Ford GoBike Exploration

Introduction

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

In [1]:
```
#importing the required libraries
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [2]:
```
#reading the dataset for exploration
df_ford = pd.read_csv('/Users/ifunanya/Downloads/201902-fordgobike-tripdata.csv')
df_ford.head()
```

Out[2]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitude	st
0	52185	2019-02-28 17:32:10.1450	2019-03-01 08:01:55.9750	21.0	Montgomery St BART Station (Market St at 2nd St)	37.789625	
1	42521	2019-02-28 18:53:21.7890	2019-03-01 06:42:03.0560	23.0	The Embarcadero at Steuart St	37.791464	
2	61854	2019-02-28 12:13:13.2180	2019-03-01 05:24:08.1460	86.0	Market St at Dolores St	37.769305	
3	36490	2019-02-28 17:54:26.0100	2019-03-01 04:02:36.8420	375.0	Grove St at Masonic Ave	37.774836	
4	1585	2019-02-28 23:54:18.5490	2019-03-01 00:20:44.0740	7.0	Frank H Ogawa Plaza	37.804562	

In [3]:
```
df_ford.shape
```

Out[3]:
```
(183412, 16)
```

The dataset contains 183412 rows and 16 columns. Next, we'll get more information on the dataset.

In [4]:
```
df_ford.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
```

In [5]:

```
df_ford.user_type.unique()
```

Out[5]:

```
array(['Customer', 'Subscriber'], dtype=object)
```

In [6]:

```
df_ford.member_gender.unique()
```

Out[6]:

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

Datatypes of columns start_time, end_time, user_type and member_gender will need to be changed. Null values are also observed in columns start_station_id, start_station_name, end_station_id, end_station_name, member_birth_year, member_gender.

In [7]:

```
df_ford.describe()
```

Out[7]:

	duration_sec	start_station_id	start_station_latitude	start_station_longitude	end_station_id	end_st
count	183412.000000	183215.000000	183412.000000	183412.000000	183215.000000	1
mean	726.078435	138.590427	37.771223	-122.352664	136.249123	
std	1794.389780	111.778864	0.099581	0.117097	111.515131	
min	61.000000	3.000000	37.317298	-122.453704	3.000000	
25%	325.000000	47.000000	37.770083	-122.412408	44.000000	
50%	514.000000	104.000000	37.780760	-122.398285	100.000000	
75%	796.000000	239.000000	37.797280	-122.286533	235.000000	
max	85444.000000	398.000000	37.880222	-121.874119	398.000000	

In [8]:

```
df_ford.sample(20)
```

Out[8]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitu
99705	795	2019-02-14 19:12:07.8180	2019-02-14 19:25:22.8750	66.0	3rd St at Townsend St	37.7787
146735	493	2019-02-07 08:30:21.1110	2019-02-07 08:38:34.9120	67.0	San Francisco Caltrain Station 2 (Townsend St...	37.7766
130519	792	2019-02-09 17:00:21.6950	2019-02-09 17:13:34.0870	91.0	Berry St at King St	37.7717

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitu
20079	676	2019-02-26 14:08:05.9120	2019-02-26 14:19:22.6250	20.0	Mechanics Monument Plaza (Market St at Bush St)	37.7913
164460	529	2019-02-05 08:24:57.1350	2019-02-05 08:33:46.9280	63.0	Bryant St at 6th St	37.7759
114287	388	2019-02-12 09:45:57.5570	2019-02-12 09:52:26.0360	60.0	8th St at Ringold St	37.7745
13901	658	2019-02-27 14:16:48.8950	2019-02-27 14:27:47.5980	6.0	The Embarcadero at Sansome St	37.8047
13329	386	2019-02-27 16:24:52.3780	2019-02-27 16:31:18.3930	309.0	San Jose City Hall	37.3373
69100	851	2019-02-19 20:06:22.1330	2019-02-19 20:20:34.1110	5.0	Powell St BART Station (Market St at 5th St)	37.7838
101761	485	2019-02-14 17:15:12.2930	2019-02-14 17:23:17.6640	256.0	Hearst Ave at Euclid Ave	37.875
136295	676	2019-02-08 10:05:56.7620	2019-02-08 10:17:12.8150	31.0	Raymond Kimbell Playground	37.7838
7926	355	2019-02-28 08:45:16.5410	2019-02-28 08:51:12.4470	80.0	Townsend St at 5th St	37.7752
4966	735	2019-02-28 14:22:05.0370	2019-02-28 14:34:20.2650	86.0	Market St at Dolores St	37.7693
105888	3108	2019-02-13 19:09:36.2630	2019-02-13 20:01:24.9820	3.0	Powell St BART Station (Market St at 4th St)	37.7863
41371	1236	2019-02-22 18:24:45.6320	2019-02-22 18:45:22.0780	341.0	Fountain Alley at S 2nd St	37.3361
86555	512	2019-02-17 12:31:18.0560	2019-02-17 12:39:51.0190	285.0	Webster St at O'Farrell St	37.7835
27767	234	2019-02-25 09:19:14.8970	2019-02-25 09:23:08.9260	127.0	Valencia St at 21st St	37.7567
146515	334	2019-02-07 08:44:00.5010	2019-02-07 08:49:34.6600	201.0	10th St at Fallon St	37.7976
169574	1413	2019-02-04 09:28:33.8130	2019-02-04 09:52:07.3950	81.0	Berry St at 4th St	37.7758
27621	289	2019-02-25 09:27:22.6680	2019-02-25 09:32:11.7830	59.0	S Van Ness Ave at Market St	37.7748

In [9]:

```
df_ford.isna().sum()
```

Out[9]:

```
duration_sec                 0
start_time                   0
end_time                     0
start_station_id           197
start_station_name         197
start_station_latitude       0
start_station_longitude      0
end_station_id             197
```

```
end_station_name             197
end_station_latitude           0
end_station_longitude          0
bike_id                        0
user_type                      0
member_birth_year           8265
member_gender               8265
bike_share_for_all_trip        0
dtype: int64
```

In [10]:

```
df_ford.duplicated().sum()
```

Out[10]:

```
0
```

Quality Issues

- Data types of start_time, end_time, user_type, member_gender
- Columns not necessary for analysis: start_station_latitude, start_station_longitude, end_station_latitude, end_station_longitude,

Define

- Convert start_time and end_time to datetime format
- Convert user_gender and member_type to category
- Drop the irrelevant columns

Data Cleaning

In [11]:

```
#copy the dataset
df = df_ford.copy()
```

In [12]:

```
#changing datatype
n_dtype = {'start_time' : 'datetime64',
          'end_time' : 'datetime64',
          'user_type' : 'category',
          'member_gender' : 'category'}

df = df.astype(n_dtype)
```

In [13]:

```
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  datetime64[ns]
 2   end_time                 183412 non-null  datetime64[ns]
 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  category
 13  member_birth_year        175147 non-null  float64
 14  member_gender            175147 non-null  category
 15  bike_share_for_all_trip  183412 non-null  object
dtypes: category(2), datetime64[ns](2), float64(7), int64(2), object(3)
memory usage: 19.9+ MB
```

In [14]:
```
#dropping columns
cols_to_drop = ['start_station_latitude', 'start_station_longitude', 'end_station_latitude
df.drop(cols_to_drop, axis = 1, inplace = True)
```

In [15]:
```
df.head()
```

Out[15]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	end_station_id	end_statio
0	52185	2019-02-28 17:32:10.145	2019-03-01 08:01:55.975	21.0	Montgomery St BART Station (Market St at 2nd St)	13.0	Commer Montgo
1	42521	2019-02-28 18:53:21.789	2019-03-01 06:42:03.056	23.0	The Embarcadero at Steuart St	81.0	Berry St a
2	61854	2019-02-28 12:13:13.218	2019-03-01 05:24:08.146	86.0	Market St at Dolores St	3.0	Powell Station (M a
3	36490	2019-02-28 17:54:26.010	2019-03-01 04:02:36.842	375.0	Grove St at Masonic Ave	70.0	Central Av
4	1585	2019-02-28 23:54:18.549	2019-03-01 00:20:44.074	7.0	Frank H Ogawa Plaza	222.0	10th Ave a

What is the structure of the dataset?

The cleaned dataset contains 183412 rows and 11 columns representing bike rides in the SanFrancisco Bay Area.

What is/are the main features of interest in your dataset?

Main features of interest are the duration, start and end times.

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

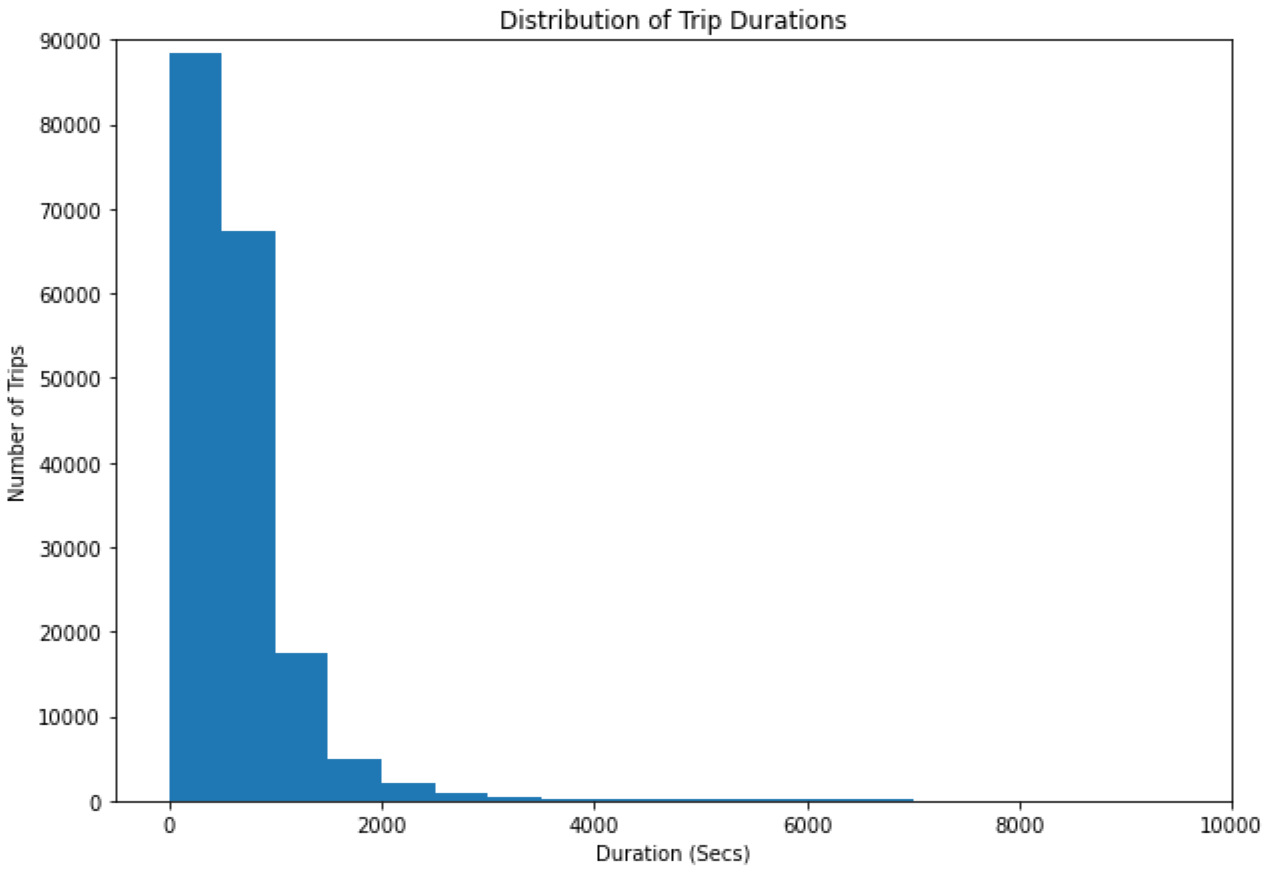
Based on the features stated, features that will help support investigation are station name, user type, member gender.

Univariate Exploration

Investigating distributions of individual variables. If unusual points or outliers are noticed, take a deeper look to clean things up and prepare yourself to look at relationships between variables.

In [16]:
```
binsize = 500
bins = np.arange(0, df['duration_sec'].max()+binsize, binsize)

