:34.4100 2019-02-26 07:06:04.4960
173242           294 2019-02-03 12:42:02.0430 2019-02-03 12:46:56.7190
5644             227 2019-02-28 12:39:08.1920 2019-02-28 12:42:55.3520
```

```
169510          269  2019-02-04 09:58:09.9640  2019-02-04 10:02:39.2100
108216          554  2019-02-13 09:11:21.5940  2019-02-13 09:20:36.3070
155609          158  2019-02-06 08:46:07.9810  2019-02-06 08:48:46.5630
161703         1094  2019-02-05 13:50:29.9470  2019-02-05 14:08:44.9430

        start_station_id               start_station_name  \
12847                8.0     The Embarcadero at Vallejo St
181506             194.0  Lakeshore Ave at Trestle Glen Rd
90577              370.0              Jones St at Post St
55846               60.0             8th St at Ringold St
94733               36.0              Folsom St at 3rd St
95428              160.0        West Oakland BART Station
62167              240.0        Haste St at Telegraph Ave
129421              76.0       McCoppin St at Valencia St
22742              101.0          15th St at Potrero Ave
173242              27.0          Beale St at Harrison St
5644               241.0               Ashby BART Station
169510             202.0          Washington St at 8th St
108216             126.0                      Esprit Park
155609              90.0            Townsend St at 7th St
161703              86.0          Market St at Dolores St

        start_station_latitude  start_station_longitude  end_station_id  \
12847                37.799953              -122.398525            22.0
181506               37.811081              -122.243268             7.0
90577                37.787327              -122.413278            79.0
55846                37.774520              -122.409449            67.0
94733                37.783830              -122.398870            84.0
95428                37.805318              -122.294837           155.0
62167                37.866043              -122.258804           189.0
129421               37.771662              -122.422423            10.0
22742                37.767079              -122.407359             3.0
173242               37.788059              -122.391865            30.0
5644                 37.852477              -122.270213           168.0
169510               37.800754              -122.274894           219.0
108216               37.761634              -122.390648           125.0
155609               37.771058              -122.402717            67.0
161703               37.769305              -122.426826            70.0

                                          end_station_name  \
12847                                 Howard St at Beale St
181506                                 Frank H Ogawa Plaza
90577                                 7th St at Brannan St
55846   San Francisco Caltrain Station 2  (Townsend St…
94733                                          Duboce Park
95428                             Emeryville Public Market
62167                                  Genoa St at 55th St
```

```
129421                           Washington St at Kearny St
22742         Powell St BART Station (Market St at 4th St)
173242     San Francisco Caltrain (Townsend St at 4th St)
5644                          Alcatraz Ave at Shattuck Ave
169510                               Marston Campbell Park
108216                                20th St at Bryant St
155609  San Francisco Caltrain Station 2  (Townsend St…
161703                               Central Ave at Fell St

        end_station_latitude  end_station_longitude  bike_id   user_type  \
12847              37.789756            -122.394643     1566  Subscriber
181506             37.804562            -122.271738     1298  Subscriber
90577              37.773492            -122.403672     5246  Subscriber
55846              37.776639            -122.395526     3263  Subscriber
94733              37.769200            -122.433812     6522  Subscriber
95428              37.840521            -122.293528     5089  Subscriber
62167              37.839649            -122.271756     5251  Subscriber
129421             37.795393            -122.404770     5039  Subscriber
22742              37.786375            -122.404904     6311  Subscriber
173242             37.776598            -122.395282     4557  Subscriber
5644               37.849595            -122.265569     6145  Subscriber
169510             37.809824            -122.280192     5165  Subscriber
108216             37.759200            -122.409851     4974  Subscriber
155609             37.776639            -122.395526     4986  Subscriber
161703             37.773311            -122.444293     4931  Subscriber

        member_birth_year member_gender bike_share_for_all_trip
12847              1987.0        Female                      No
181506             1974.0          Male                      No
90577              1997.0        Female                      No
55846              1989.0          Male                      No
94733              1981.0        Female                      No
95428              1978.0          Male                      No
62167              1989.0          Male                      No
129421             1991.0          Male                      No
22742              1993.0          Male                      No
173242             1989.0          Male                      No
5644               1965.0        Female                      No
169510             1993.0          Male                     Yes
108216             1990.0          Male                      No
155609             1988.0        Female                      No
161703             1990.0         Other                      No
```

Issues

- Incorrect datatype for start_time, end_time, member_birth, start_station_id, end_station_id, member_birth_year

- Missing values in member_gender, member_birth_year, end_station_id, start_station_name, start_station_id and end_station_name
- No special column for age, day, and month
- Lattitude and longitude are great features but we cannot immediately get insight for them without performing some calculations of the distance covered.

[3]:
```
ford_go_bike.describe()
```

[3]:
```
         duration_sec  start_station_id  start_station_latitude  \
count   183412.000000     183215.000000           183412.000000
mean       726.078435        138.590427               37.771223
std       1794.389780        111.778864                0.099581
min         61.000000          3.000000               37.317298
25%        325.000000         47.000000               37.770083
50%        514.000000        104.000000               37.780760
75%        796.000000        239.000000               37.797280
max      85444.000000        398.000000               37.880222

       start_station_longitude  end_station_id  end_station_latitude  \
count            183412.000000   183215.000000         183412.000000
mean               -122.352664      136.249123             37.771427
std                   0.117097      111.515131              0.099490
min                -122.453704        3.000000             37.317298
25%                -122.412408       44.000000             37.770407
50%                -122.398285      100.000000             37.781010
75%                -122.286533      235.000000             37.797320
max                -121.874119      398.000000             37.880222

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

[4]:
```
#change  start_time , end_time and member_birth_year datatypes to datetime
ford_go_bike['start_time'] = pd.to_datetime(ford_go_bike['start_time'])
ford_go_bike['end_time'] = pd.to_datetime(ford_go_bike['end_time'])
ford_go_bike['member_birth_year'] = pd.
 ↪to_datetime(ford_go_bike['member_birth_year'])
```

[5]:
```
#test change  start_time , end_time and member_birth_year datatypes to datetime
ford_go_bike.dtypes
```

[5]:

```
duration_sec                            int64
start_time                     datetime64[ns]
end_time                       datetime64[ns]
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              datetime64[ns]
member_gender                          object
bike_share_for_all_trip                object
dtype: object
```

[6]:

```
# Let examine duration sec to find out if any duration is more than 24 hrs
↪(86400)
ford_go_bike['duration_sec'].max()
```

[6]: 85444

Maximum duration is 85444 , so it is safe to assume that all rides occured in one day. With that asssumption we shall exact the day and month for each ride. Given the dataset we also assume that all rides occurs in the same year 2019.

[7]:

```
ford_go_bike['day'] = ford_go_bike['start_time'].dt.day_name()
ford_go_bike['month'] = ford_go_bike['start_time'].dt.month_name()
```

[8]:

```
# Converting float to int
ford_go_bike.member_birth_year = ford_go_bike.member_birth_year.astype(np.int)
```

```
/tmp/ipykernel_16761/1718661354.py:2: DeprecationWarning: `np.int` is a
deprecated alias for the builtin `int`. To silence this warning, use `int` by
itself. Doing this will not modify any behavior and is safe. When replacing
`np.int`, you may wish to use e.g. `np.int64` or `np.int32` to specify the
precision. If you wish to review your current use, check the release note link
for additional information.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  ford_go_bike.member_birth_year = ford_go_bike.member_birth_year.astype(np.int)
```

[9]:
```python
#Let define a function to allow us extract age form member_birth_year
def get_age(dob):
    today = dt.now().year
    return today - dob
```

[10]:
```python
# We use the get_age function that returns age to create a new column␣
↪`member_age` which would hold member ages.
ford_go_bike["member_age"] = get_age(ford_go_bike["member_birth_year"])
```

[11]:
```python
#Let us examine the memeber_age column
ford_go_bike["member_age"].describe()
```

[11]:
```
count    1.834120e+05
mean    -4.156280e+17
std      1.913313e+18
min     -9.223372e+18
25%      2.900000e+01
50%      3.400000e+01
75%      4.100000e+01
max      1.440000e+02
Name: member_age, dtype: float64
```

[12]:
```python
ford_go_bike[ford_go_bike["member_age"] > 70].count()
```

[12]:
```
duration_sec               1032
start_time                 1032
end_time                   1032
start_station_id           1032
start_station_name         1032
start_station_latitude     1032
start_station_longitude    1032
end_station_id             1032
end_station_name           1032
end_station_latitude       1032
end_station_longitude      1032
bike_id                    1032
user_type                  1032
member_birth_year          1032
member_gender              1032
bike_share_for_all_trip    1032
day                        1032
month                      1032
member_age                 1032
dtype: int64
```

[13]:
```python
# Lets look at the 99% of bike riders age
ford_go_bike.member_age.describe(percentiles=[.99])
```

[13]:
```
count    1.834120e+05
mean    -4.156280e+17
std      1.913313e+18
min     -9.223372e+18
50%      3.400000e+01
99%      6.600000e+01
max      1.440000e+02
Name: member_age, dtype: float64
```

- It seems their is an outlier in the `member_age`. The maximun age is 144 which appears to be abnormal, and over 99% for all age are belove 70.
- With the above in view it would be safe to limit our analyis to ages below 70.

