exploratory

June 27, 2021

1 Introduction

The Bay Area's bike share system is called Ford GoBike. Bay Area Bike Share began as a regional trial program in 2013, with 700 bikes and 70 stations spread across San Francisco and San Jose. Ford GoBike will have 7,000 bikes throughout San Francisco, the East Bay, and San Jose after the expansion is complete. Ford GoBike, like other bike sharing systems, is made up of a fleet of specifically built, strong, and durable bikes that are docked at various locations across the city. The bikes may be unlocked at any station in the system and returned to any other, making them perfect for one-way excursions. Bike share is used to travel to work or school, do errands, and attend appointments.

1.1 Wrangling

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import glob
import os
import datetime
```

1.2 Dataset Overview

My source data was Ford GoBike System Data: https://www.fordgobike.com/system-data This data collection contains data about individual bike-sharing system trips. If a complete year of coverage is needed, multiple data files will need to be linked together. This document delves into the public trip data for the Ford GoBike, which includes about 1,850,000 bike rides from FY2018. The trip start/end time, but also additional variables like user type, gender, and age, were all included in the data.

[2]:
```
df= pd.read_csv('201902-fordgobike-tripdata.csv')
```

[3]:
```
df.sample(10)
```

[3]:
```
        duration_sec                start_time                  end_time  \
149118           414  2019-02-06 19:56:46.5360  2019-02-06 20:03:41.1170
117289           435  2019-02-11 22:57:15.4970  2019-02-11 23:04:30.6580
```

```
101693          568  2019-02-14 17:17:20.2420  2019-02-14 17:26:48.9770
124351          430  2019-02-11 08:38:18.0140  2019-02-11 08:45:28.8350
171655          296  2019-02-03 19:35:06.5200  2019-02-03 19:40:03.4260
97406           722  2019-02-15 08:54:12.9500  2019-02-15 09:06:15.4090
164780          711  2019-02-05 08:03:56.4440  2019-02-05 08:15:48.3850
180802          378  2019-02-01 10:04:25.4510  2019-02-01 10:10:43.9680
107441          747  2019-02-13 16:07:40.7090  2019-02-13 16:20:07.9510
108580          154  2019-02-13 07:48:32.2210  2019-02-13 07:51:07.2050

        start_station_id                                start_station_name  \
149118             355.0                            23rd St at Tennessee St
117289             124.0                              19th St at Florida St
101693              25.0                                Howard St at 2nd St
124351              22.0                               Howard St at Beale St
171655              96.0                               Dolores St at 15th St
97406              369.0                                  Hyde St at Post St
164780             356.0                          Valencia St at Clinton Park
180802              15.0  San Francisco Ferry Building (Harry Bridges Pl…
107441             104.0                                   4th St at 16th St
108580             343.0                                 Bryant St at 2nd St

        start_station_latitude  start_station_longitude  end_station_id  \
149118                37.755367              -122.388795           364.0
117289                37.760447              -122.410807           115.0
101693                37.787522              -122.397405            61.0
124351                37.789756              -122.394643           349.0
171655                37.766210              -122.426614            99.0
97406                 37.787349              -122.416651            79.0
164780                37.769188              -122.422285           284.0
180802                37.795392              -122.394203            21.0
107441                37.767045              -122.390833            15.0
108580                37.783172              -122.393572            66.0

                                      end_station_name  \
149118                        China Basin St at 3rd St
117289                              Jackson Playground
101693                             Howard St at 8th St
124351                            Howard St at Mary St
171655                            Folsom St at 15th St
97406                             7th St at Brannan St
164780  Yerba Buena Center for the Arts (Howard St at …
180802   Montgomery St BART Station (Market St at 2nd St)
107441  San Francisco Ferry Building (Harry Bridges Pl…
108580                           3rd St at Townsend St

        end_station_latitude  end_station_longitude  bike_id   user_type  \
149118             37.772000            -122.389970     4629  Subscriber
```

```
117289             37.765026           -122.398773     4979  Subscriber
101693             37.776513           -122.411306     4738  Subscriber
124351             37.781010           -122.405666     4603  Subscriber
171655             37.767037           -122.415443     5565  Subscriber
97406              37.773492           -122.403673     6233  Subscriber
164780             37.784872           -122.400876     5528  Subscriber
180802             37.789625           -122.400811     5120  Subscriber
107441             37.795392           -122.394203      140    Customer
108580             37.778742           -122.392741     6210  Subscriber

        member_birth_year member_gender bike_share_for_all_trip
149118             1992.0          Male                      No
117289             1986.0          Male                      No
101693                NaN           NaN                      No
124351             1987.0          Male                      No
171655             1982.0          Male                      No
97406              1981.0          Male                      No
164780                NaN           NaN                      No
180802             1951.0          Male                      No
107441             1980.0        Female                      No
108580             1993.0          Male                      No
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             183412 non-null  int64
 1   start_time               183412 non-null  object
 2   end_time                 183412 non-null  object
 3   start_station_id         183215 non-null  float64
 4   start_station_name       183215 non-null  object
 5   start_station_latitude   183412 non-null  float64
 6   start_station_longitude  183412 non-null  float64
 7   end_station_id           183215 non-null  float64
 8   end_station_name         183215 non-null  object
 9   end_station_latitude     183412 non-null  float64
 10  end_station_longitude    183412 non-null  float64
 11  bike_id                  183412 non-null  int64
 12  user_type                183412 non-null  object
 13  member_birth_year        175147 non-null  float64
 14  member_gender            175147 non-null  object
 15  bike_share_for_all_trip  183412 non-null  object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