plt.figure(figsize=[10, 7])
plt.hist(data = df, x = 'duration_sec', bins = bins)
```

```
plt.title('Distribution of Trip Durations')
plt.xlabel('Duration (Secs)')
plt.ylabel('Number of Trips')
plt.axis([-500, 10000, 0, 90000])
plt.show()
```

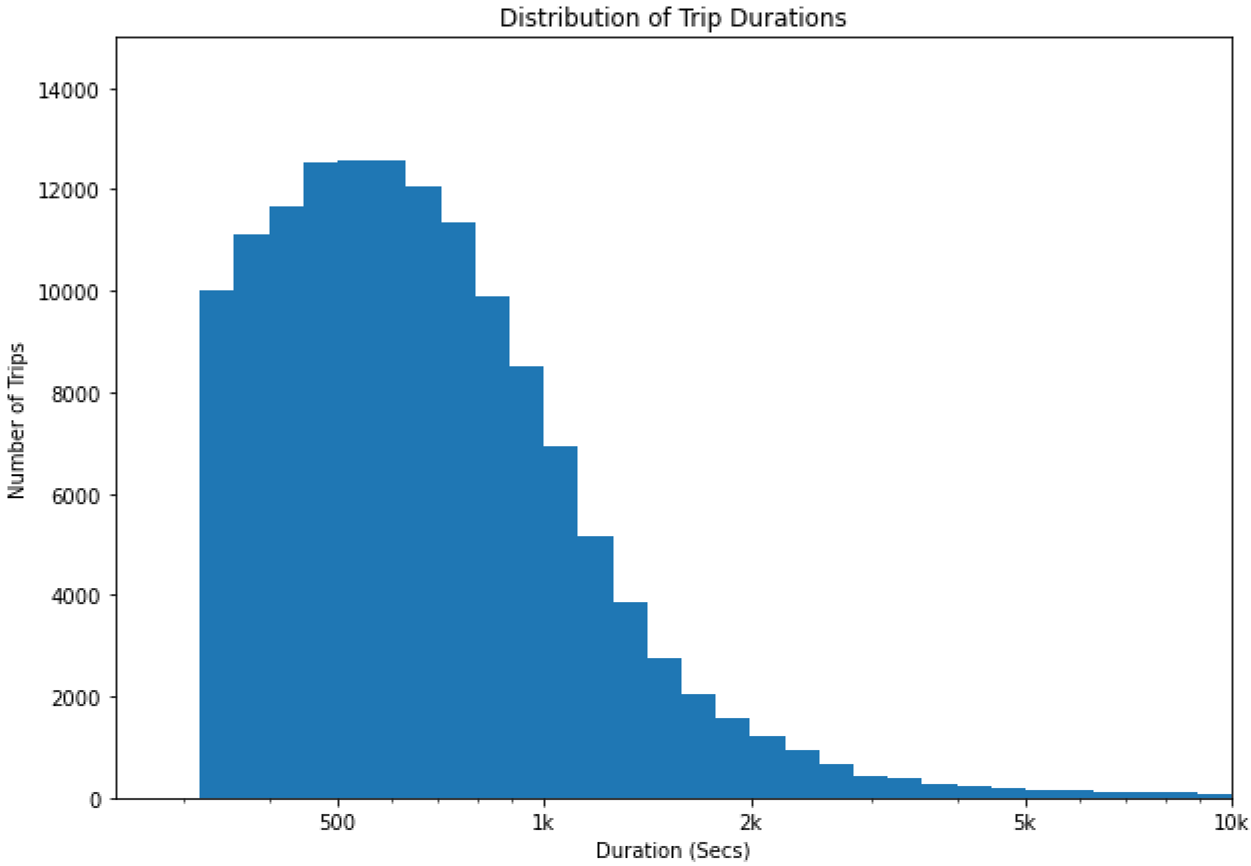


Trip durations have majority falling between 0 and 2000 seconds. To get more details, a log scale transformation will be done.

In [17]:

```
#getting more details from a log scale
log_binsize = 0.05
bins_log = 10 ** np.arange(2.5, np.log10(df['duration_sec'].max()) + log_binsize, log_bins

plt.figure(figsize=[10, 7])
plt.hist(data = df, x = 'duration_sec', bins = bins_log)
plt.title('Distribution of Trip Durations')
plt.xlabel('Duration (Secs)')
plt.ylabel('Number of Trips')
plt.xscale('log')
plt.xticks([500, 1e3, 2e3, 5e3, 1e4], [500, '1k', '2k', '5k', '10k'])
plt.axis([0, 10000, 0, 15000])
plt.show()
```

```
/var/folders/1l/vb42vw715ndd_r3d14zshrjr0000gn/T/ipykernel_48829/2511378949.py:12: UserWar
ning: Attempted to set non-positive left xlim on a log-scaled axis.
Invalid limit will be ignored.
  plt.axis([0, 10000, 0, 15000])
```



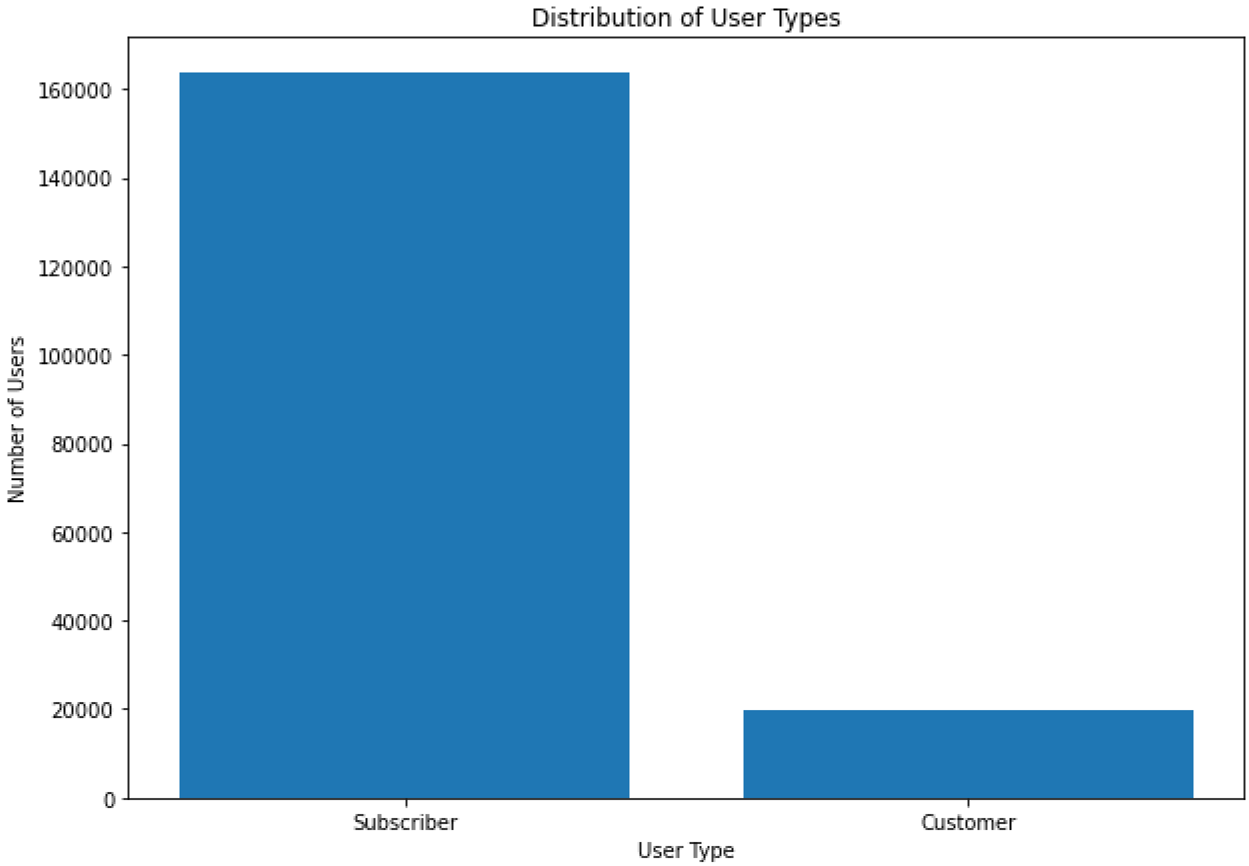
Most trip durations fall between 0 and 2000 seconds. Peak of the distribution falls around 600 and 700 seconds.

In [18]:

```
# distribution of user types

def column (a, b, x, y, title, xlabel, ylabel):
    plt.figure(figsize=[a,b])
    plt.bar(x = x, height = y)
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    return plt.show()
```

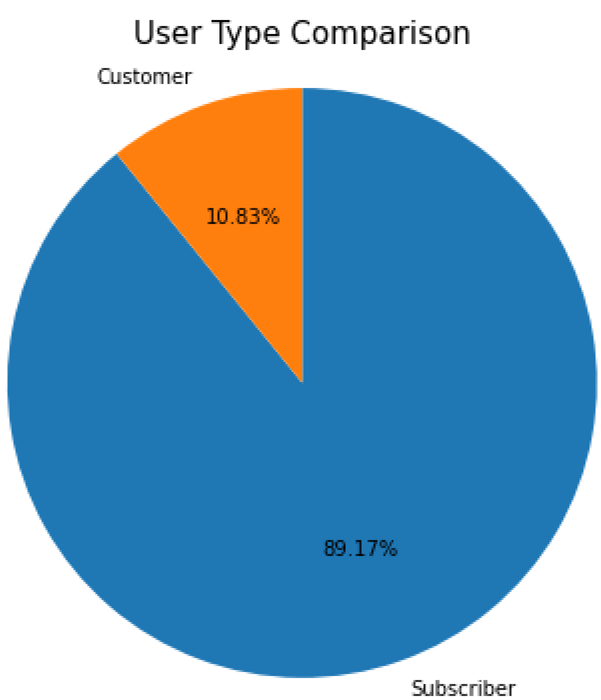
In [19]:

```
dist_user_types = column(10, 7, df.user_type.value_counts().keys(),  df.user_type.value_co
```



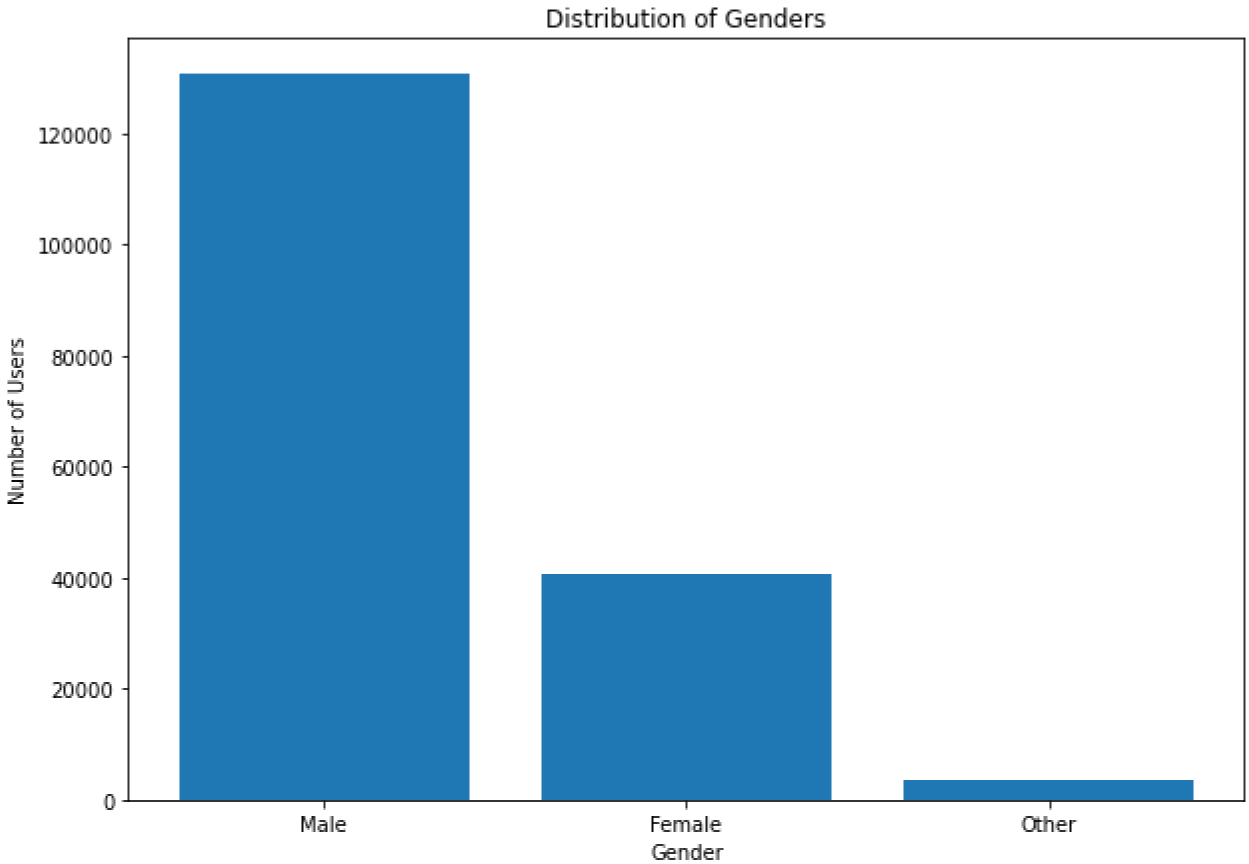
Subscribers make up the highest number of user types. To get the exact difference in percentage, a pie chart will be plotted below.

In [20]:
```
#by percentage
plt.figure(figsize=(10,6))
sorted_counts = df['user_type'].value_counts()
plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90,
        counterclock = False, autopct='%1.2f%%');
plt.axis('square')
plt.title('User Type Comparison', fontsize=15);
```



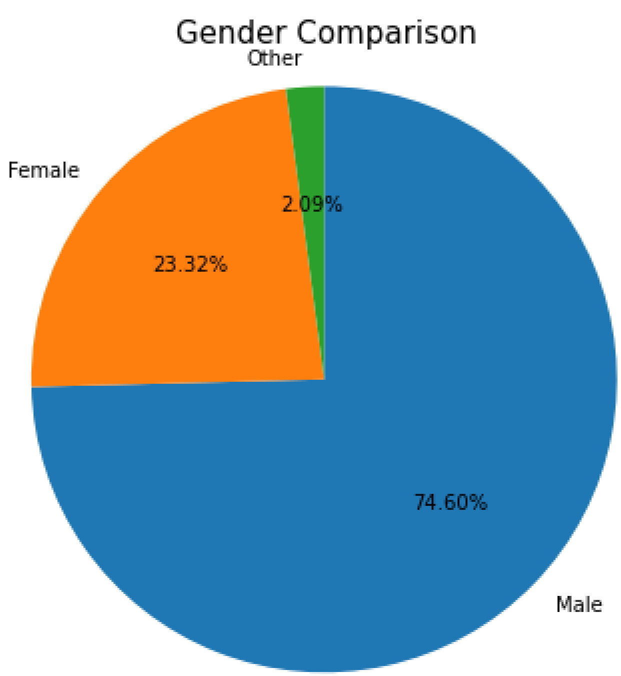
User type subscriber makes 89% of all users

In [21]:
```
dist_genders = column(10, 7, df.member_gender.value_counts().keys(),  df.member_gender.val
```



Male is the most common gender of bike share users. More details will be gotten from the pie chart below.

In [22]:
```
#by percentage
plt.figure(figsize=(10,6))
sorted_counts = df['member_gender'].value_counts()
plt.pie(sorted_counts, labels = sorted_counts.index, startangle = 90,
        counterclock = False, autopct='%1.2f%%');
plt.axis('square')
plt.title('Gender Comparison', fontsize=15);
```



Male is the most common gender making 74.60% of users, females make up 23.32% while other gender make up 2.09%

Exploring by dates

In [23]:
```
df['hour'] = df['start_time'].dt.hour
df['start_day'] = df['start_time'].dt.day_name()
df['month'] = df['start_time'].dt.month_name()

df.head()
```

Out[23]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	end_station_id	end_statio
0	52185	2019-02-28 17:32:10.145	2019-03-01 08:01:55.975	21.0	Montgomery St BART Station (Market St at 2nd St)	13.0	Commerc Montgo
1	42521	2019-02-28 18:53:21.789	2019-03-01 06:42:03.056	23.0	The Embarcadero at Steuart St	81.0	Berry St a
2	61854	2019-02-28 12:13:13.218	2019-03-01 05:24:08.146	86.0	Market St at Dolores St	3.0	Powell Station (M a
3	36490	2019-02-28 17:54:26.010	2019-03-01 04:02:36.842	375.0	Grove St at Masonic Ave	70.0	Central Av
4	1585	2019-02-28 23:54:18.549	2019-03-01 00:20:44.074	7.0	Frank H Ogawa Plaza	222.0	10th Ave a

In [24]:
```
print(df['start_time'].min())
print(df['start_time'].max())
print(df['month'].value_counts())
```