[14]:
```
#select only records with member_age <= 70
ford_go_bike = ford_go_bike.query("member_age <= 70")
```

[15]:
```
#test member_age values are less than 70
ford_go_bike.member_age.describe()
```

[15]:
```
count    1.823800e+05
mean    -4.179799e+17
std      1.918462e+18
min     -9.223372e+18
25%      2.900000e+01
50%      3.400000e+01
75%      4.100000e+01
max      7.000000e+01
Name: member_age, dtype: float64
```

Calcluate distance covered form Lattitude and longitude Reference: https://stackoverflow.com/questions/19412462/getting-distance-between-two-points-based-on-latitude-longitude

[16]:
```
# We would use # Will be using the math radians, sin, cos, sqrt and atan2
from math import radians, sin, cos, sqrt, atan2
# A function that would accept longitude stat and lat stat and long. end and␣
 ↪lat. end
# to return the total distance between two points.
def distance(start, end):

    lat1, long1 = start
    lat2, long2 = end
    radius = 6371 # Approximate raidius of the earth

    dlat = radians(lat2 - lat1)
    dlong = radians(long2 - long1)
```

```
    a = (sin(dlat / 2) * sin(dlat / 2) + cos(radians(lat1)) *␣
↪cos(radians(lat2)) * sin(dlong / 2) * sin(dlong / 2))
    c = 2 * atan2(sqrt(a), sqrt(1 - a))
    distance = radius * c

    # Round up the values to two decimal places
    return round(distance, 2)
```

[17]:
```
ford_go_bike['distance_km'] = ford_go_bike.apply(lambda x:␣
↪distance((x['start_station_latitude'], x['start_station_longitude']),
                                                                    ␣
↪(x['end_station_latitude'], x['end_station_longitude'])),
                                              axis=1)
```

[18]:
```
ford_go_bike.sample(5)
```

[18]:
```
        duration_sec              start_time                end_time  \
6984             711 2019-02-28 09:24:34.441 2019-02-28 09:36:25.728
82017            638 2019-02-18 11:37:38.673 2019-02-18 11:48:17.377
102281          1285 2019-02-14 16:28:52.287 2019-02-14 16:50:17.537
119454           960 2019-02-11 17:42:49.634 2019-02-11 17:58:49.795
57360            338 2019-02-21 08:23:34.038 2019-02-21 08:29:12.072

        start_station_id                                start_station_name  \
6984                22.0                               Howard St at Beale St
82017              243.0                           Bancroft Way at College Ave
102281              16.0                               Steuart St at Market St
119454              58.0                                  Market St at 10th St
57360               43.0  San Francisco Public Library (Grove St at Hyde…

        start_station_latitude  start_station_longitude  end_station_id  \
6984                 37.789756              -122.394643            28.0
82017                37.869360              -122.254337           171.0
102281               37.794130              -122.394430            87.0
119454               37.776619              -122.417385           126.0
57360                37.778768              -122.415929           350.0

                    end_station_name  end_station_latitude  \
6984    The Embarcadero at Bryant St             37.787168
82017         Rockridge BART Station             37.844279
102281           Folsom St at 13th St             37.769757
119454                    Esprit Park             37.761634
57360            8th St at Brannan St             37.771431

        end_station_longitude  bike_id   user_type   member_birth_year  \
6984              -122.388098     1142  Subscriber                1979
```

```
82017              -122.251900     4565  Subscriber -9223372036854775808
102281             -122.415674     5331  Subscriber                 1980
119454             -122.390648     3356  Subscriber                 1988
57360              -122.405787     6094  Subscriber                 1990

       member_gender bike_share_for_all_trip       day     month  \
6984          Female                      No  Thursday  February
82017            NaN                      No    Monday  February
102281          Male                      No  Thursday  February
119454        Female                      No    Monday  February
57360           Male                      No  Thursday  February

                 member_age  distance_km
6984                     43         0.64
82017  -9223372036854773786         2.80
102281                   42         3.29
119454                   34         2.88
57360                    32         1.21
```

[19]:
```
#Let check for null values
ford_go_bike.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 182380 entries, 0 to 183411
Data columns (total 20 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             182380 non-null  int64
 1   start_time               182380 non-null  datetime64[ns]
 2   end_time                 182380 non-null  datetime64[ns]
 3   start_station_id         182183 non-null  float64
 4   start_station_name       182183 non-null  object
 5   start_station_latitude   182380 non-null  float64
 6   start_station_longitude  182380 non-null  float64
 7   end_station_id           182183 non-null  float64
 8   end_station_name         182183 non-null  object
 9   end_station_latitude     182380 non-null  float64
 10  end_station_longitude    182380 non-null  float64
 11  bike_id                  182380 non-null  int64
 12  user_type                182380 non-null  object
 13  member_birth_year        182380 non-null  int64
 14  member_gender            174115 non-null  object
 15  bike_share_for_all_trip  182380 non-null  object
 16  day                      182380 non-null  object
 17  month                    182380 non-null  object
 18  member_age               182380 non-null  int64
 19  distance_km              182380 non-null  float64
```

```
dtypes: datetime64[ns](2), float64(7), int64(4), object(7)
memory usage: 29.2+ MB
```

[20]:
```python
# Let check unique values in the member_gender
ford_go_bike['member_gender'].unique()
```

[20]:
```
array(['Male', nan, 'Other', 'Female'], dtype=object)
```

[21]:
```python
# Lets confirm unique values in the day
ford_go_bike['day'].unique()
```

[21]:
```
array(['Thursday', 'Wednesday', 'Tuesday', 'Monday', 'Sunday', 'Saturday',
       'Friday'], dtype=object)
```

[22]:
```python
ford_go_bike.dropna(inplace=True)
```

[23]:
```python
# Lets confim that there are no empty "NaN" and other "None cells"
ford_go_bike.isna().sum()
```

[23]:
```
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
day                        0
month                      0
member_age                 0
distance_km                0
dtype: int64
```

[24]:
```python
# Let check for outliers in the duration_sec column
ford_go_bike.duration_sec.describe([.99])
```

[24]:
```
count    173920.000000
mean        704.223149
std        1645.440119
```

```
min           61.000000
50%          511.000000
99%         3176.000000
max        84548.000000
Name: duration_sec, dtype: float64
```

There seem to be outliers in the duration_sec column. 99% for the duration_sec fall under 3176 seconds. There is pretty awkward jump to 84548 as the maximum value suggests.

[25]:
```
# Limiting duration in seconds to only  3200 seconds
ford_go_bike = ford_go_bike.query("duration_sec <= 3200")
```

[26]:
```
#Test that duration in seconds is limited to only  3200 seconds
ford_go_bike.duration_sec.describe(percentiles=[.99])
```

[26]:
```
count    172207.000000
mean        613.170580
std         426.521236
min          61.000000
50%         507.000000
99%        2280.000000
max        3200.000000
Name: duration_sec, dtype: float64
```

1.3.1 Saving

[27]:
```
ford_go_bike.to_csv('fordbike_clean.csv', index = False)
fordbike_clean = pd.read_csv('fordbike_clean.csv');
fordbike_clean.head(3)
```

[27]:
```
   duration_sec                start_time                  end_time  \
0          1585  2019-02-28 23:54:18.549  2019-03-01 00:20:44.074
1          1793  2019-02-28 23:49:58.632  2019-03-01 00:19:51.760
2          1147  2019-02-28 23:55:35.104  2019-03-01 00:14:42.588

   start_station_id            start_station_name  start_station_latitude  \
0               7.0           Frank H Ogawa Plaza               37.804562
1              93.0  4th St at Mission Bay Blvd S               37.770407
2             300.0          Palm St at Willow St               37.317298

   start_station_longitude  end_station_id          end_station_name  \
0              -122.271738           222.0     10th Ave at E 15th St
1              -122.391198           323.0        Broadway at Kearny
2              -121.884995           312.0  San Jose Diridon Station

   end_station_latitude  end_station_longitude  bike_id   user_type  \
```

```
0            37.792714           -122.248780     4898  Subscriber
1            37.798014           -122.405950     5200  Subscriber
2            37.329732           -121.901782     3803  Subscriber

   member_birth_year member_gender bike_share_for_all_trip       day  \
0               1974          Male                     Yes  Thursday
1               1959          Male                      No  Thursday
2               1983        Female                      No  Thursday

      month  member_age  distance_km
0  February          48         2.41
1  February          63         3.33
2  February          39         2.03
```