[5]:
```
df.shape
```

[5]:
```
(183412, 16)
```

[6]:
```
df.describe()
```

[6]:
```
         duration_sec  start_station_id  start_station_latitude  \
count  183412.000000     183215.000000           183412.000000
mean      726.078435        138.590427               37.771223
std      1794.389780        111.778864                0.099581
min        61.000000          3.000000               37.317298
25%       325.000000         47.000000               37.770083
50%       514.000000        104.000000               37.780760
75%       796.000000        239.000000               37.797280
max     85444.000000        398.000000               37.880222

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

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

[7]:
```
df.duplicated().sum()
```

[7]:
```
0
```

[8]:
```
df_cleaned = df.copy()
```

[9]:
```
df_cleaned['member_age'] = 2021 - df_cleaned['member_birth_year']
```

[10]:
```
df_cleaned = df_cleaned.query('member_age <=60')
```

[11]:
```
df_cleaned.member_age = df_cleaned.member_age.astype(int)
df_cleaned.member_birth_year = df_cleaned.member_birth_year.astype(int)
```

[12]:
```
df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 170186 entries, 0 to 183411
Data columns (total 17 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             170186 non-null  int64
 1   start_time               170186 non-null  object
 2   end_time                 170186 non-null  object
 3   start_station_id         169992 non-null  float64
 4   start_station_name       169992 non-null  object
 5   start_station_latitude   170186 non-null  float64
 6   start_station_longitude  170186 non-null  float64
 7   end_station_id           169992 non-null  float64
 8   end_station_name         169992 non-null  object
 9   end_station_latitude     170186 non-null  float64
 10  end_station_longitude    170186 non-null  float64
 11  bike_id                  170186 non-null  int64
 12  user_type                170186 non-null  object
 13  member_birth_year        170186 non-null  int32
 14  member_gender            170186 non-null  object
 15  bike_share_for_all_trip  170186 non-null  object
 16  member_age               170186 non-null  int32
dtypes: float64(6), int32(2), int64(2), object(7)
memory usage: 22.1+ MB
```

[13]:
```
df_cleaned.start_time = pd.to_datetime(df_cleaned.start_time)
df_cleaned.end_time = pd.to_datetime(df_cleaned.end_time)
```

[14]:
```
df_cleaned['start_time_month'] = df_cleaned['start_time'].dt.strftime('%B')
```

[15]:
```
df_cleaned['start_time_day'] = df_cleaned['start_time'].dt.strftime('%a')
```

[16]:
```
df_cleaned['start_time_hour'] = df_cleaned['start_time'].dt.hour
```

[17]:
```
df_cleaned.sample(10)
```

[17]:

	duration_sec	start_time	end_time	\
57000	288	2019-02-21 08:41:30.963	2019-02-21 08:46:19.144	
98097	362	2019-02-15 08:17:01.717	2019-02-15 08:23:04.163	
182867	433	2019-02-01 07:40:41.036	2019-02-01 07:47:54.194	
29503	507	2019-02-25 07:19:02.470	2019-02-25 07:27:29.734	
133994	578	2019-02-08 18:00:52.076	2019-02-08 18:10:30.437	

```
109635          835 2019-02-12 18:41:46.198 2019-02-12 18:55:42.122
84133          1086 2019-02-17 18:33:48.689 2019-02-17 18:51:54.722
79327           400 2019-02-18 17:44:28.829 2019-02-18 17:51:09.662
115247          218 2019-02-12 08:54:00.474 2019-02-12 08:57:38.889
170684          306 2019-02-04 07:55:24.074 2019-02-04 08:00:30.659

        start_station_id             start_station_name  \
57000               64.0           5th St at Brannan St
98097              181.0        Grand Ave at Webster St
182867             107.0          17th St at Dolores St
29503               66.0          3rd St at Townsend St
133994             160.0      West Oakland BART Station
109635             356.0    Valencia St at Clinton Park
84133              241.0             Ashby BART Station
79327                6.0  The Embarcadero at Sansome St
115247             114.0     Rhode Island St at 17th St
170684             310.0      San Fernando St at 4th St

        start_station_latitude  start_station_longitude  end_station_id  \
57000                37.776754              -122.399018           284.0
98097                37.811377              -122.265192           159.0
182867               37.763015              -122.426497            58.0
29503                37.778742              -122.392741             8.0
133994               37.805318              -122.294837           213.0
109635               37.769188              -122.422285           141.0
84133                37.852477              -122.270213           249.0
79327                37.804770              -122.403234            25.0
115247               37.764478              -122.402570           116.0
170684               37.335885              -121.885660           317.0

                                       end_station_name  \
57000   Yerba Buena Center for the Arts (Howard St at …
98097                                24th St at Market St
182867                               Market St at 10th St
29503                     The Embarcadero at Vallejo St
133994                           32nd St at Adeline St
109635                   Valencia St at Cesar Chavez St
84133                         Russell St at College Ave
79327                               Howard St at 2nd St
115247                        Mississippi St at 17th St
170684                        San Salvador St at 9th St

        end_station_latitude  end_station_longitude  bike_id   user_type  \
57000              37.784872           -122.400876     4826  Subscriber
98097              37.816060           -122.278244     4587  Subscriber
182867             37.776619           -122.417385     4654  Subscriber
29503              37.799953           -122.398525     4962  Subscriber
```

```
133994            37.823847          -122.281193     4483  Subscriber
109635            37.747998          -122.420219     5346  Subscriber
84133             37.858473          -122.253253     1550  Subscriber
79327             37.787522          -122.397405     4927  Subscriber
115247            37.764802          -122.394771      357  Subscriber
170684            37.333955          -121.877349     1124  Subscriber

        member_birth_year member_gender bike_share_for_all_trip  member_age  \
57000                1982          Male                      No          39
98097                1965          Male                      No          56
182867               1992          Male                      No          29
29503                1982        Female                      No          39
133994               1994        Female                      No          27
109635               1980        Female                      No          41
84133                1965          Male                      No          56
79327                1980          Male                      No          41
115247               1986          Male                      No          35
170684               1992          Male                     Yes          29

       start_time_month start_time_day  start_time_hour
57000          February            Thu                8
98097          February            Fri                8
182867         February            Fri                7
29503          February            Mon                7
133994         February            Fri               18
109635         February            Tue               18
84133          February            Sun               18
79327          February            Mon               17
115247         February            Tue                8
170684         February            Mon                7
```

[18]:
```python
import math
from math import radians, sin, cos, acos

def distance(origin, destination):

    lat1, long1 = origin
    lat2, long2 = destination
    radius = 6371
    # this is in kilometers - will convert to US units of miles after

    dlat = math.radians(lat2 - lat1)
    dlong = math.radians(long2 - long1)

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

```
    d = radius * c

    return d
```

[19]:
```
df_cleaned['distance'] = df_cleaned.apply(lambda x:␣
↪distance((x['start_station_latitude'], x['start_station_longitude']),␣
↪(x['end_station_latitude'], x['end_station_longitude'])), axis=1)
```