```
2019-02-01 00:00:20.636000
2019-02-28 23:59:18.548000
February    183412
Name: month, dtype: int64
```

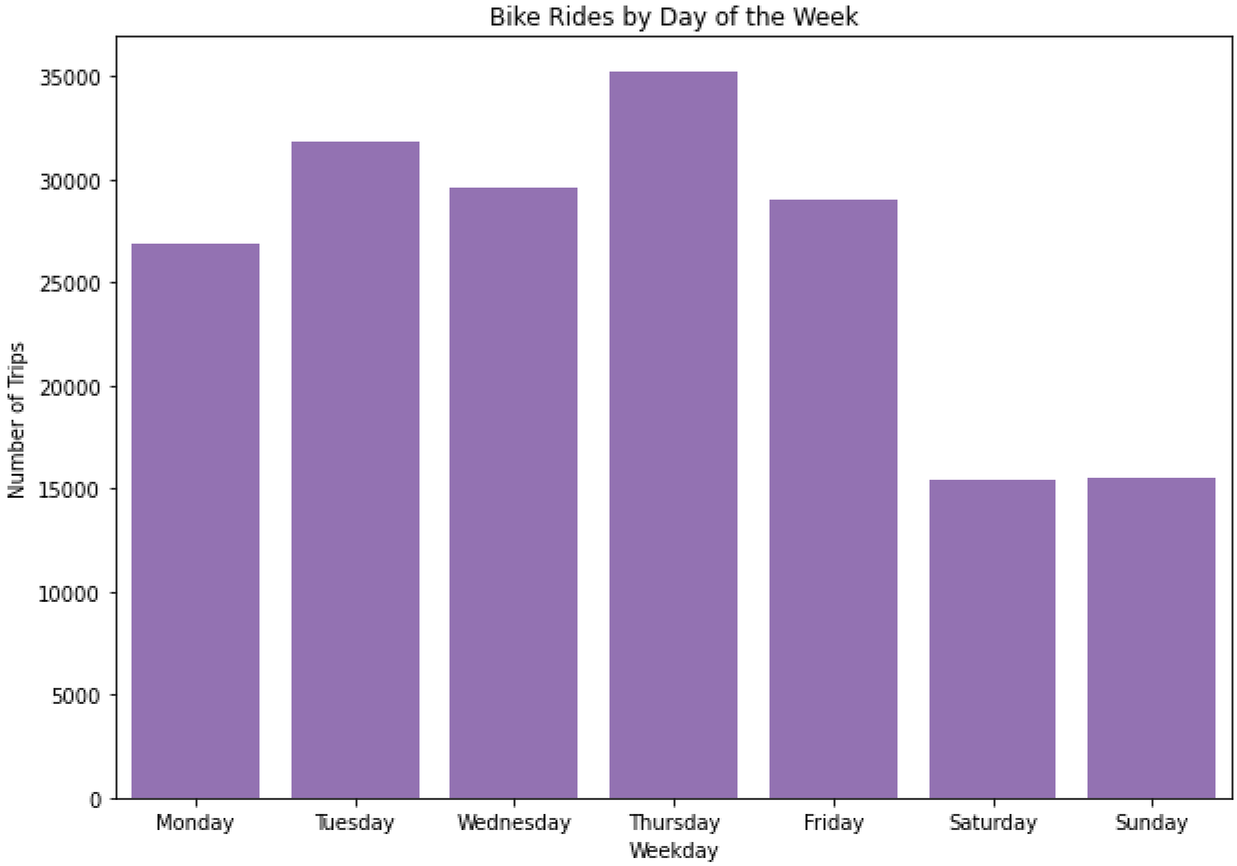
All bike rides were made in February 2019 (1st to 28th)

By Weekday

In [25]:
```
df['start_day'].value_counts()
```

Out[25]:
```
Thursday     35197
Tuesday      31813
Wednesday    29641
Friday       28981
Monday       26852
Sunday       15523
Saturday     15405
Name: start_day, dtype: int64
```

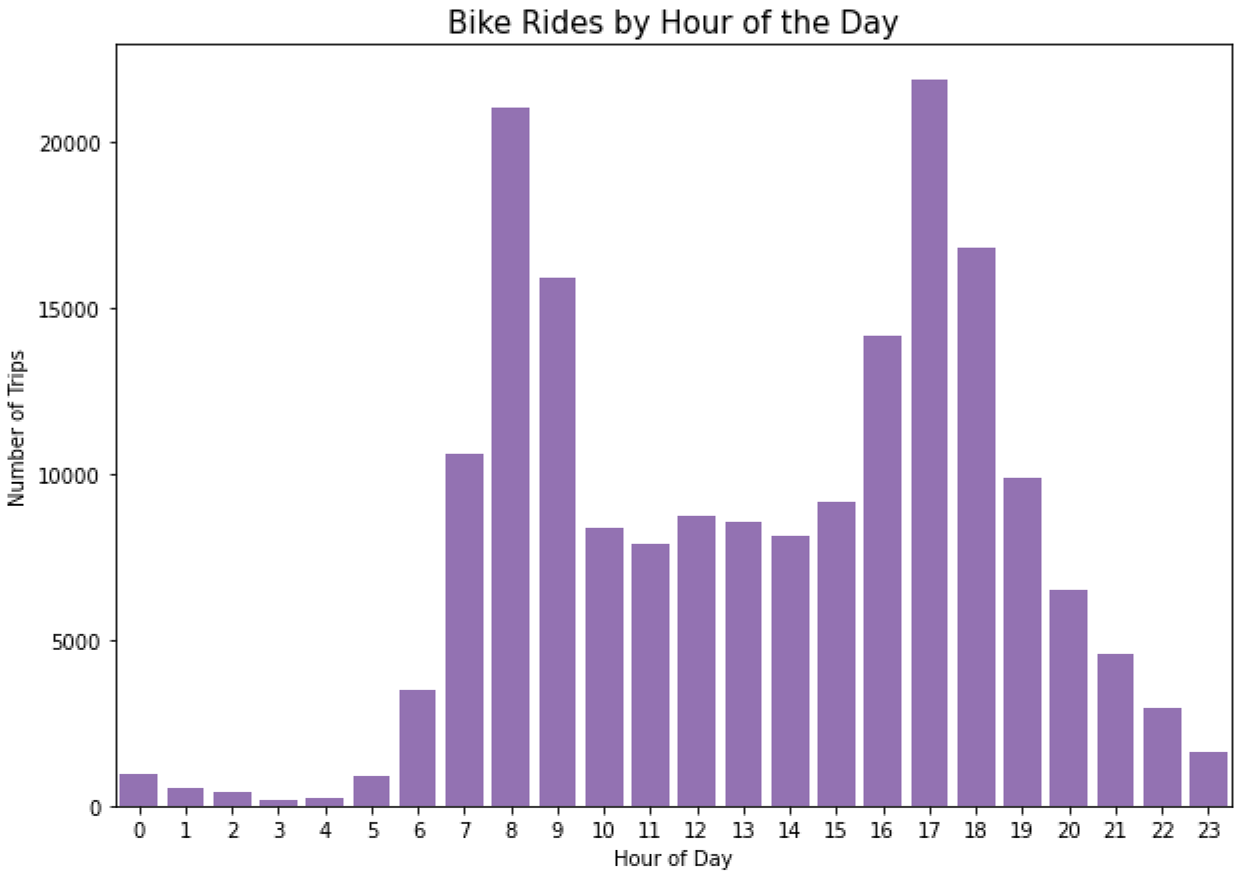
In [26]:
```
base_color = sns.color_palette()[4]

day_labels = ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday']

plt.figure(figsize = (10,7))
plt.title('Bike Rides by Day of the Week')
sns.countplot(data = df, x = 'start_day', order = day_labels, color = base_color)
plt.xlabel('Weekday')
plt.ylabel('Number of Trips');
```



Thursday is the weekday with the highest number of trips. We see that weekdays generally have more trips than the weeekends.

In [27]:

```
order_hour = np.arange(0,24)

plt.figure(figsize = (10,7))
plt.title('Bike Rides by Hour of the Day', fontsize=15)
ax = sns.countplot(data = df, x = 'hour', order = order_hour, color = base_color)
plt.ylabel('Number of Trips')
plt.xlabel('Hour of Day');
```

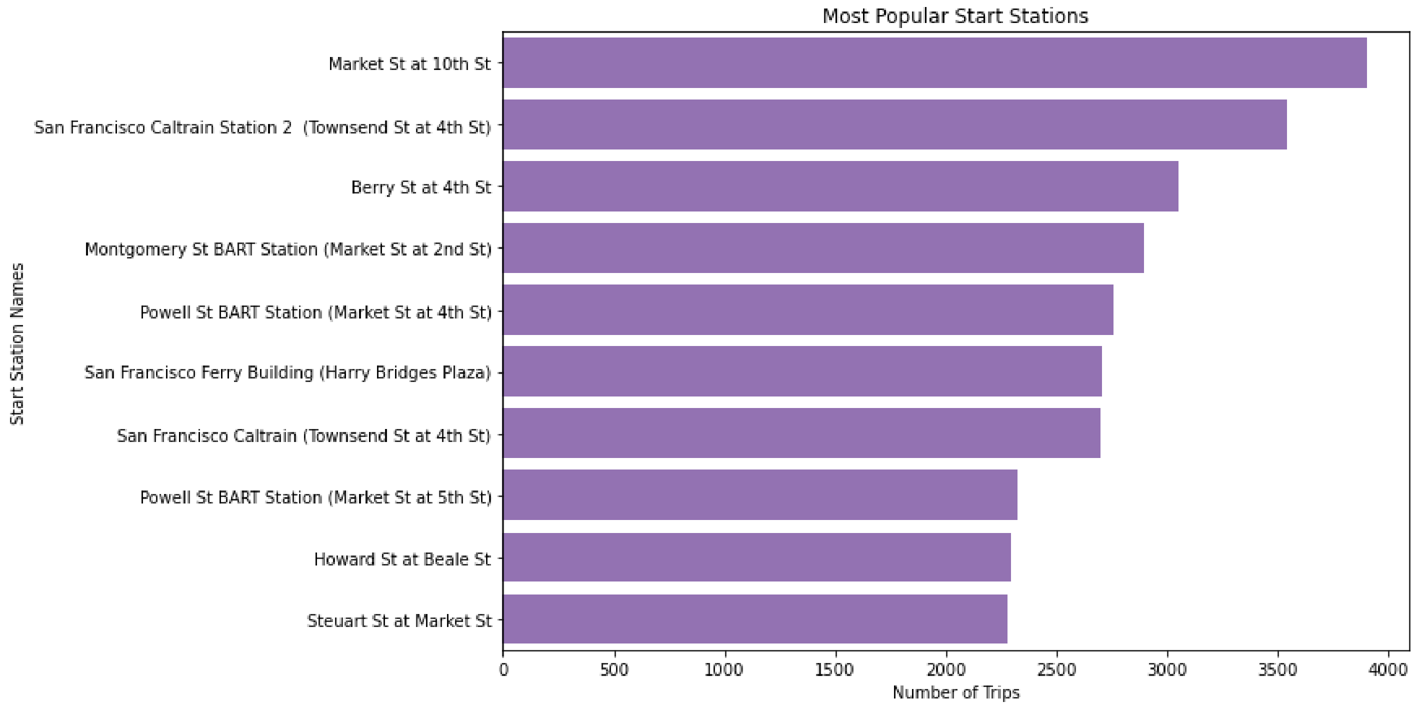


We see more rides occuring at typical peak hours (0800 hours and 1700 hours). Generally, most rides are taken between 0700 hours and 1900 hours.

Exploring Station names

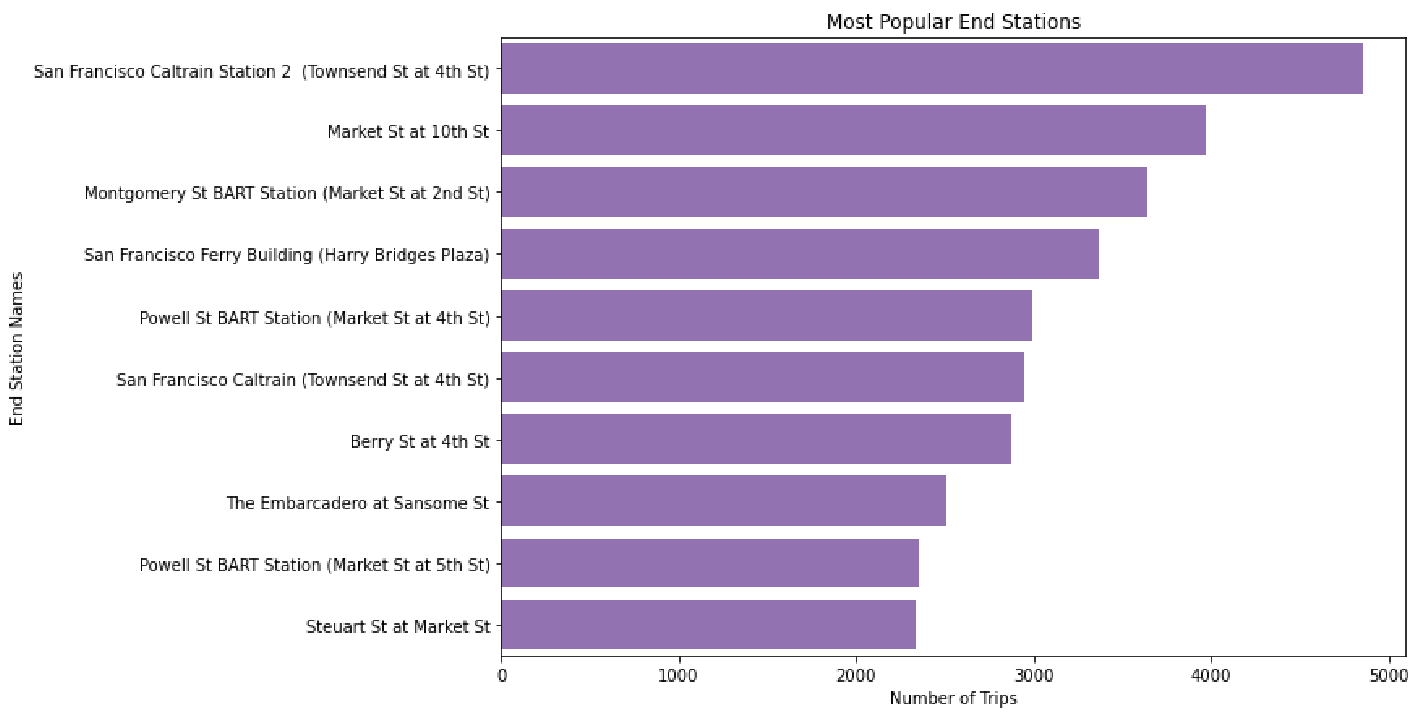
In [28]:
```
#start station names