[28]:
```
# high- leve overview of data shape and compositon
print(fordbike_clean.shape)
print(fordbike_clean.dtypes)
print(fordbike_clean.head(10))
```

```
(172207, 20)
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            int64
member_gender               object
bike_share_for_all_trip     object
day                         object
month                       object
member_age                   int64
distance_km                float64
dtype: object
   duration_sec               start_time                 end_time  \
0          1585  2019-02-28 23:54:18.549  2019-03-01 00:20:44.074
1          1793  2019-02-28 23:49:58.632  2019-03-01 00:19:51.760
2          1147  2019-02-28 23:55:35.104  2019-03-01 00:14:42.588
3          1615  2019-02-28 23:41:06.766  2019-03-01 00:08:02.756
4          1570  2019-02-28 23:41:48.790  2019-03-01 00:07:59.715
```

```
5        1049  2019-02-28 23:49:47.699  2019-03-01 00:07:17.025
6         458  2019-02-28 23:57:57.211  2019-03-01 00:05:35.435
7         506  2019-02-28 23:56:55.540  2019-03-01 00:05:21.733
8        1176  2019-02-28 23:45:12.651  2019-03-01 00:04:49.184
9         395  2019-02-28 23:56:26.848  2019-03-01 00:03:01.947

   start_station_id                                  start_station_name  \
0               7.0                                 Frank H Ogawa Plaza
1              93.0                        4th St at Mission Bay Blvd S
2             300.0                                Palm St at Willow St
3              10.0                          Washington St at Kearny St
4              10.0                          Washington St at Kearny St
5              19.0                                Post St at Kearny St
6             370.0                                 Jones St at Post St
7              44.0  Civic Center/UN Plaza BART Station (Market St …
8             127.0                              Valencia St at 21st St
9             243.0                          Bancroft Way at College Ave

   start_station_latitude  start_station_longitude  end_station_id  \
0               37.804562              -122.271738           222.0
1               37.770407              -122.391198           323.0
2               37.317298              -121.884995           312.0
3               37.795393              -122.404770           127.0
4               37.795393              -122.404770           127.0
5               37.788975              -122.403452           121.0
6               37.787327              -122.413278            43.0
7               37.781074              -122.411738           343.0
8               37.756708              -122.421025           323.0
9               37.869360              -122.254337           252.0

                                 end_station_name  end_station_latitude  \
0                              10th Ave at E 15th St             37.792714
1                                 Broadway at Kearny             37.798014
2                           San Jose Diridon Station             37.329732
3                             Valencia St at 21st St             37.756708
4                             Valencia St at 21st St             37.756708
5                                 Mission Playground             37.759210
6  San Francisco Public Library (Grove St at Hyde…           37.778768
7                                Bryant St at 2nd St             37.783172
8                                 Broadway at Kearny             37.798014
9                        Channing Way at Shattuck Ave             37.865847

   end_station_longitude  bike_id   user_type  member_birth_year  \
0            -122.248780     4898  Subscriber               1974
1            -122.405950     5200  Subscriber               1959
2            -121.901782     3803  Subscriber               1983
3            -122.421025     6329  Subscriber               1989
4            -122.421025     6548  Subscriber               1988
```

```
5           -122.421339     6488  Subscriber              1992
6           -122.415929     5318  Subscriber              1996
7           -122.393572     5848  Subscriber              1993
8           -122.405950     5328    Customer              1990
9           -122.267443     4786  Subscriber              1988

  member_gender bike_share_for_all_trip       day     month  member_age  \
0          Male                     Yes  Thursday  February          48
1          Male                      No  Thursday  February          63
2        Female                      No  Thursday  February          39
3          Male                      No  Thursday  February          33
4         Other                      No  Thursday  February          34
5          Male                      No  Thursday  February          30
6        Female                     Yes  Thursday  February          26
7          Male                      No  Thursday  February          29
8          Male                      No  Thursday  February          32
9          Male                      No  Thursday  February          34

   distance_km
0         2.41
1         3.33
2         2.03
3         4.53
4         4.53
5         3.66
6         0.98
7         1.61
8         4.78
9         1.21
```

1.3.2 What is the structure of your dataset?

> After prelimiary wrangling and feature engineering we are now left with (172207 bike rides that occurred in the year 2019 with 20 features(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, day, month, member_age, distance_km). 5 ints (duration_sec, member_age, member_birth_year , and bike_id)
> 7 floats(distance_km, start_station_id,start_station_latitude, start_station_longitude, end_station_id, end_station_latitude, end_station_longitude
> 9 string objects (user_type, end_station_name, start_time,end_time, start_station_name, member_gender, bike_share_for_all_trip, day, month

The feature engineered columns:

- day

- month
- member_age
- distance_km

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

I'm most interested in determining which features are most effective at predicting the duration of trips in the dataset.

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

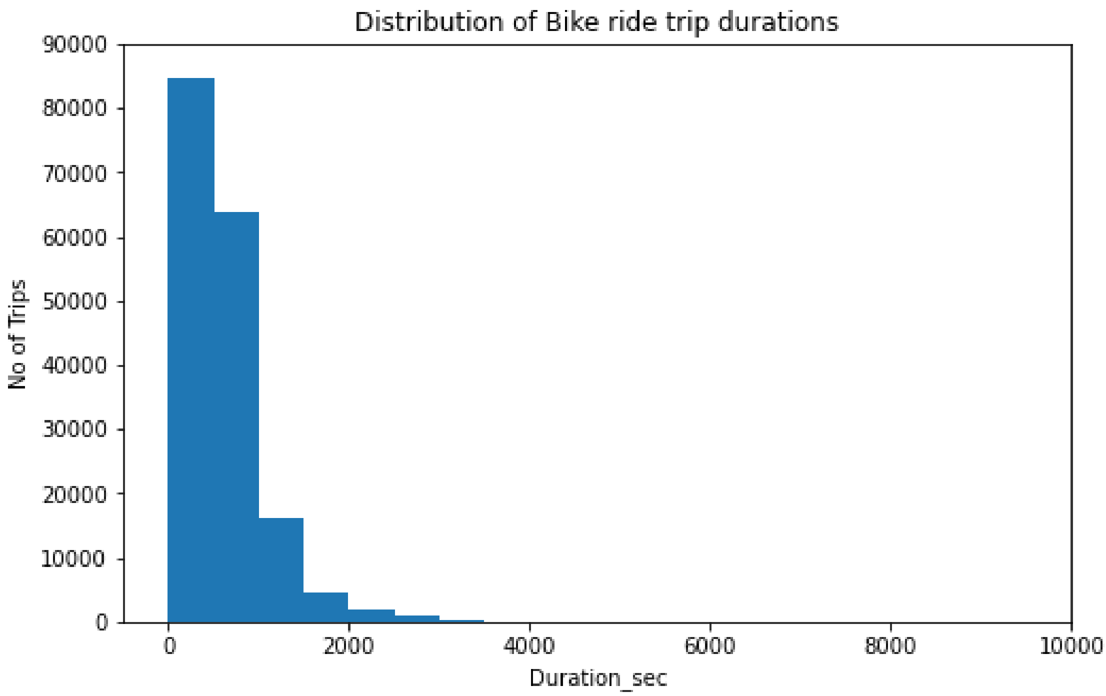
I expect that day, month, member_age, distance_km would affect ride duration_sec.

1.4 Univariate Exploration

We will begin by examining the distribution of the main variable of interest: duration sec

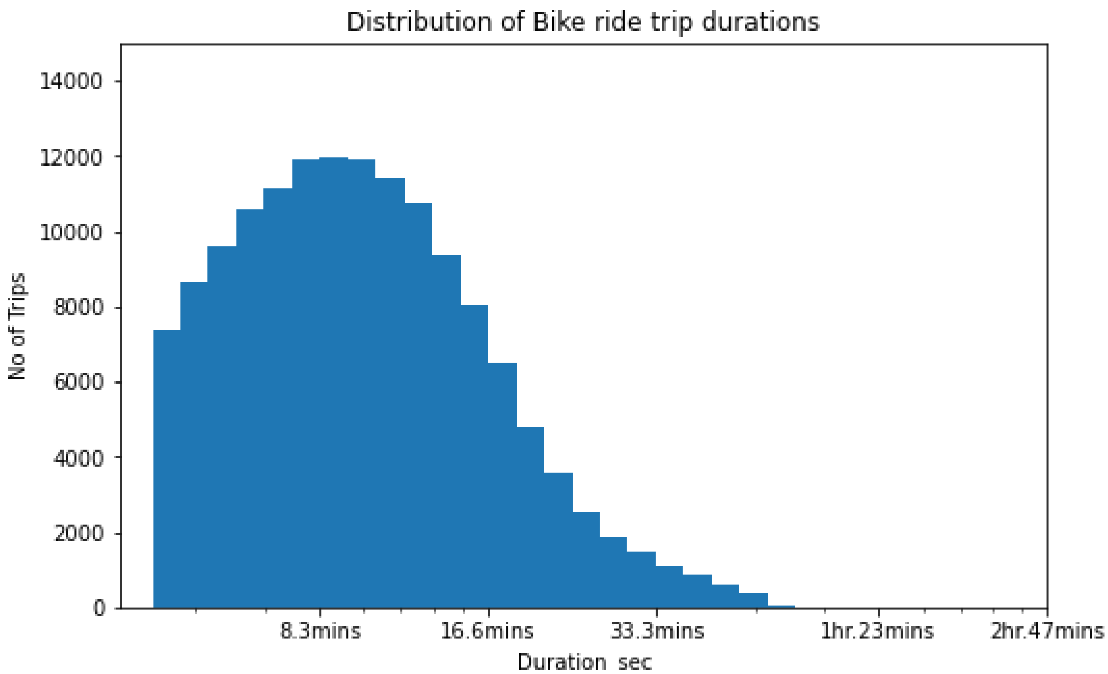
1.4.1 In what duration(sec/mins) do we have the most number of trips ?