[20]:
```
df_cleaned.start_time = pd.to_datetime(df_cleaned.start_time)
df_cleaned.end_time = pd.to_datetime(df_cleaned.end_time)
df_cleaned.bike_id = df_cleaned.bike_id.astype(str)
df_cleaned.start_station_id = df_cleaned.start_station_id.astype(str)
df_cleaned.end_station_id = df_cleaned.end_station_id.astype(str)
```

[21]:
```
df_cleaned.info()
```

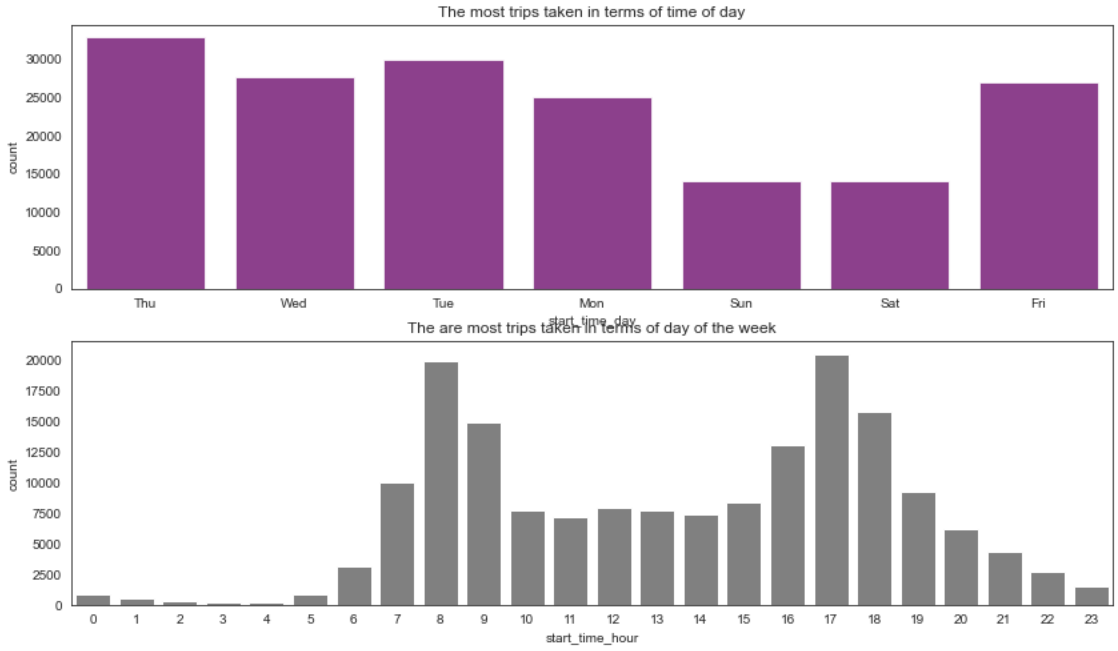
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 170186 entries, 0 to 183411
Data columns (total 21 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             170186 non-null  int64
 1   start_time               170186 non-null  datetime64[ns]
 2   end_time                 170186 non-null  datetime64[ns]
 3   start_station_id         170186 non-null  object
 4   start_station_name       169992 non-null  object
 5   start_station_latitude   170186 non-null  float64
 6   start_station_longitude  170186 non-null  float64
 7   end_station_id           170186 non-null  object
 8   end_station_name         169992 non-null  object
 9   end_station_latitude     170186 non-null  float64
 10  end_station_longitude    170186 non-null  float64
 11  bike_id                  170186 non-null  object
 12  user_type                170186 non-null  object