[29]:
```
# lets start with a standard-scaled plot
binsize = 500
bins = np.arange(0, ford_go_bike['duration_sec'].max()+binsize, binsize )
plt.figure(figsize=[8, 5])
plt.hist(data = ford_go_bike, x = 'duration_sec', bins=bins);
plt.title('Distribution of Bike ride trip durations')
plt.xlabel('Duration_sec')
plt.ylabel('No of Trips')
plt.axis([-500, 10000, 0, 90000])
plt.show()
```



[30]:
```
# There is a long tail in hte distribution , so let us put it on a log scale
log_binsize = 0.05
bins = 10 ** np.arange(2.4, np.log10(ford_go_bike['duration_sec'].max()) +␣
↪log_binsize, log_binsize)

plt.figure(figsize=[8, 5])
plt.hist(data = ford_go_bike, x = 'duration_sec', bins = bins)
plt.title('Distribution of Bike ride trip durations')
plt.xlabel('Duration_sec')
plt.ylabel('No of Trips')
plt.xscale('log')
plt.xticks([500, 1e3, 2e3,  5e3, 1e4], ['8.3mins', '16.6mins', '33.3mins', '1hr.
↪23mins', '2hr.47mins'])
plt.axis([0, 10000, 0, 15000])
plt.show()
```

```
/tmp/ipykernel_16761/1134385293.py:12: UserWarning: Attempted to set non-
positive left xlim on a log-scaled axis.
Invalid limit will be ignored.
  plt.axis([0, 10000, 0, 15000])
```



Initially `duration_sec` had a long-tailed distribution with very few rides at the high end duration. When plotted on a log-scale, most trip duration occured in less than 33mins 20 secs (2000 seconds). The highest record of trips occured in 10mins (600 secs). The number of trips initially increases from around 8000 values at 0 to 12000 values at around 600 seconds, but then begins to fall, reaching below 2000 values in less than 33 minutes.

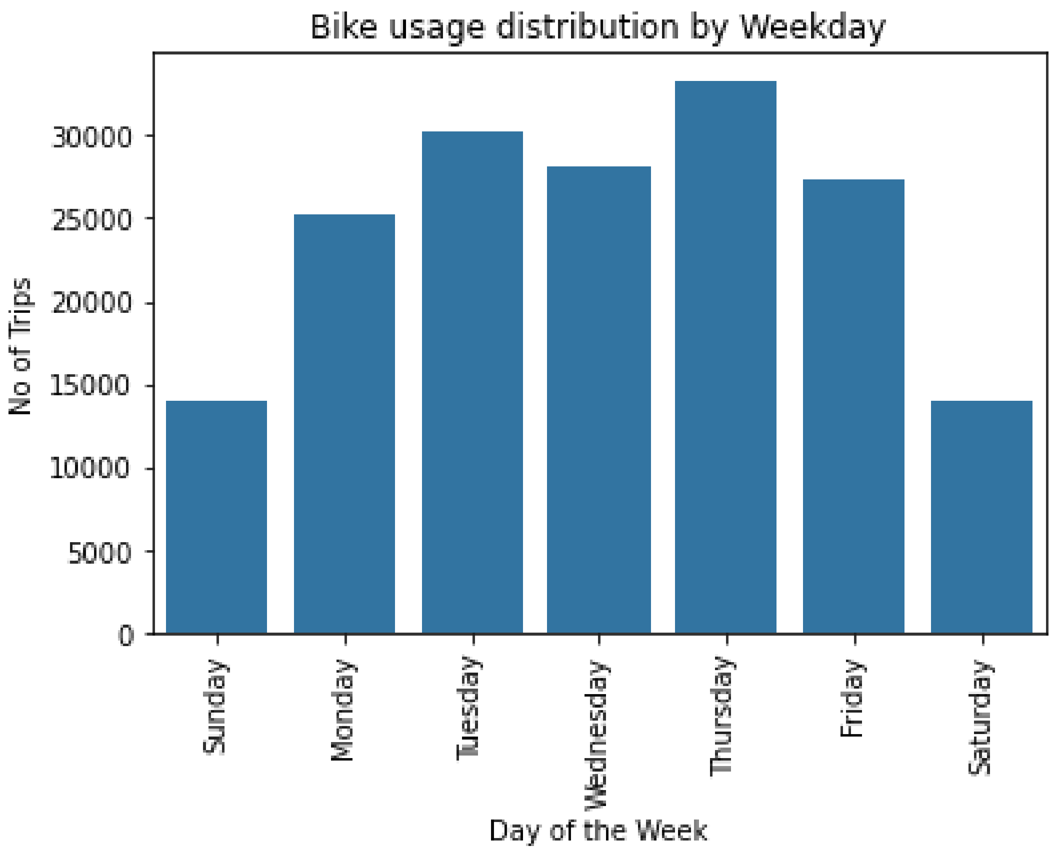
1.4.2 What day of the week have the most bike rides ?

Let us visualize `day` a categorical variable using Bar plt

[31]:
```
#Let define a function that would be used regulaly to label our visualizations
def label_visual(x_label, y_label, title):
    plt.xlabel(x_label)
    plt.ylabel(y_label)
    plt.title(title)
```

[32]:
```
# bar plot of `day` categorical variable

#let order the chat base on weekdays
weekdays = ["Sunday", "Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
 ↪"Saturday"]

# plotting with one base color
```

```
base_color = sb.color_palette()[0]

sb.countplot(data = fordbike_clean, x = 'day', order=weekdays,␣
 ↪color=base_color);
label_visual("Day of the Week", "No of Trips", "Bike usage distribution by␣
 ↪Weekday")

plt.xticks(rotation=90);
```



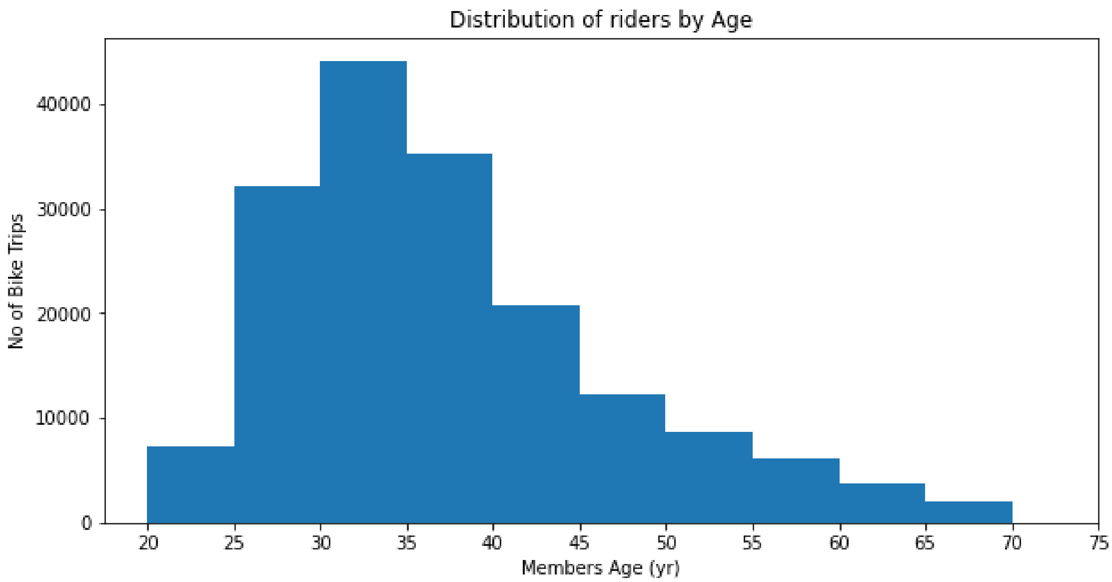
Thursdays had the highest usage, followed by Tuesdays and Fridays. Saturdays and Sundays saw a significant decrease in usage. This suggests that bikes are mostly used during the week and/or that people prefer to stay at home on weekends, resulting in less use of bikes.

1.4.3 What is the age distribution of the of the bike riders ?

Histogram of the discrete variable `age`

[33]:
```
plt.figure(figsize = [10,5])
bin_age = np.arange(20, fordbike_clean.member_age.max()+5, 5)
```

```
ticks = [20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75]
labels = ['{}'. format(i) for i in ticks]
plt.hist(data = fordbike_clean, x= 'member_age', bins= bin_age);
plt.xticks(ticks, labels);
label_visual('Members Age (yr)', 'No of Bike Trips', 'Distribution of riders by␣
 ↪Age')
```



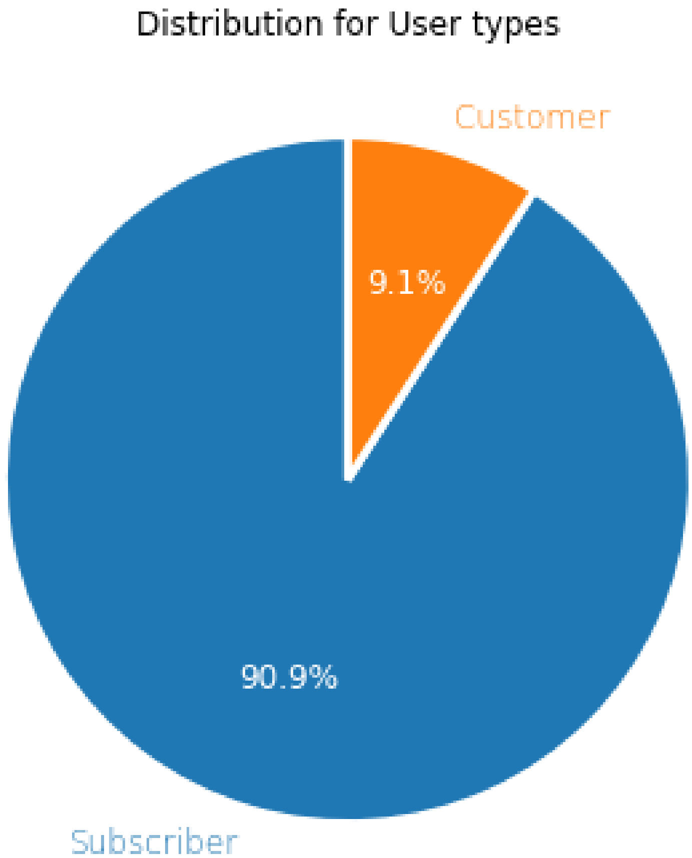
The histogram shows that most bike riders fall between the ages of 25 to 40 year. Individual between 30-35 have the heighest number of rides.

1.4.4 What is the distribution of users type ?

[34]:

```
# Pie plot distribution of the user type (nominal categorical variable)



fig, ax = plt.subplots(figsize=(10, 5))

user_count = fordbike_clean.user_type.value_counts()

patches, texts, pcts = ax.pie(
    user_count, labels=user_count.index, autopct='%.1f%%',
    wedgeprops={'linewidth': 3.0, 'edgecolor': 'white'},
    textprops={'size': 'large'},
    startangle=90)
# For each wedge, set the corresponding text label color to the wedge's
# face color.
for i, patch in enumerate(patches):
```

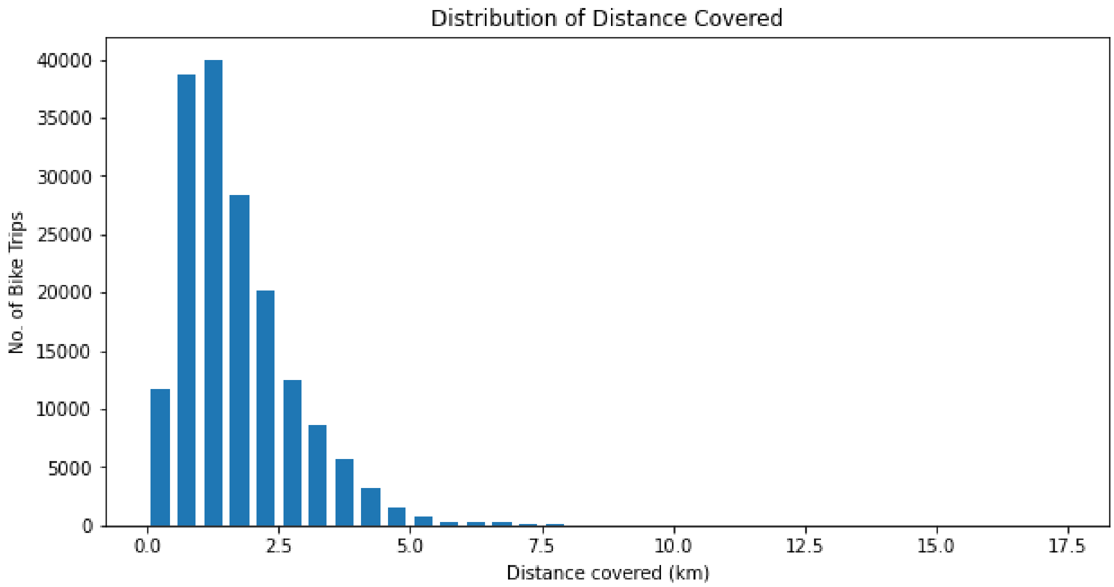
```
    texts[i].set_color(patch.get_facecolor())
plt.setp(pcts, color='white')
plt.setp(texts, fontweight=100)
ax.set_title('Distribution for User types')
plt.tight_layout()
```



Subscriber users account for 90.9% of all bike rides, while customer users account for only 9.1% of all bike rides.

1.4.5 What is the most distance covered by number of bike trips ?

```
[35]: plt.figure(figsize=[10, 5])
bins_distance = np.arange(0, fordbike_clean.distance_km.max()+2, 0.5)
plt.hist(data = fordbike_clean, x = 'distance_km', bins = bins_distance,␣
    ↪rwidth=0.7)
label_visual('Distance covered (km)', 'No. of Bike Trips', 'Distribution of␣
    ↪Distance Covered')
```



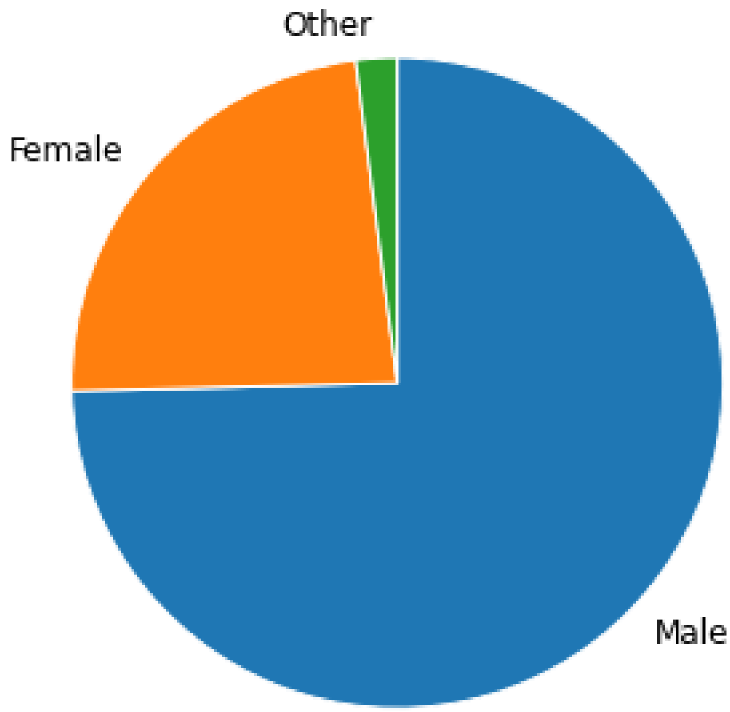
The historam above show the distribution of distance covered (km). Majority of the distances covered ranged from 0.1 to 2.5 km. This demonstrates that the majority of trips were not long distances.

1.4.6 Which gender has the most bike rides ?

[36]:
```
#Which gender has the most bike rides ?¶
print("%3.1f"%(((fordbike_clean['member_gender'].value_counts()[0])/
 ↪fordbike_clean['member_gender'].value_counts().sum())*100))
print("%3.1f"%(((fordbike_clean['member_gender'].value_counts()[1])/
 ↪fordbike_clean['member_gender'].value_counts().sum())*100))
print("%3.1f"%(((fordbike_clean['member_gender'].value_counts()[2])/
 ↪fordbike_clean['member_gender'].value_counts().sum())*100))
```

```
74.6
23.4
2.0
```

[37]:
```
#pie plot of member_gender distribution
plt.figure(figsize=[10, 5])
sorted_counts = fordbike_clean['member_gender'].value_counts()

plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90,␣
 ↪counterclock = False, wedgeprops={'edgecolor': 'white'}, textprops={'size':␣
 ↪'large'});
plt.axis('square');
```



The plot shows that we have mostly Male riders constituting 75%, Female riders 23% and others 2%

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

Intially, after visual and programmatic assessement we made serious attempts to eliminate outliers in some columns such as `duration_sec` , `member_age` and a few other columns.