 13  member_birth_year        170186 non-null  int32
 14  member_gender            170186 non-null  object
 15  bike_share_for_all_trip  170186 non-null  object
 16  member_age               170186 non-null  int32
 17  start_time_month         170186 non-null  object
 18  start_time_day           170186 non-null  object
 19  start_time_hour          170186 non-null  int64
 20  distance                 170186 non-null  float64
dtypes: datetime64[ns](2), float64(5), int32(2), int64(2), object(10)
memory usage: 27.3+ MB
```

[22]:
```
df_cleaned.to_csv('df_cleaned.csv', index=False)
```

1.2.1 When are most trips taken in terms of time of day and day of the week?

[23]:
```
sns.set_style('white')
fig, (ax1, ax2) = plt.subplots(nrows=2, figsize = [14, 8])
ax1.set_title('The most trips taken in terms of time of day')
ax2.set_title('The are most trips taken in terms of day of the week')
sns.countplot(data = df_cleaned, x = 'start_time_day', color = 'purple',␣
↪alpha=0.8, ax = ax1)
sns.countplot(data = df_cleaned, x = 'start_time_hour', color = 'gray', ax =␣
↪ax2)
```

[23]:
```
<AxesSubplot:title={'center':'The are most trips taken in terms of day of the
week'}, xlabel='start_time_hour', ylabel='count'>