1.4.8 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?

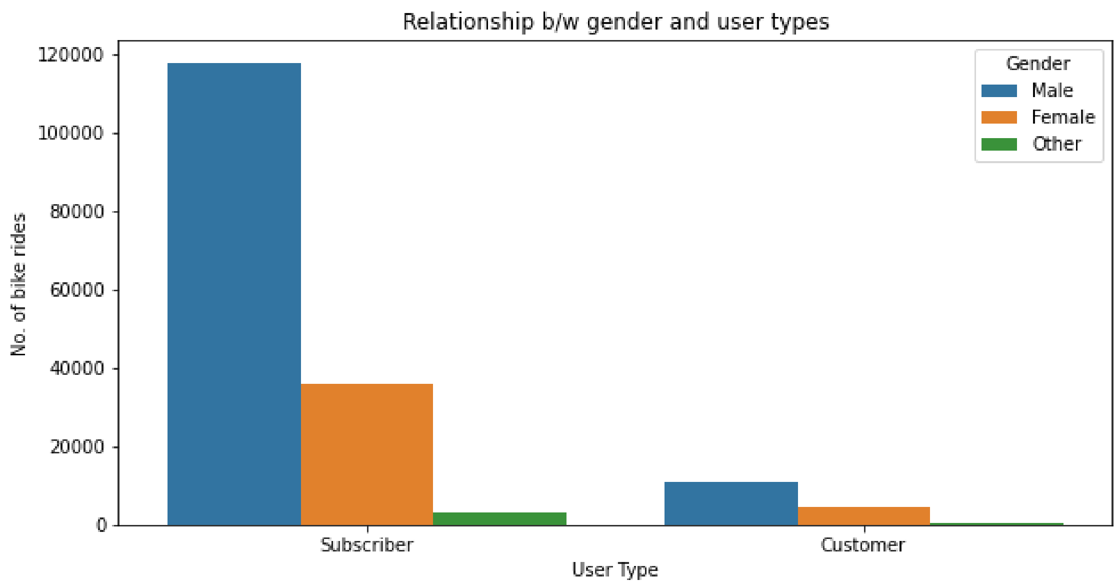
We limited most of the dataset to the values of 99% of the entire dataset. This was done to eliminate outliers in the dataset.

1.5 Bivariate Exploration

In this section, we shall investigate relationships between different pairs of variables in our dataset

1.5.1 What is the relationship between gender and user type

[38]:
```
# We use a cluster bar chat to show the relationship btw to qualitative␣
↪variables.
plt.figure(figsize=[10, 5])

sb.countplot(data =fordbike_clean, x = 'user_type', hue = 'member_gender')
legend = plt.legend([ "Male","Female", "Other"])
legend.set_title("Gender")

label_visual("User Type", "No. of bike rides", "Relationship b/w gender and␣
↪user types")
```



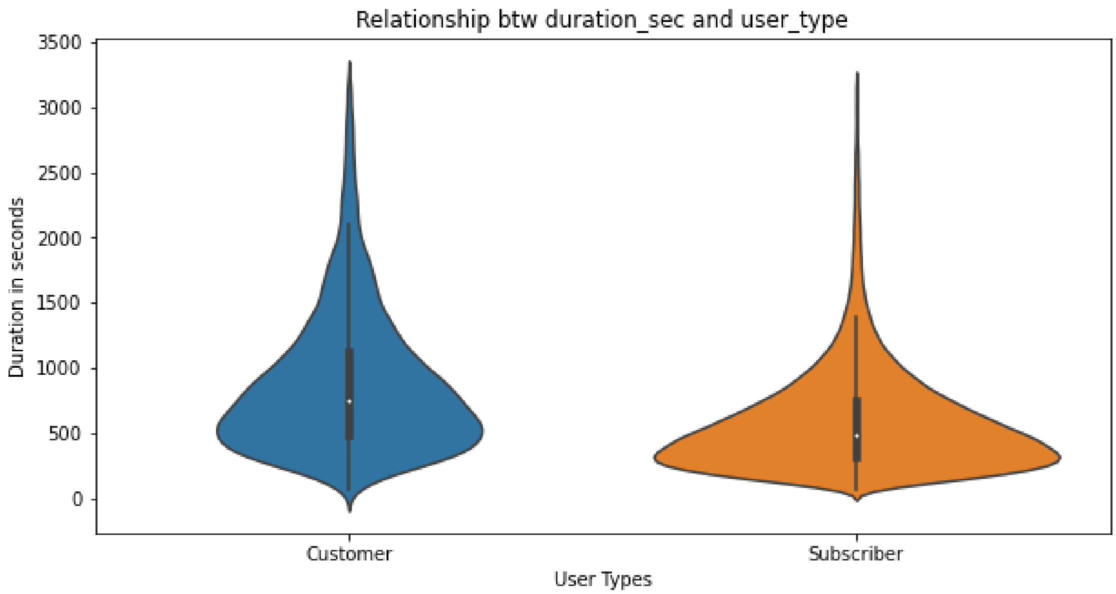
The plot demonstrates that there are more male subscribers than male customers, while there are little or no `others` gender in customer users and a few male and female customers

1.5.2 Which user type spends the most time riding ?

We shall look at the relationship between duration_sec (quantitative) and user_type(qualitative) using a Violin Plot.

[39]:
```
#Violent plot showing the relationship btw duration_sec and user_type
# set and create the figure size
plt.figure(figsize=[10, 5])
users = ["Customer", "Subscriber"]
sb.violinplot(data=fordbike_clean, x = "user_type", y="duration_sec",␣
↪order=users)
```

```
label_visual("User Types","Duration in seconds", "Relationship btw duration_sec␣
↪and user_type")
```

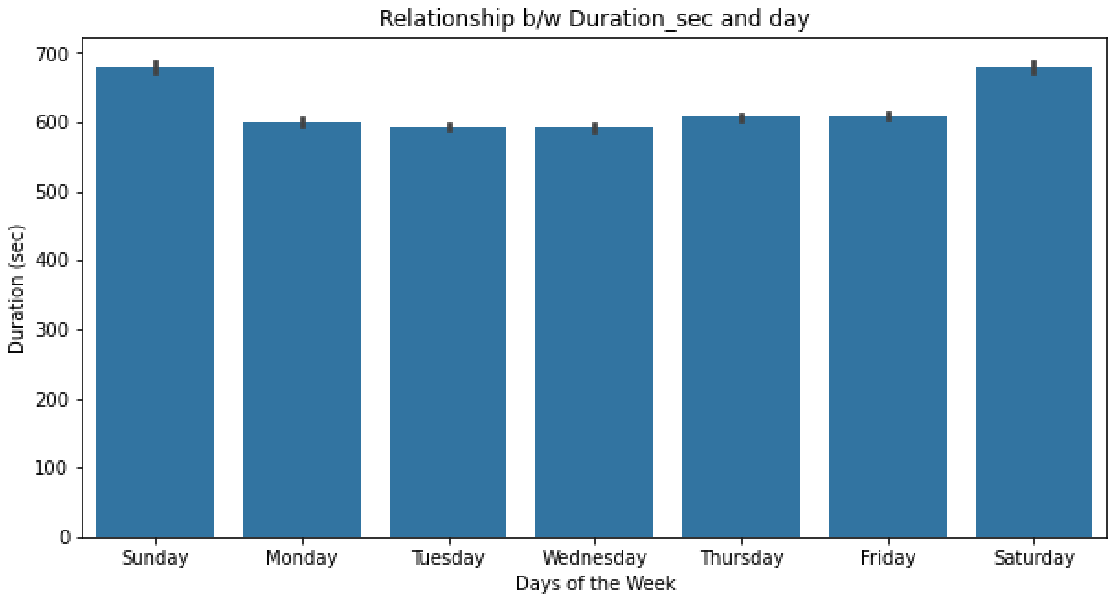


The figure demonstrates the relationship btw duration_sec and user_type. More Customers types send greater time between 500sec and 1000secs. While Subscriber users mostly spend an average of 500sec.

1.5.3 In which day of the Week do riders spends the most time.?

We shall look at the relationship between duration_sec (quantitative) and week`day` (qualitative) using a Bar Plot.