```

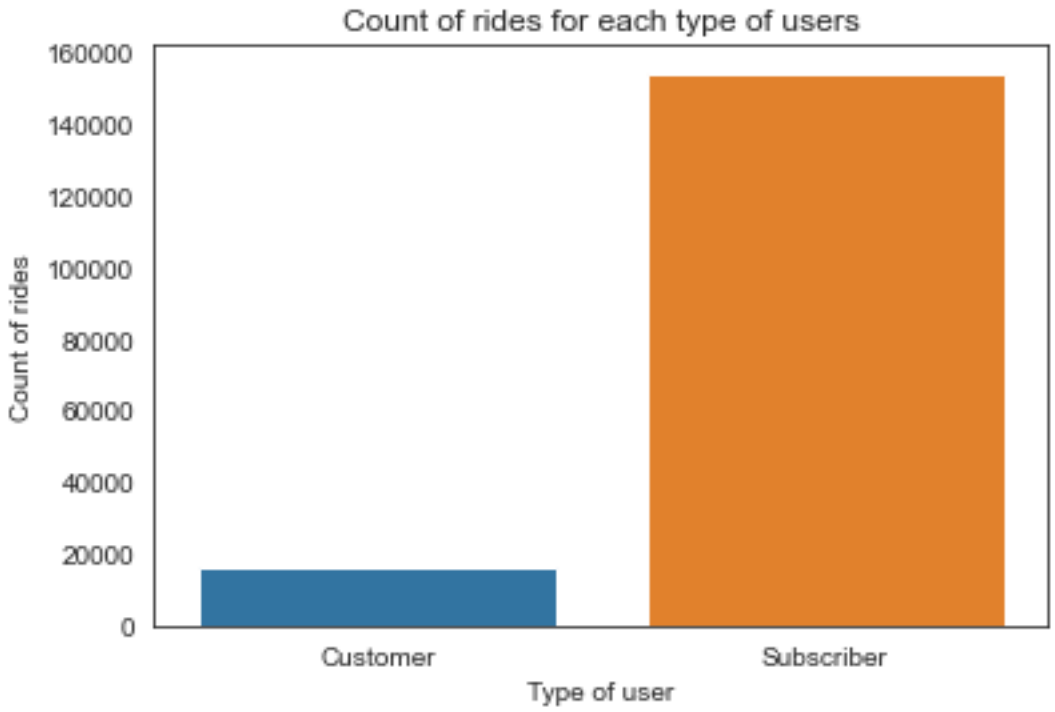


- People tend to not go in bike trips during the weekends
- People tend to go for bike trrips early in the morning and the hours before the sunset

1.2.2 what is the count of trips for each user type?

[24]:
```
b=sns.countplot(data = df_cleaned, x = 'user_type');
plt.title('Count of rides for each type of users')
b.set(xlabel='Type of user', ylabel='Count of rides')
```

[24]:
```
[Text(0.5, 0, 'Type of user'), Text(0, 0.5, 'Count of rides')]
```

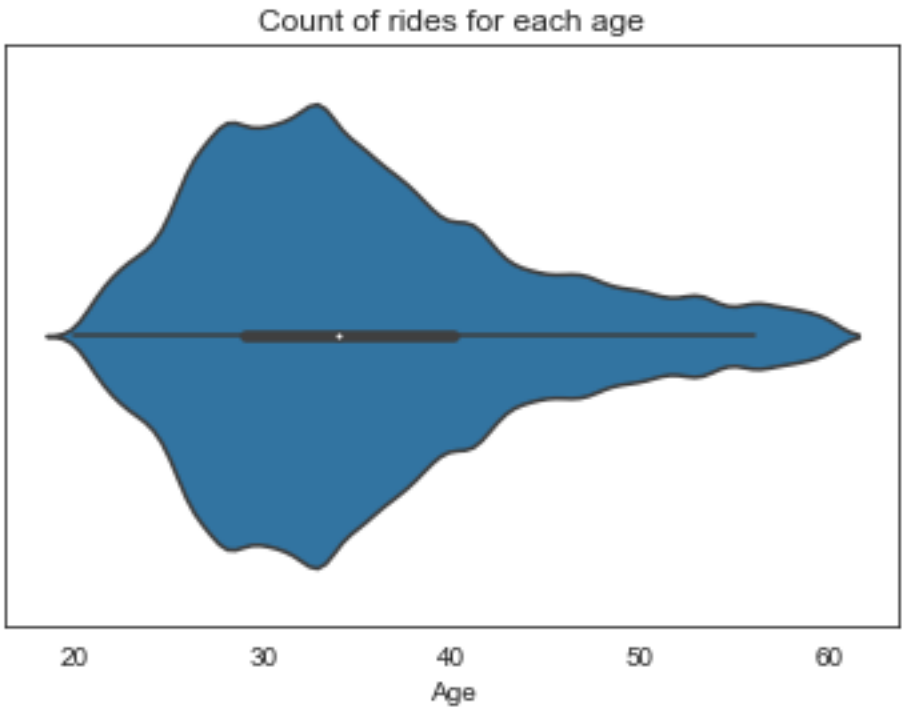


- Subscribers have x8 more count of rides than customers

1.2.3 What are the ages of bike riders?

[25]:
```
c=sns.violinplot(data = df_cleaned, x = 'member_age');
plt.title('Count of rides for each age')
c.set(xlabel='Age')
```

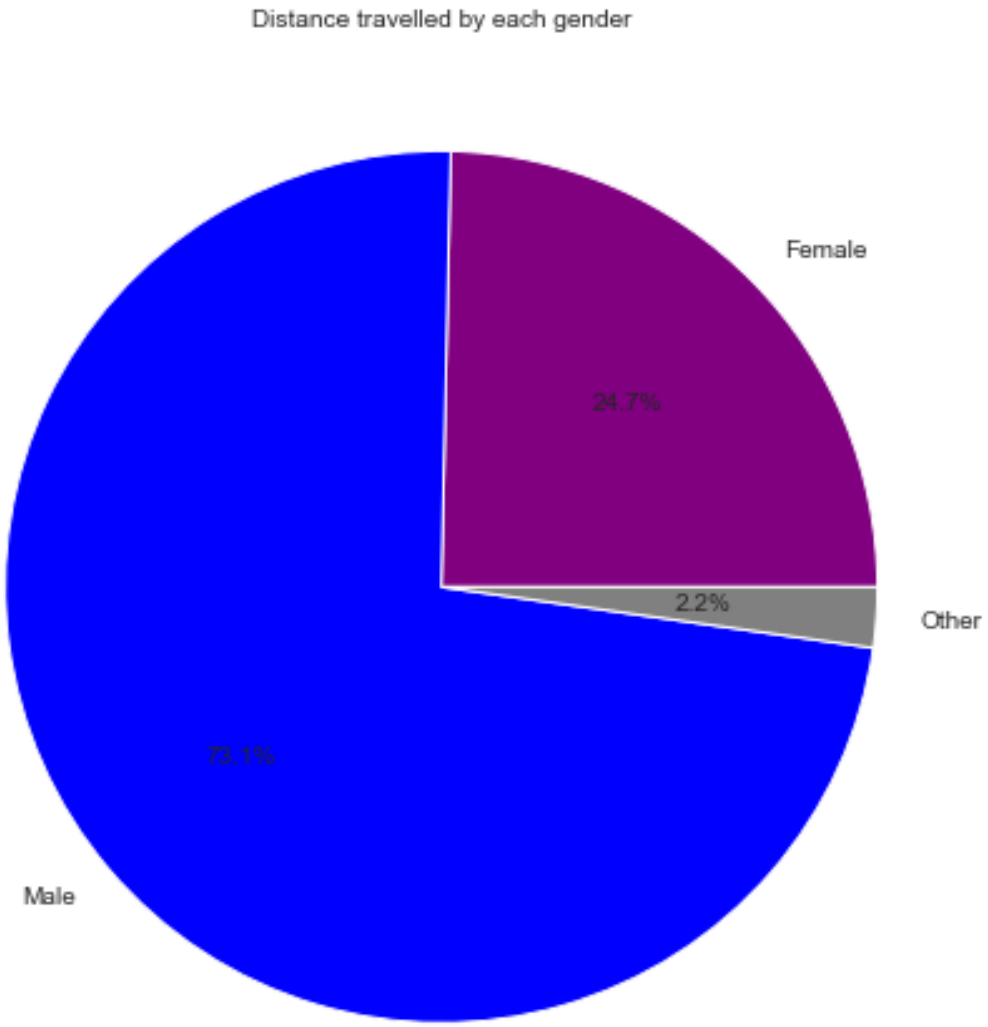
[25]:
```
[Text(0.5, 0, 'Age')]
```



- People in their early 30s make the majority of rides count.

1.2.4 What gender travelled more?

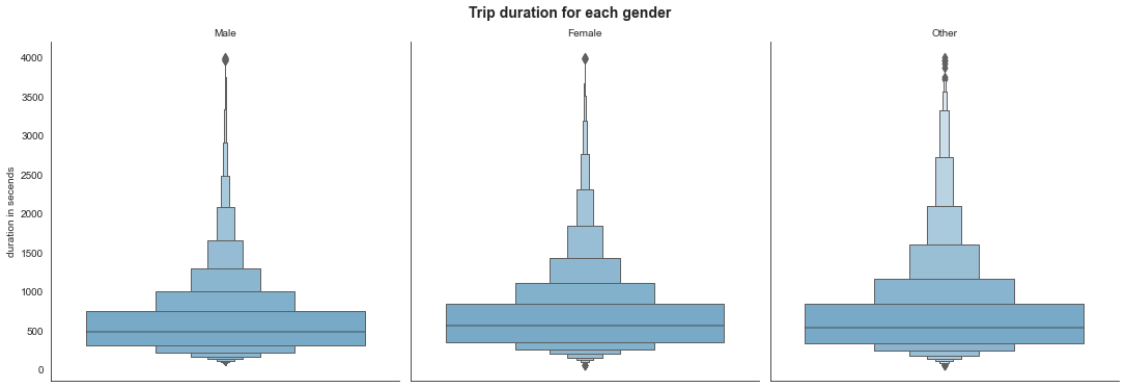
[26]:
```
plt.figure(figsize= [8,8])
a = df_cleaned[df_cleaned.member_gender == 'Female'].distance.sum()
b = df_cleaned[df_cleaned.member_gender == 'Male'].distance.sum()
c = df_cleaned[df_cleaned.member_gender == 'Other'].distance.sum()

plt.pie([a, b,c], autopct='%1.1f%%', labels=['Female', 'Male','Other'],␣
 ↪colors=["purple","blue", "gray"])
plt.title("Distance travelled by each gender", fontsize=10)
plt.show()
```



- Females make around quarter of the total distance traveled while males travel almost x3 more.

1.2.5 what is the trip duration for each gender?

[27]:
```
data = df_cleaned.query('duration_sec < 4000')
g = sns.catplot(data=data, y='duration_sec', col="member_gender", kind='boxen',␣
↪palette = 'Blues')
g.set_titles(col_template = '{col_name}')
g.set_axis_labels("", "duration in secends")
g.fig.suptitle('Trip duration for each gender', y=1.03, fontsize=14,␣
↪fontweight='semibold');
```



- females have a higher trip duration than males around 650 secends.

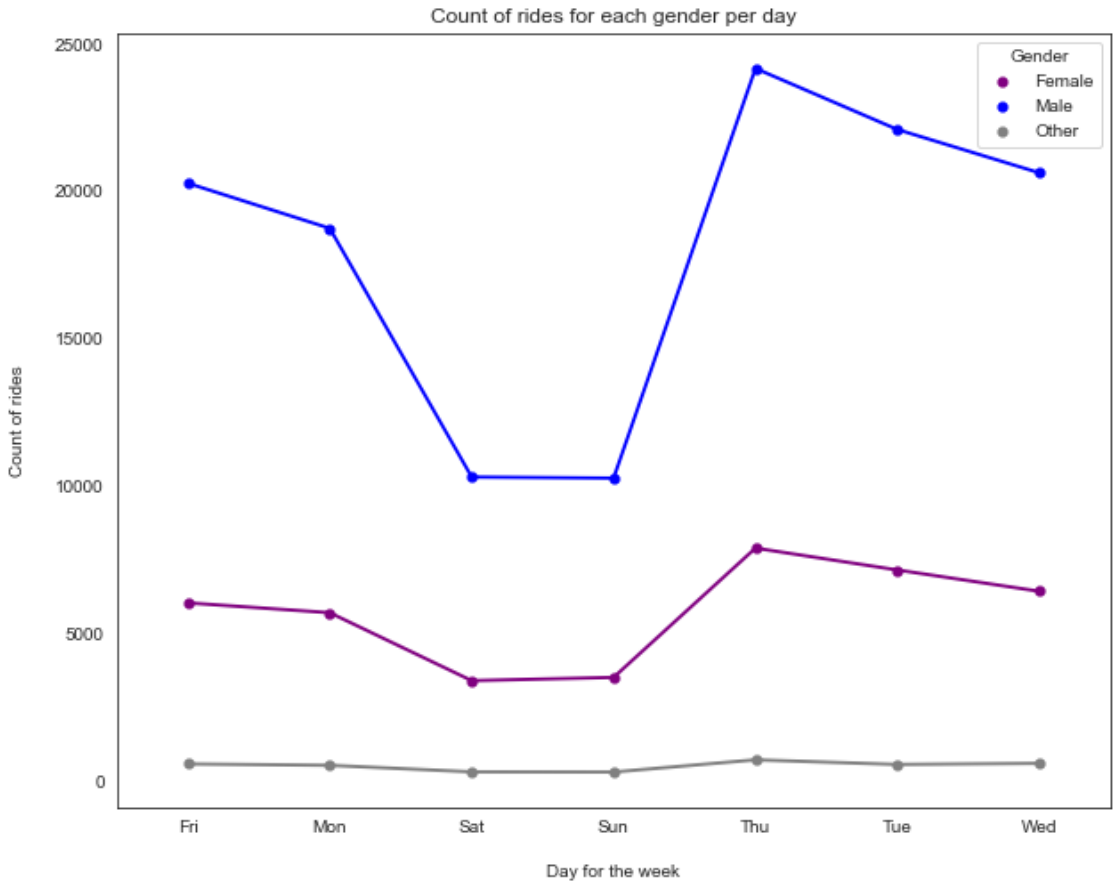
1.2.6 Does the the count for the start day and hour depend on if a user is a female or male?

[28]:
```
Genderdf = df_cleaned.groupby(["member_gender", "start_time_day"]).size().
↪reset_index()
Genderdf
```

[28]:

	member_gender	start_time_day	0
0	Female	Fri	6038
1	Female	Mon	5705
2	Female	Sat	3401
3	Female	Sun	3511
4	Female	Thu	7896
5	Female	Tue	7154
6	Female	Wed	6432
7	Male	Fri	20269
8	Male	Mon	18740
9	Male	Sat	10306
10	Male	Sun	10269
11	Male	Thu	24163
12	Male	Tue	22091
13	Male	Wed	20623
14	Other	Fri	576
15	Other	Mon	530
16	Other	Sat	308
17	Other	Sun	302
18	Other	Thu	716
19	Other	Tue	559
20	Other	Wed	597

[29]:
```
plt.figure(figsize=(10,8))
colors = {'Female':'purple', 'Male':'blue', 'Other':'gray'}
ax = sns.pointplot(x='start_time_day', y=0, hue='member_gender',␣
 ↪palette=colors, scale=.7, data=Genderdf)
plt.title('Count of rides for each gender per day')
plt.xlabel('Day for the week', labelpad=16)
plt.ylabel('Count of rides', labelpad=16)
leg = ax.legend()
leg.set_title('Gender')
```



- Gender has nothing to do with the preferred start date all genders prefer to start on thursdays and weekends seems like an unprefered choice

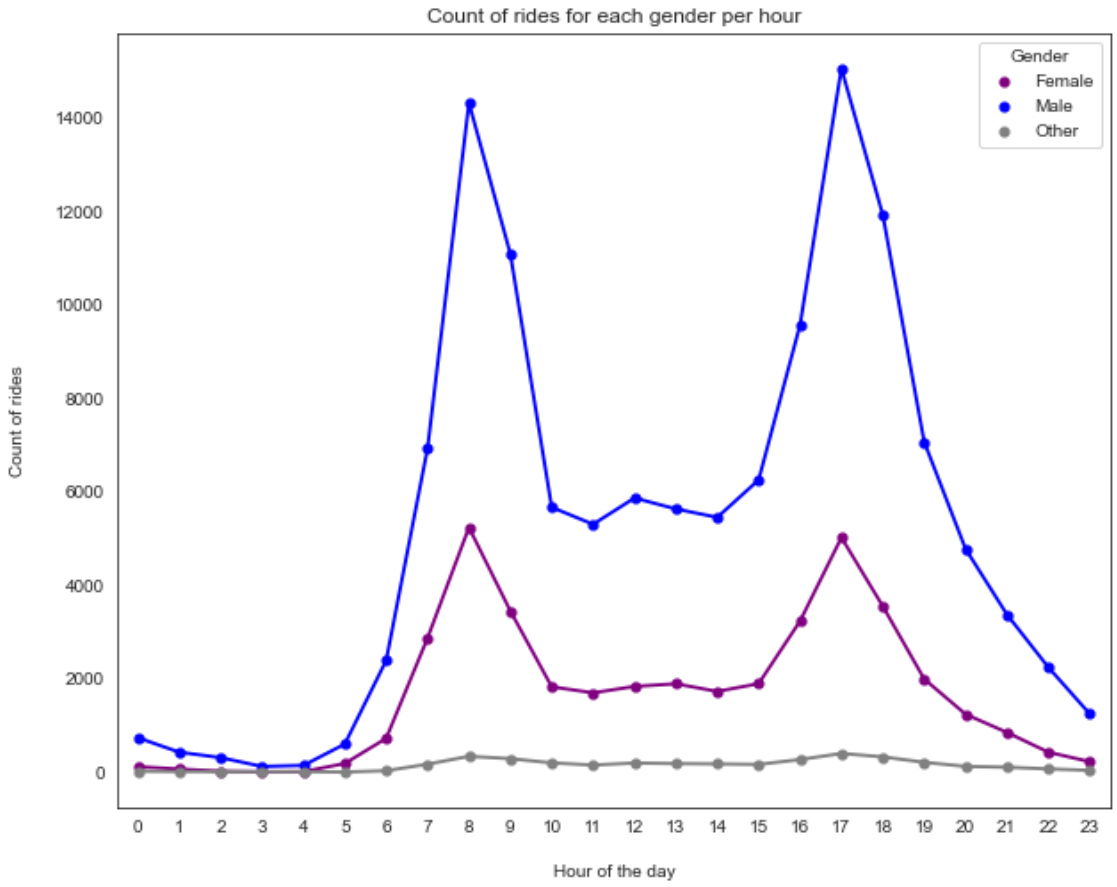
[30]:
```
Genderdf1 = df_cleaned.groupby(["member_gender", "start_time_hour"]).size().
 ↪reset_index()
Genderdf1
```

[30]:

	member_gender	start_time_hour	0
0	Female	0	119