[40]:
```
#relationship between duration_sec (quantitative) and weekday (qualitative)␣
↪using a bar Plot.
plt.figure(figsize = [10, 5])
weekdays = ["Sunday", "Monday", "Tuesday", "Wednesday", "Thursday", "Friday",␣
↪"Saturday"]
sb.barplot(data= fordbike_clean, x = "day", y="duration_sec" , order=weekdays,␣
↪color=base_color)
label_visual("Days of the Week", "Duration (sec)", "Relationship b/w␣
↪Duration_sec and day")
```

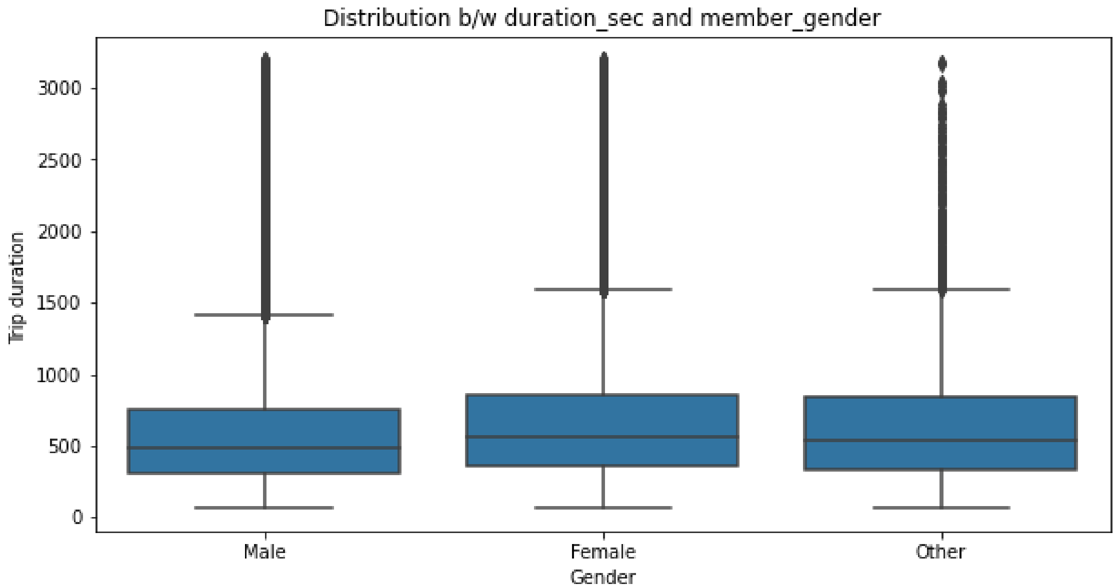


The graph show the relationship between duration_sec (quantitative) and weekday (qualitative) using a Bar Plot. Riders spend more time riding on Sunday, Saturday than on workdays(Mon - Friday)

1.5.4 Which gender spends the most time riding bikes ?

Using a Box Plot we shall examine the distribution between trip duration(quantitative variable) and gender (qualitative variable)

[41]:
```
#Box plot showing distribution b/w duration_sec and member_gender
plt.figure(figsize = [10, 5])
sb.boxplot(data=fordbike_clean, x='member_gender', y= 'duration_sec',␣
 ↪color=base_color)
label_visual('Gender', 'Trip duration ', 'Distribution b/w duration_sec and␣
 ↪member_gender'  )
```

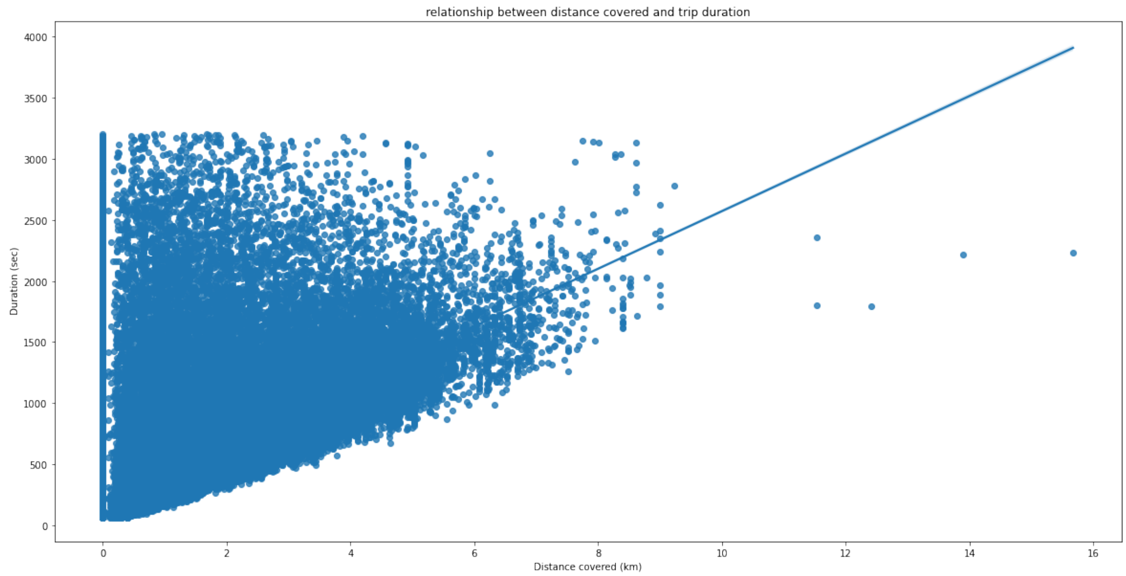


From the distribution, Females spent more time on their bikes than men on average.

1.5.5 What is the relationship between distance covered and trip duration. ?

We use Seaborn's regplot() function that combines scatterplot creation with regression function fitting:

[42]:
```
#the  relationship between distance covered and trip duration
plt.figure(figsize= [20, 10])
sb.regplot(data = fordbike_clean, x = 'distance_km', y='duration_sec')
label_visual('Distance covered (km)', ' Duration (sec)', 'relationship between␣
↪distance covered and trip duration')
```



As expected, the regression line in the scatter plot shows a positive correlation bwtween distance covered and duration

1.5.6 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 are more male subscribers than male customers, while there are little or no `others` gender in customer users and a few male and female customers. More Customers types send greater time between 500sec and 1000secs. While Subscriber users mostly spend an average of 500sec. Riders spend more time riding on Sunday, Saturday than on workdays(Mon - Friday). As expected there is a positive correlation bwtween distance covered and duration.

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

It is intesting to know that Riders spend more time riding on Sunday, Saturday than on workdays(Mon - Friday)