```
1          Female                 1   70
2          Female                 2   24
3          Female                 3   13
4          Female                 4   16
..            …                 …   …
67          Other                19  214
68          Other                20  126
69          Other                21  109
70          Other                22   73
71          Other                23   42

[72 rows x 3 columns]
```

[31]:
```
plt.figure(figsize=(10,8))
colors = {'Female':'purple', 'Male':'blue', 'Other':'gray'}
ax = sns.pointplot(x='start_time_hour', y=0, hue='member_gender',␣
 ↪palette=colors, scale=.7, data=Genderdf1)
plt.title('Count of rides for each gender per hour')
plt.xlabel('Hour of the day', labelpad=16)
plt.ylabel('Count of rides', labelpad=16)
leg = ax.legend()
leg.set_title('Gender')
```



- Gender has nothing to do with the preferred start date all genders prefer to start on 8th and 17th day of the month

[32]:
```
Genderdf2 = df_cleaned.groupby(["member_age","member_gender"]).size().
 ↪reset_index()
Genderdf2
```

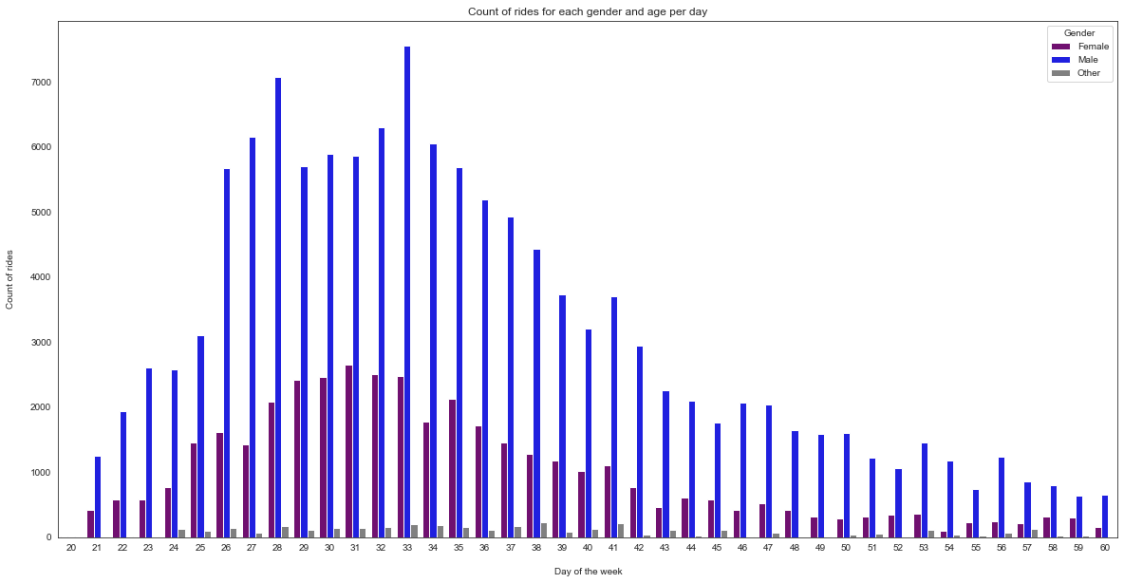
[32]:

	member_age	member_gender	0
0	20	Female	18
1	20	Male	16
2	21	Female	427
3	21	Male	1249
4	21	Other	2
..	…	…	…
117	59	Male	635
118	59	Other	19
119	60	Female	163
120	60	Male	656
121	60	Other	2

[122 rows x 3 columns]

1.2.7 Is the count of riders affected by gender and age?

[33]:
```
plt.figure(figsize=(20,10))
ax = sns.barplot(x="member_age", y=0, hue="member_gender", palette=colors,␣
↪data=Genderdf2)
plt.title('Count of rides for each gender and age per day')
plt.xlabel('Day of the week', labelpad=16)
plt.ylabel('Count of rides', labelpad=16)
leg = ax.legend()
leg.set_title('Gender')
```

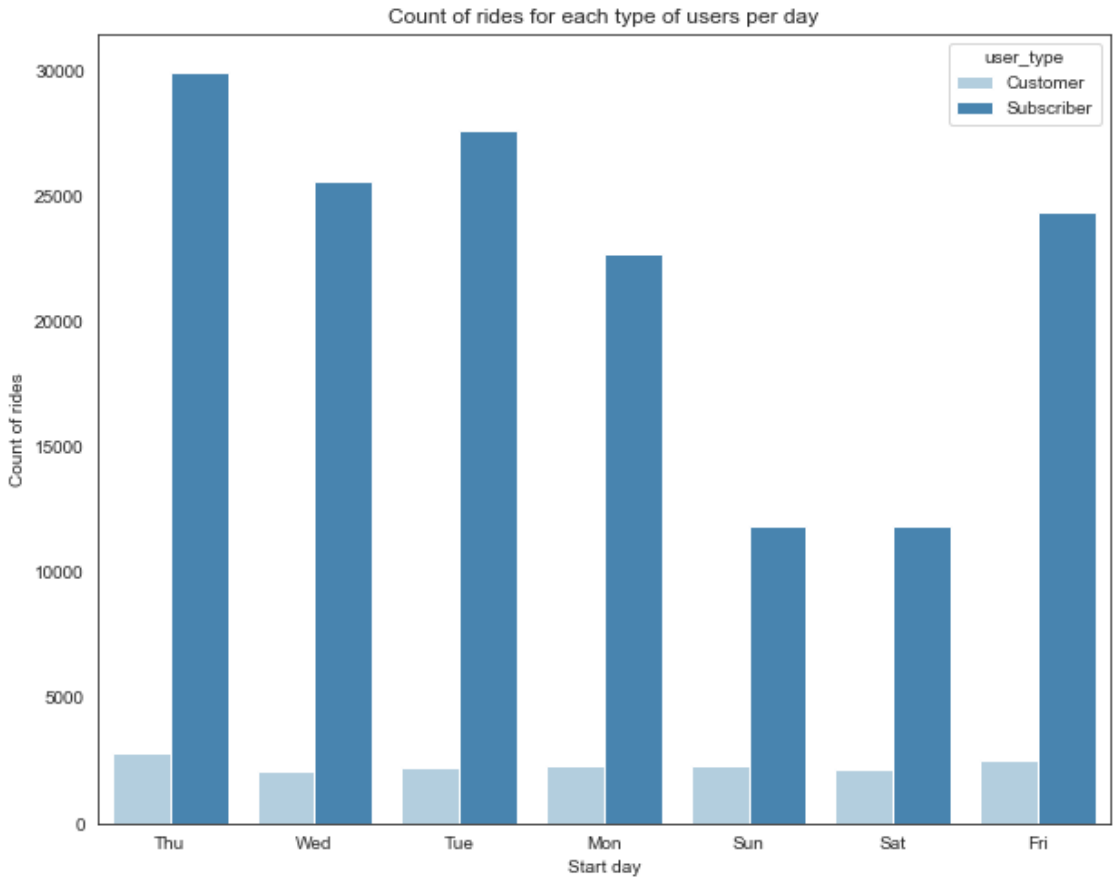


- Most female bike riders are 31 while males are of age 33. In general, riders are in their late 20s to middel 30s.

1.2.8 What is the count of rides based on user type and day?

[34]:
```
plt.figure(figsize=(10,8))
plt.title('Count of rides for each type of users per day')