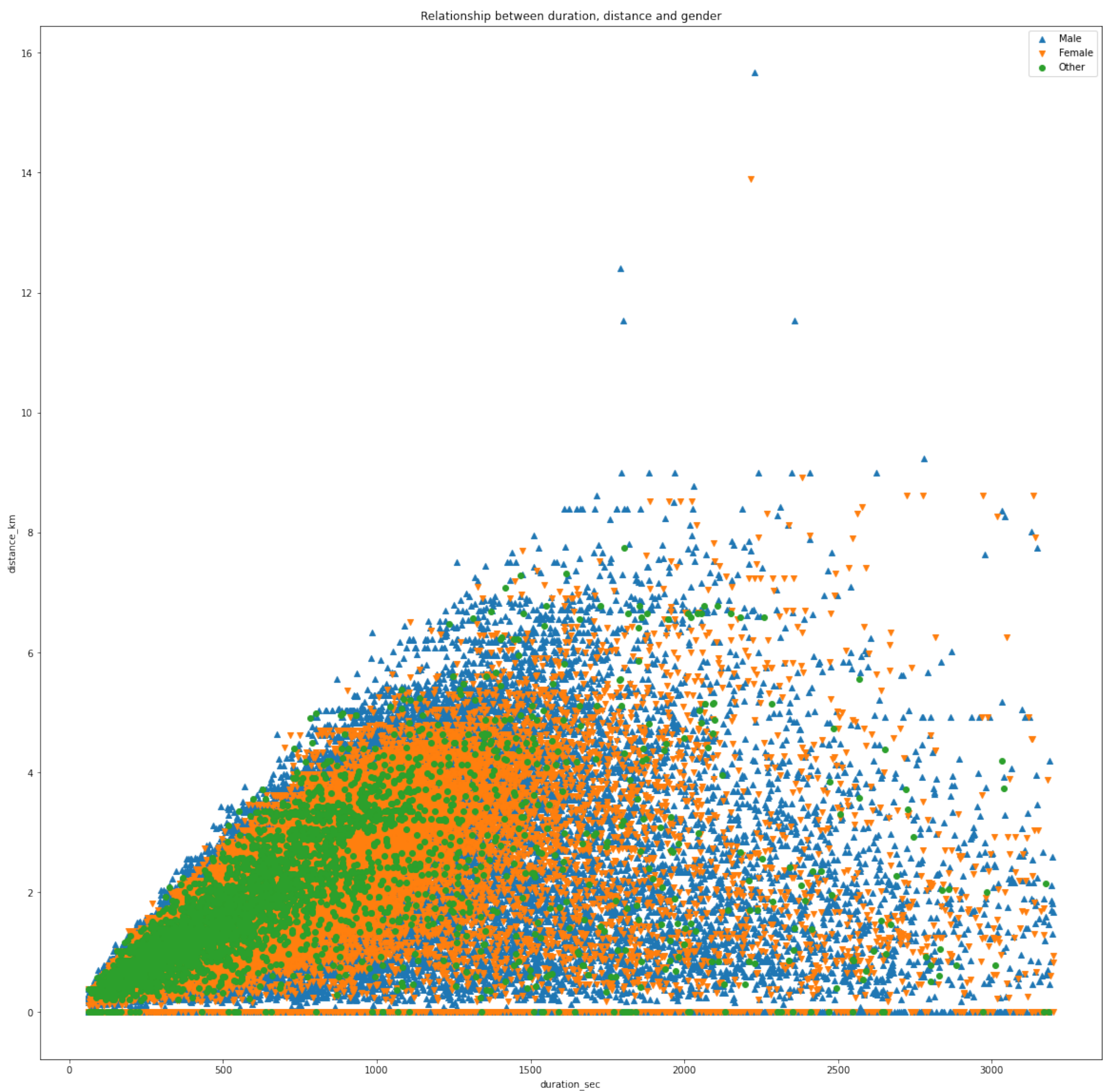
[ ]:
```

```

1.6 Multivariate Exploration

In this section we shall investigate the relationship in more that 2 variables at once.

1.6.1 What is the relationship between duration, distance and age ?

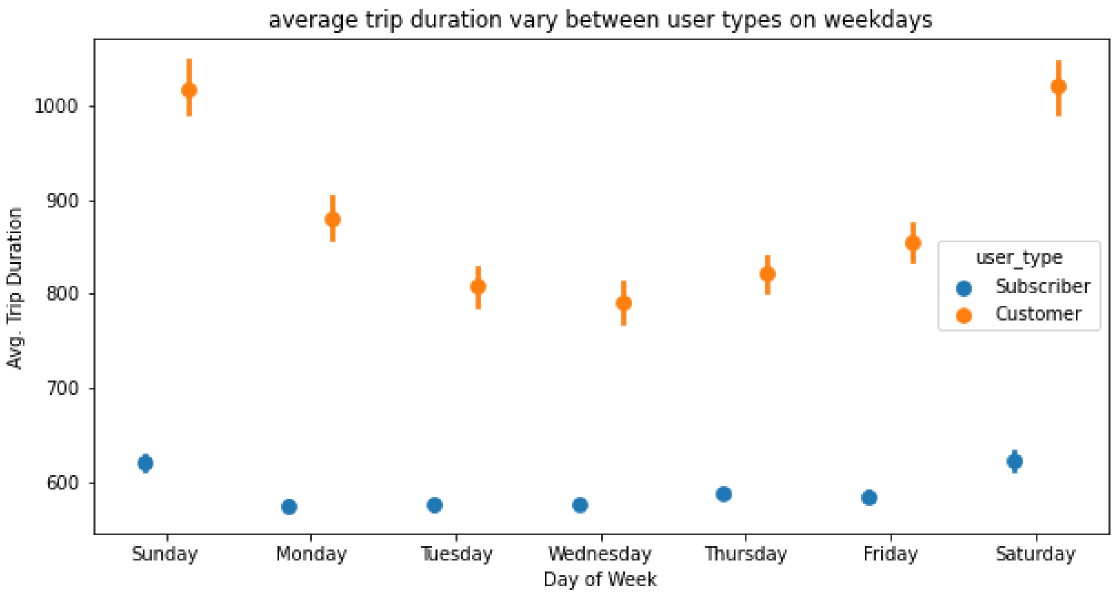
[43]:
```
plt.figure(figsize= [20, 20])
cat_markers = [['Male', "^"],
               ['Female', "v"],
               ['Other', "o"]]

for cat, marker in cat_markers:
    df_cat = fordbike_clean[fordbike_clean['member_gender'] == cat]
    plt.scatter(data = df_cat, x = 'duration_sec', y = 'distance_km', marker =␣
 ↪marker)
plt.legend(['Male','Female', 'Other'])
label_visual('duration_sec', 'distance_km', 'Relationship between duration,␣
 ↪distance and gender')
```



The graph shows the relationship between duration, distance and gender. There are more males covering longer distances than females. There are more females spending more time riding bikes.

1.6.2 What is the do the average trip duration vary between user types on weekdays?

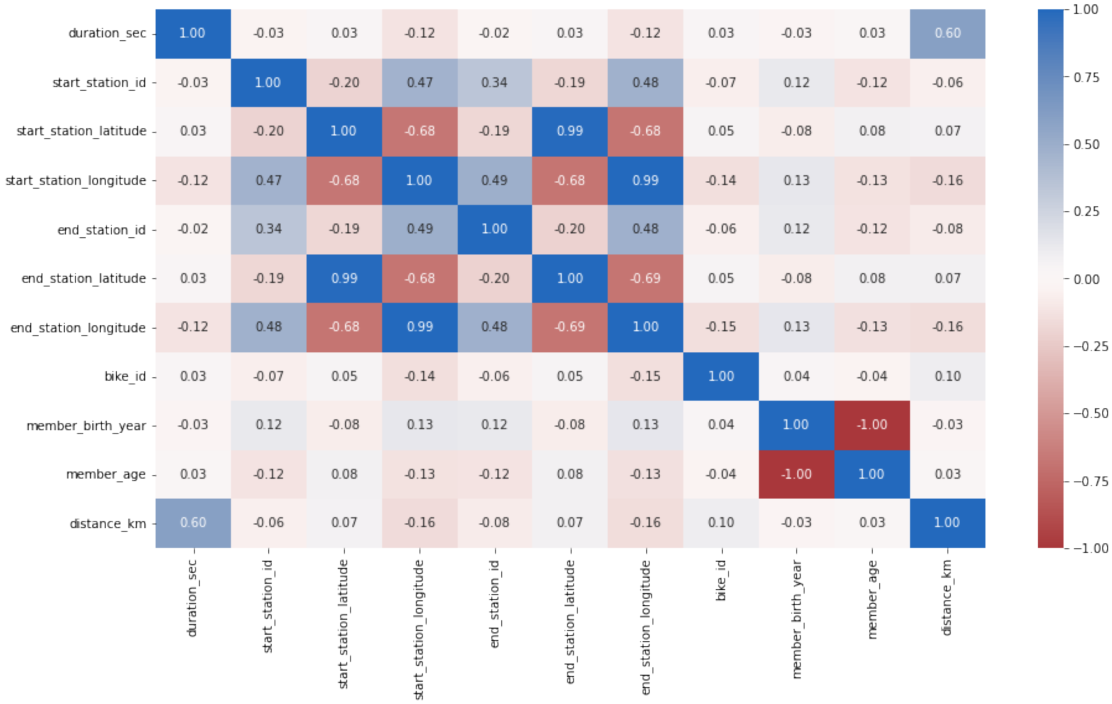
[44]:
```
# Let look at the relationship between user_type, duration_sec and day.
plt.figure(figsize= [10, 5])

sb.pointplot(data=fordbike_clean, x='day', y='duration_sec',
             hue='user_type', dodge=0.3, linestyles="", order=weekdays);
label_visual('Day of Week', 'Avg. Trip Duration', 'average trip duration vary␣
 ↪between user types on weekdays')
```



Generally more Customers spend more time riding bikes thatn subscribers. Both customers and subscribers spend more time on Sundays and Saturdays. There is not much preference in workdays(Mon - Fri) for subscribers however, for customers most trip durtion occured on Monday

Finally let examine the Correlation matrices among all numberical variables

[45]:
```
plt.figure(figsize=[15, 8])
sb.heatmap(fordbike_clean.corr(), annot= True, fmt='.2f',
           cmap = 'vlag_r', center = 0);
```



There is a strong relationship between duration in seconds and minutes and distance traveled in kilometers.

1.6.3 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?

Males are more likely to travel longer distances than females. Females are riding their bikes more frequently. Customers ride their bikes more than subscribers. On Sundays and Saturdays, both customers and subscribers spend more time. Subscribers have little preference for workdays (Mon-Fri), but customers have the most trip duration on Monday. The duration in seconds and minutes and the distance traveled in kilometers have a strong relationship.

1.6.4 Were there any interesting or surprising interactions between features?

Males are more likely to travel longer distances than females while females ride their bikes more frequently than males.

[ ]:

1.7 Conclusions

In conclusion, bike riders tend to be between the ages of 25 and 40, who use their bikes the most frequently and ride for the longest periods of time during the workweek. The trend among riders is to travel exclusively by bicycle on Thursdays. Males are more likely to travel longer distances than females while females ride their bikes more frequently than males.

A lot of effort was put into wrangling to ensure the best outcome of the analysis.

```
[ ]:
```