d=sns.countplot(data = df_cleaned, x = 'start_time_day', hue = 'user_type',␣
↪palette = 'Blues');
d.set(xlabel='Start day', ylabel='Count of rides')
```

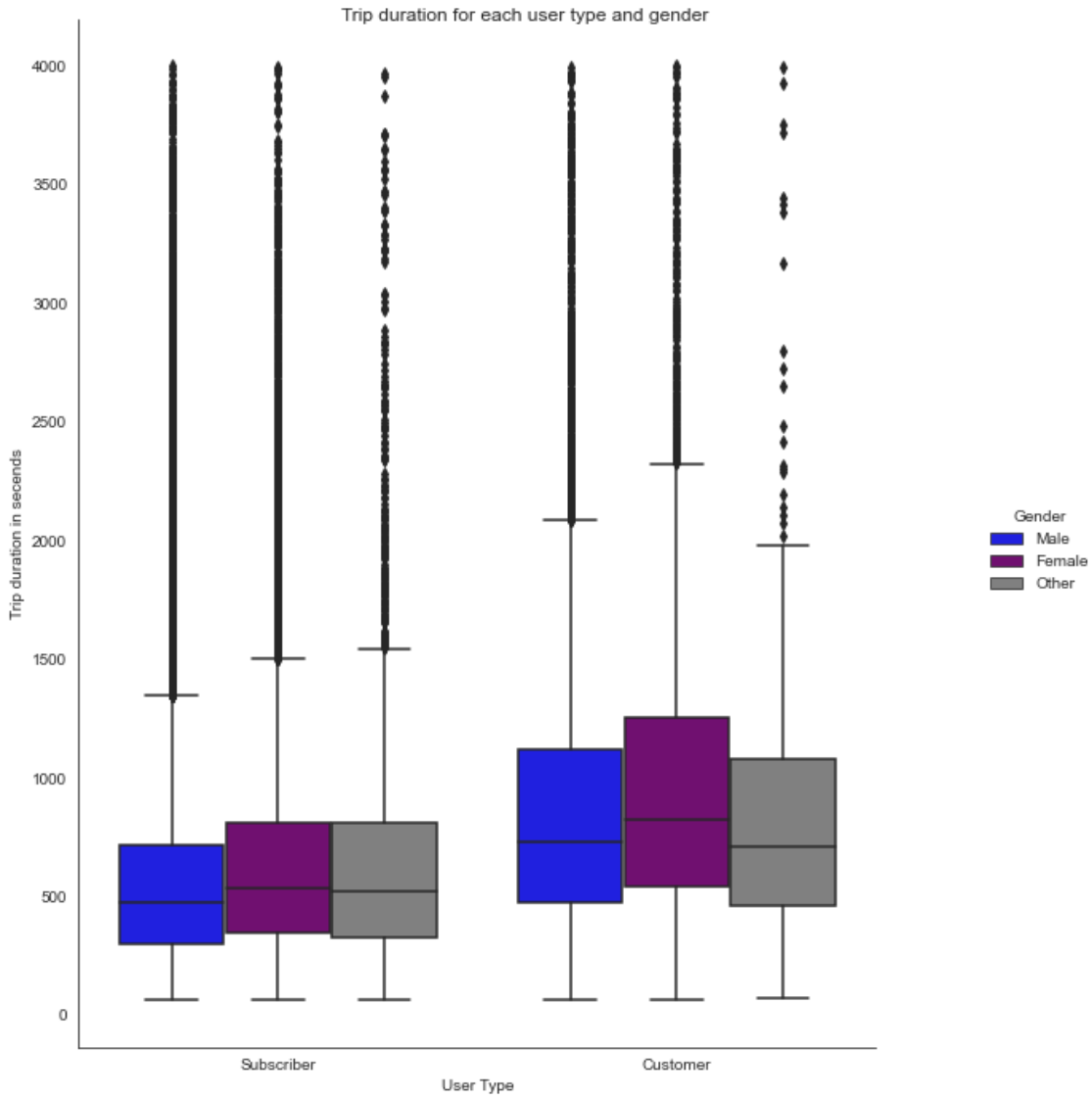
[34]:
```
[Text(0.5, 0, 'Start day'), Text(0, 0.5, 'Count of rides')]
```



- Subscriber tend not to start during the weekend while customers are less likely to start on wednesdays

1.2.9 What is the trip duration for user type and gender?

[35]:
```
box = sns.catplot(data=data, x='user_type', y="duration_sec",␣
↪hue="member_gender", kind="box", palette = colors)
box.set_axis_labels("User Type", "Trip duration in secends")
box._legend.set_title('Gender')
box.fig.suptitle('Trip duration for each user type and gender');
box.fig.set_size_inches(10,10)
```



- In general customers has a higher trip duration than customers. males and other gender has same maximum value of duration which is around 550 seconds.

1.3 Summary of main findings

- People tend to not go in bike trips during the weekends
- People tend to go for bike trrips early in the morning and the hours before the sunset
- Subscribers have x8 more count of rides than customers
- People in their early 30s make the majority of rides count.
- Females make around quarter of the total distance traveled while males travel almost x3 more.
- females have a higher trip duration than males around 650 secends.
- Gender has nothing to do with the preferred start date all genders prefer to start on thursdays and weekends seems like an unprefered choice

- Gender has nothing to do with the preferred start date all genders prefer to start on 8th and 17th day of the month
- Most female bike riders are 31 while males are of age 33. In general, riders are in their late 20s to middel 30s.
- Subscriber tend not to start during the weekend while customers are less likely to start on wednesdays
- In general customers has a higher trip duration than customers. males and other gender has same maximum value of duration which is around 550 seconds.