def stat(name, a, b, d, yname, xlabel, ylabel, title):
    order_stat = df[name].value_counts().index[:10]
    plt.figure(figsize=[a,b])
    sns.countplot(data = d, y = yname, color = base_color, order = order_stat);
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title);
```

In [29]:
```
mst_pop_start = stat('start_station_name', 10, 7, df, 'start_station_name', 'Number of Tri
```



Market St at 10th St is the start station with the the highest number of trips.

In [30]:
```
mst_pop_end = stat('end_station_name', 10, 7, df, 'end_station_name', 'Number of Trips', '
```



SanFrancisco Caltrain Station 2 (Townsend St at 4th St) is the end station with the highest number of trips.

Compare most popular station from both start and end stations

In [31]:
```
 start = df.start_station_name.value_counts(ascending=False).head(10)
end = df.end_station_name.value_counts(ascending=False).head(10)

# checking for popularity in both start and end stations
for s in start.index:
    if s in end:
        print(s)
```

```
Market St at 10th St
```

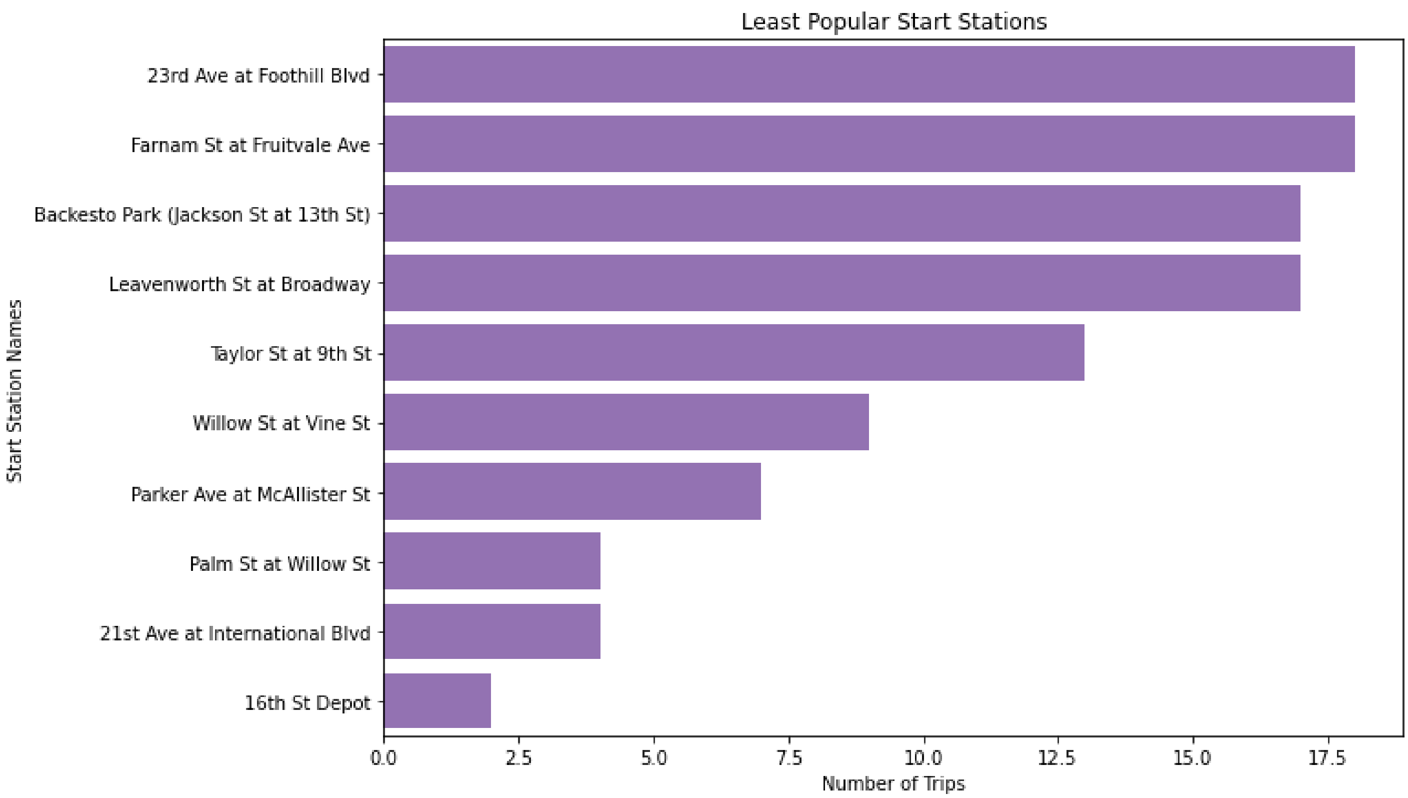
```
San Francisco Caltrain Station 2  (Townsend St at 4th St)
Berry St at 4th St
Montgomery St BART Station (Market St at 2nd St)
Powell St BART Station (Market St at 4th St)
San Francisco Ferry Building (Harry Bridges Plaza)
San Francisco Caltrain (Townsend St at 4th St)
Powell St BART Station (Market St at 5th St)
Steuart St at Market St
```

In [32]:

```
def stati(name, a, b, d, yname, xlabel, ylabel, title):
    order_stat = df[name].value_counts().index[-10:]
    plt.figure(figsize=[a,b])
    sns.countplot(data = d, y = yname, color = base_color, order = order_stat);
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title(title);
```

In [33]:

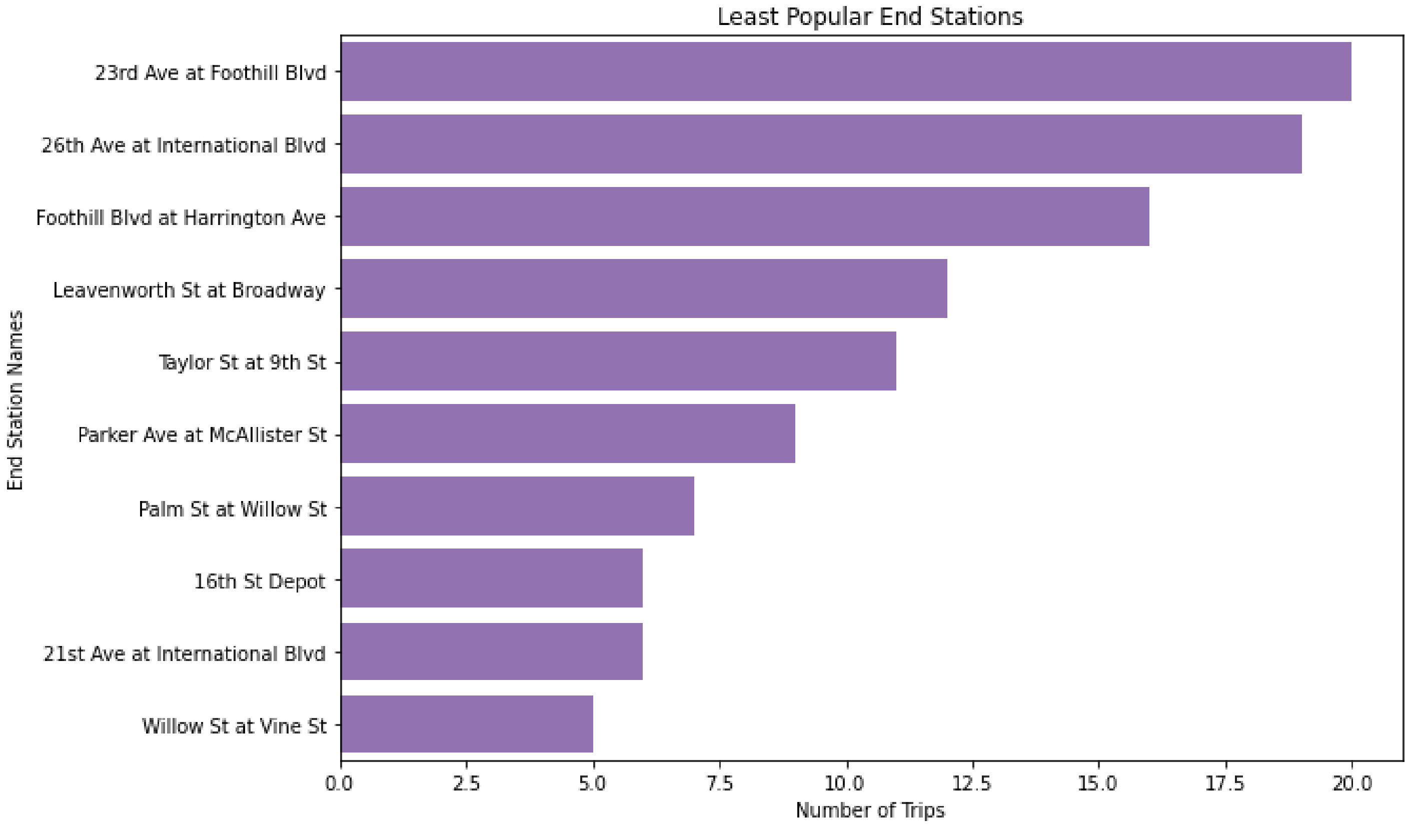
```
lst_pop_start = stati('start_station_name', 10, 7, df, 'start_station_name', 'Number of Tr
```



23rd Avenue at Foothill Blvd is the least popular start station

In [34]:

```
lst_pop_end = stati('end_station_name', 10, 7, df, 'end_station_name', 'Number of Trips',
```



23rd Avenue at Foothill Blvd is also the least popular end station

Compare least popular stations from both start and end stations

In [35]:

```
start = df.start_station_name.value_counts(ascending=False).tail(10)
end = df.end_station_name.value_counts(ascending=False).tail(10)

# checking for popularity in both start and end stations
for s in start.index:
    if s in end:
        print(s)
```

```
23rd Ave at Foothill Blvd
Leavenworth St at Broadway
Taylor St at 9th St
Willow St at Vine St
Parker Ave at McAllister St
Palm St at Willow St
21st Ave at International Blvd
16th St Depot
```

In [36]:

```
# Age distribution from member's birth year.
df['member_age'] = 2019 - df['member_birth_year']

df.head()
```

Out[36]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	end_station_id	end_statio
0	52185	2019-02-28 17:32:10.145	2019-03-01 08:01:55.975	21.0	Montgomery St BART Station (Market St at 2nd St)	13.0	Commerc Montgo
1	42521	2019-02-28 18:53:21.789	2019-03-01 06:42:03.056	23.0	The Embarcadero at Steuart St	81.0	Berry St a

	duration_sec	start_time	end_time	start_station_id	start_station_name	end_station_id	end_statio
2	61854	2019-02-28 12:13:13.218	2019-03-01 05:24:08.146	86.0	Market St at Dolores St	3.0	Powell Station (M a
3	36490	2019-02-28 17:54:26.010	2019-03-01 04:02:36.842	375.0	Grove St at Masonic Ave	70.0	Central Av
4	1585	2019-02-28 23:54:18.549	2019-03-01 00:20:44.074	7.0	Frank H Ogawa Plaza	222.0	10th Ave a

In [37]:

```
df.member_age.min()
```

Out[37]:

```
18.0
```

In [38]:

```
df.member_age.max()
```

Out[38]:

```
141.0
```

In [39]:

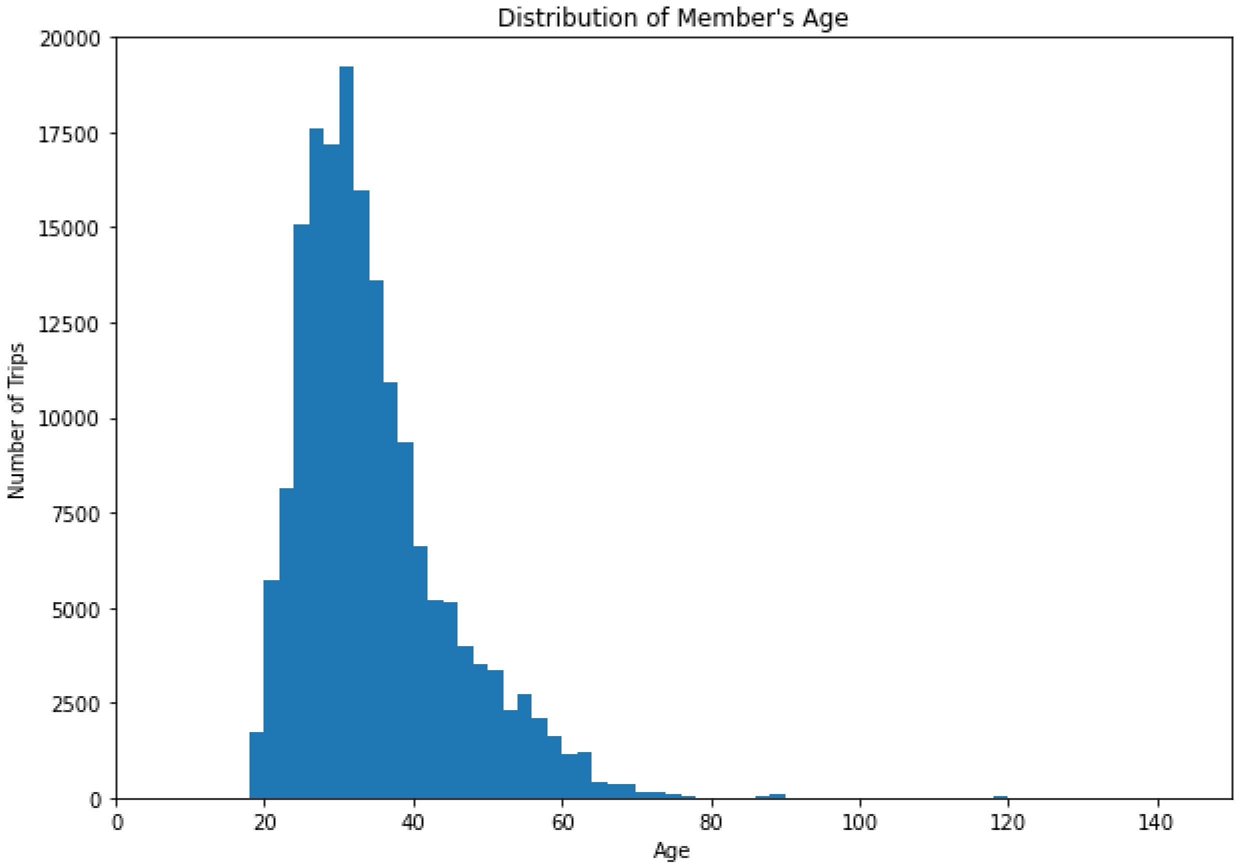
```
df.member_age.describe()
```

Out[39]:

```
count    175147.000000
mean         34.193563
std          10.116689
min          18.000000
25%          27.000000
50%          32.000000
75%          39.000000
max         141.000000
Name: member_age, dtype: float64
```

In [40]:

```
binsize = 2
bins = np.arange(0, df['member_age'].max()+binsize, binsize)

plt.figure(figsize=[10, 7])
plt.hist(data = df, x = 'member_age', bins = bins)
plt.title("Distribution of Member's Age")
plt.xlabel('Age')
plt.ylabel('Number of Trips')
plt.axis([0, 150, 0, 20000])
plt.show()
```



Member's ages ranges between 18 and 140 years. Peak age of members is located at age 32 and most members fall between ages 18 and 60 years.

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

Most trips fall between 0 and 2000 seconds. Peak point of trip was around 600 and 700 seconds. I transformes it to a log scale to get more granular details.

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?

Before investigating, I had to fix some quality issues to ensure that all datatypes were in order. To explore dates and member's age, I had to derive some columns from the available columns in the dataset to get more infromation.

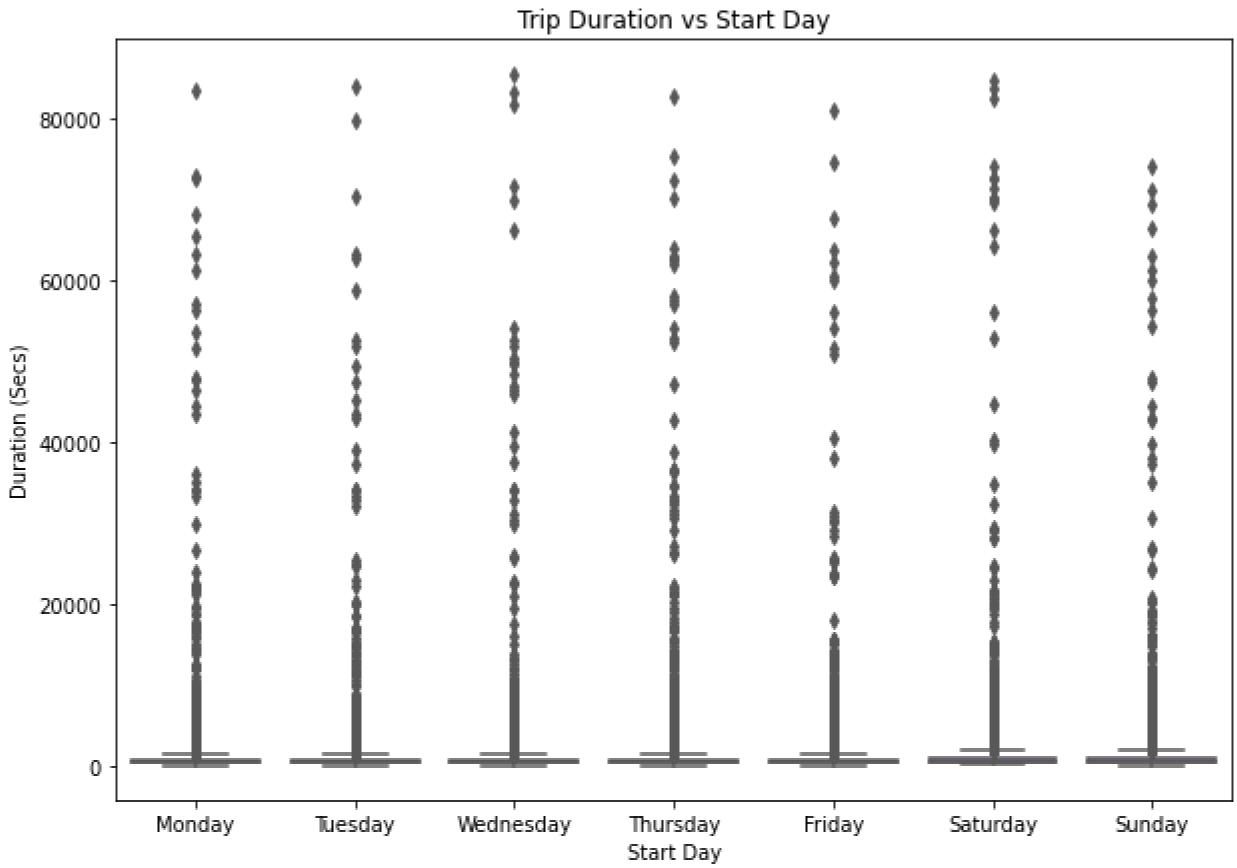
Bivariate Exploration

In this section, investigate relationships between pairs of variables in your data. Make sure the variables that you cover here have been introduced in some fashion in the previous section (univariate exploration).

Duration and day of the week

In [41]:

```
plt.figure(figsize = [10, 7])
sns.boxplot(data = df, x = 'start_day', y = 'duration_sec', color = base_color, order = da
plt.title('Trip Duration vs Start Day')
plt.xlabel('Start Day')
plt.ylabel('Duration (Secs)')
plt.show()
```

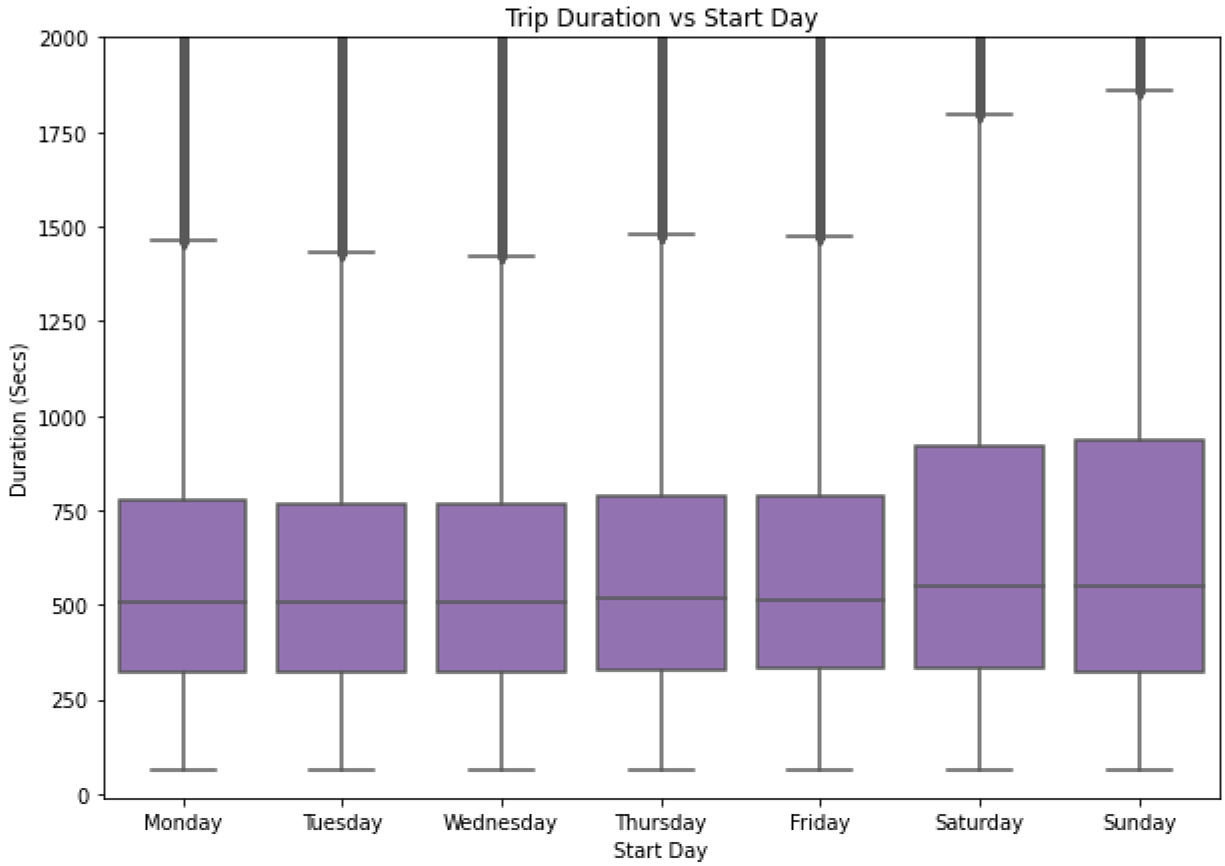


Returned plot has too many widespread values. To get more details, I'll limit the visualization to the concentration of values (0 - 2000 seconds)

Duration and User Type

In [42]:

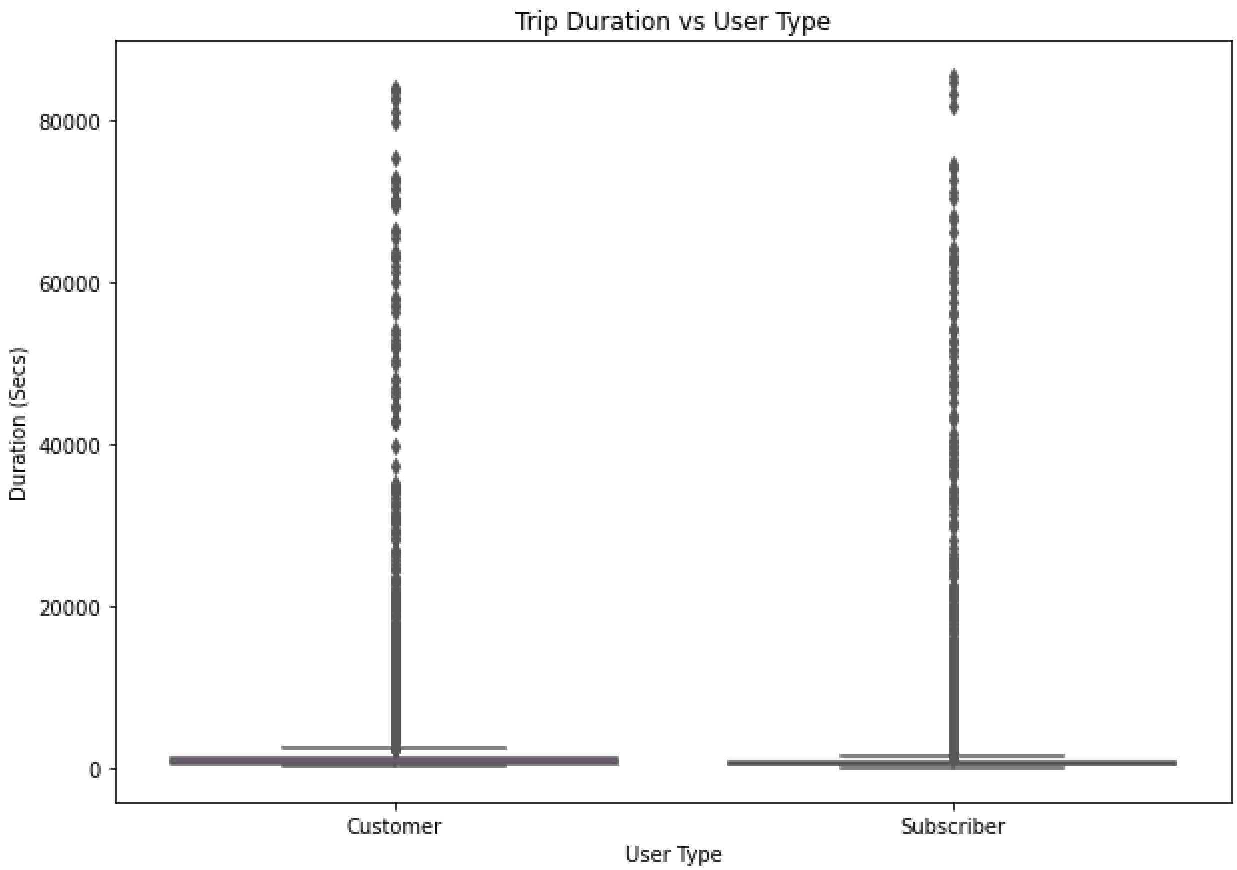
```
plt.figure(figsize = [10, 7])
sns.boxplot(data = df, x = 'start_day', y = 'duration_sec', color = base_color, order = da
plt.ylim([-10, 2000])
plt.title('Trip Duration vs Start Day')
plt.xlabel('Start Day')
plt.ylabel('Duration (Secs)')
plt.show()
```



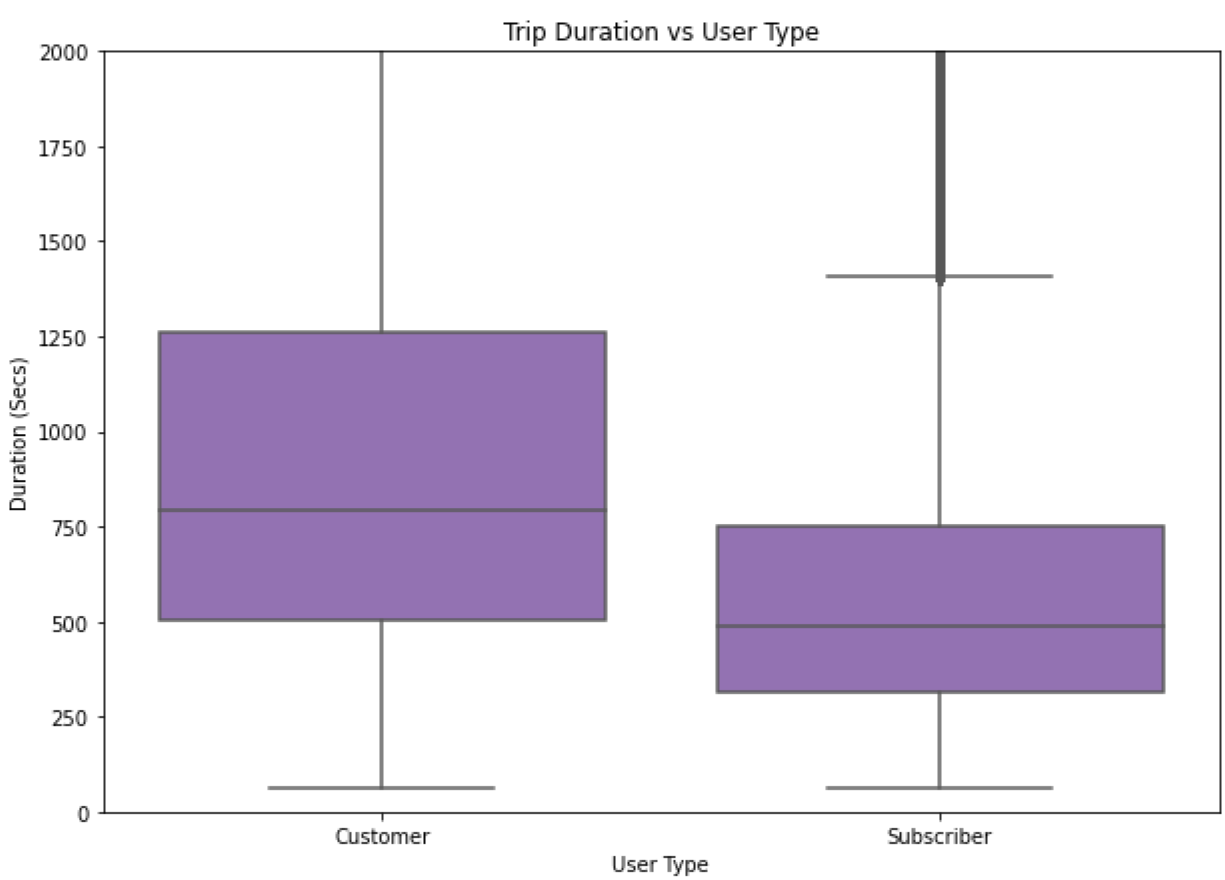
Despite lesser rides on Saturdays and Sundays, we see higher trip durations on the weekends.

In [43]:

```
plt.figure(figsize = [10, 7])
sns.boxplot(data = df, x = 'user_type', y = 'duration_sec', color = base_color)
plt.title('Trip Duration vs User Type')
plt.xlabel('User Type')
plt.ylabel('Duration (Secs)')
plt.show()
```



In [44]:
```
plt.figure(figsize = [10, 7])
sns.boxplot(data = df, x = 'user_type', y = 'duration_sec', color = base_color)
plt.ylim([0, 2000])
plt.title('Trip Duration vs User Type')
plt.xlabel('User Type')
plt.ylabel('Duration (Secs)')
plt.show()
```

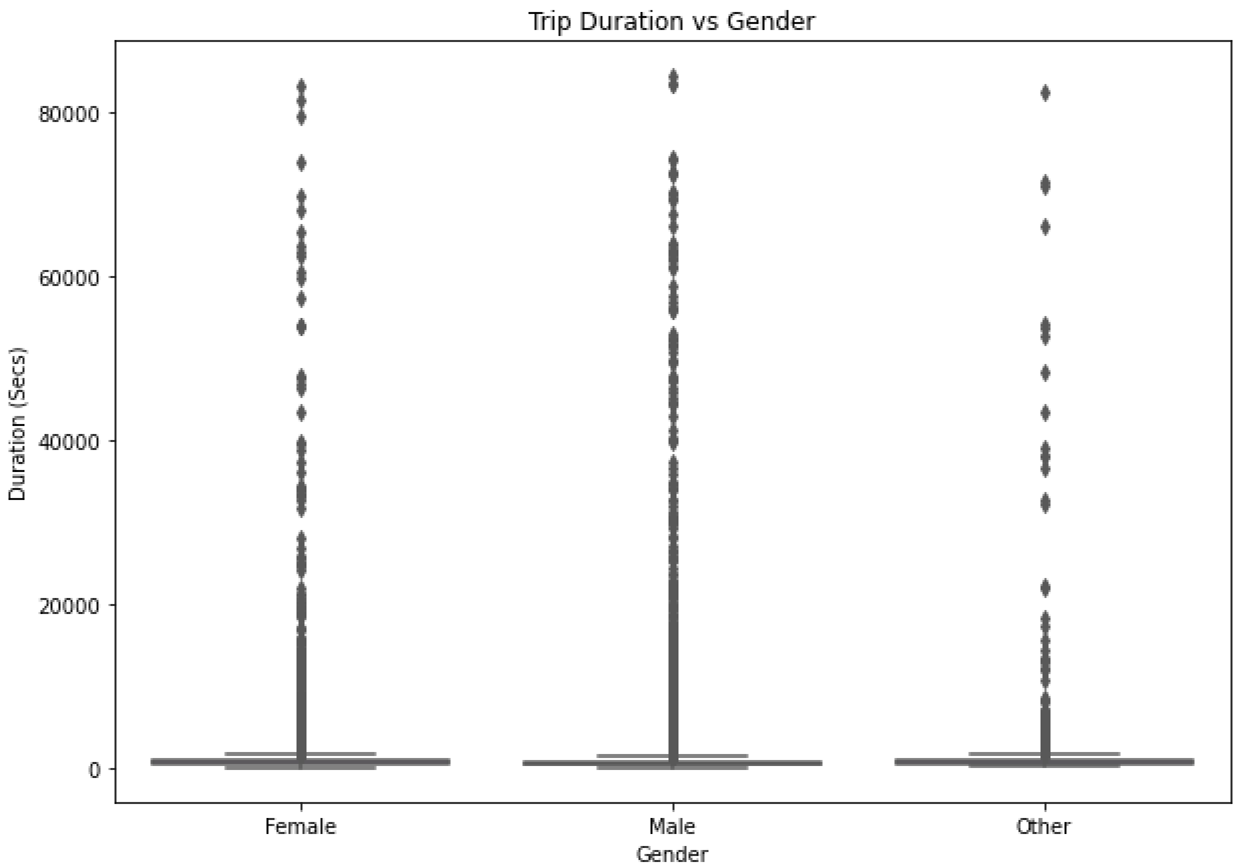


Duration of customer's rides is generally higher than that of subscribers

Duration and Gender

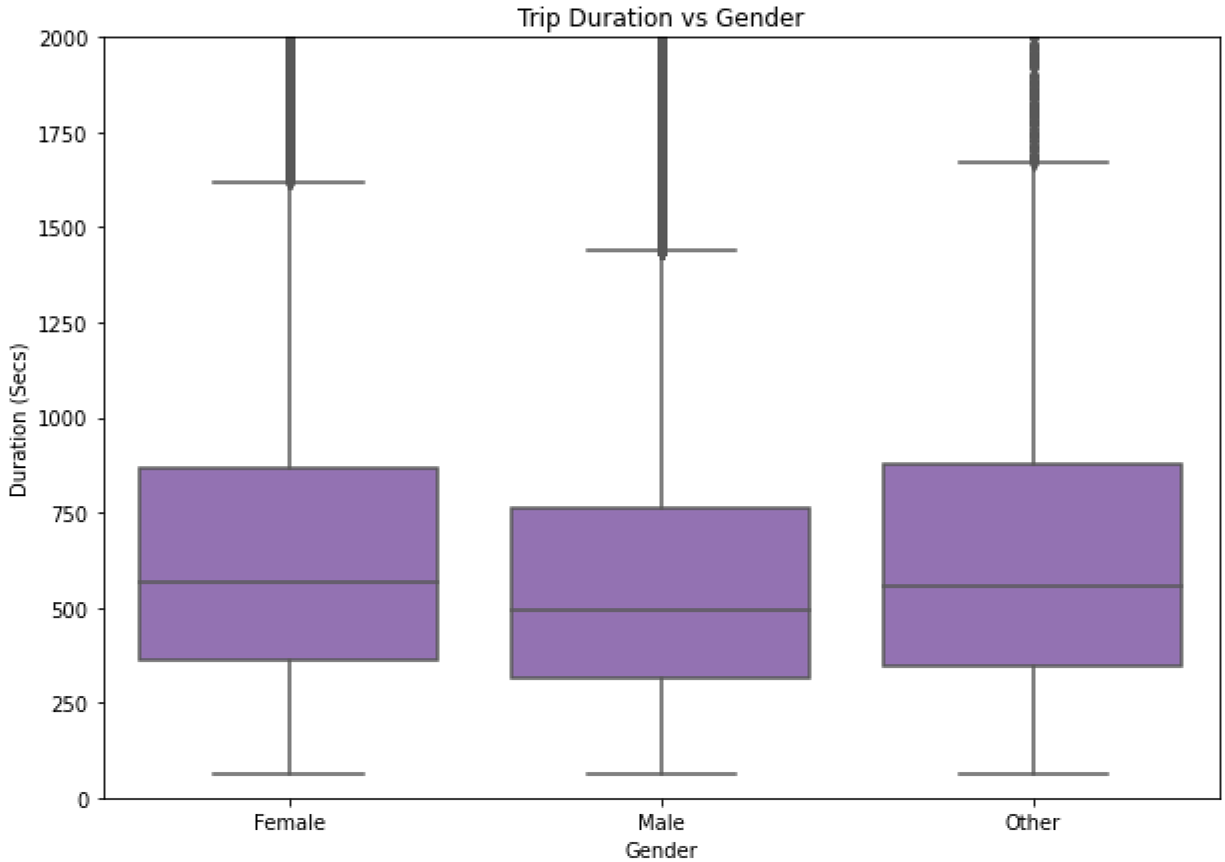
In [45]:

```
plt.figure(figsize = [10, 7])
sns.boxplot(data = df, x = 'member_gender', y = 'duration_sec', color = base_color)
plt.title('Trip Duration vs Gender')
plt.xlabel('Gender')
plt.ylabel('Duration (Secs)')
plt.show()
```



In [46]:

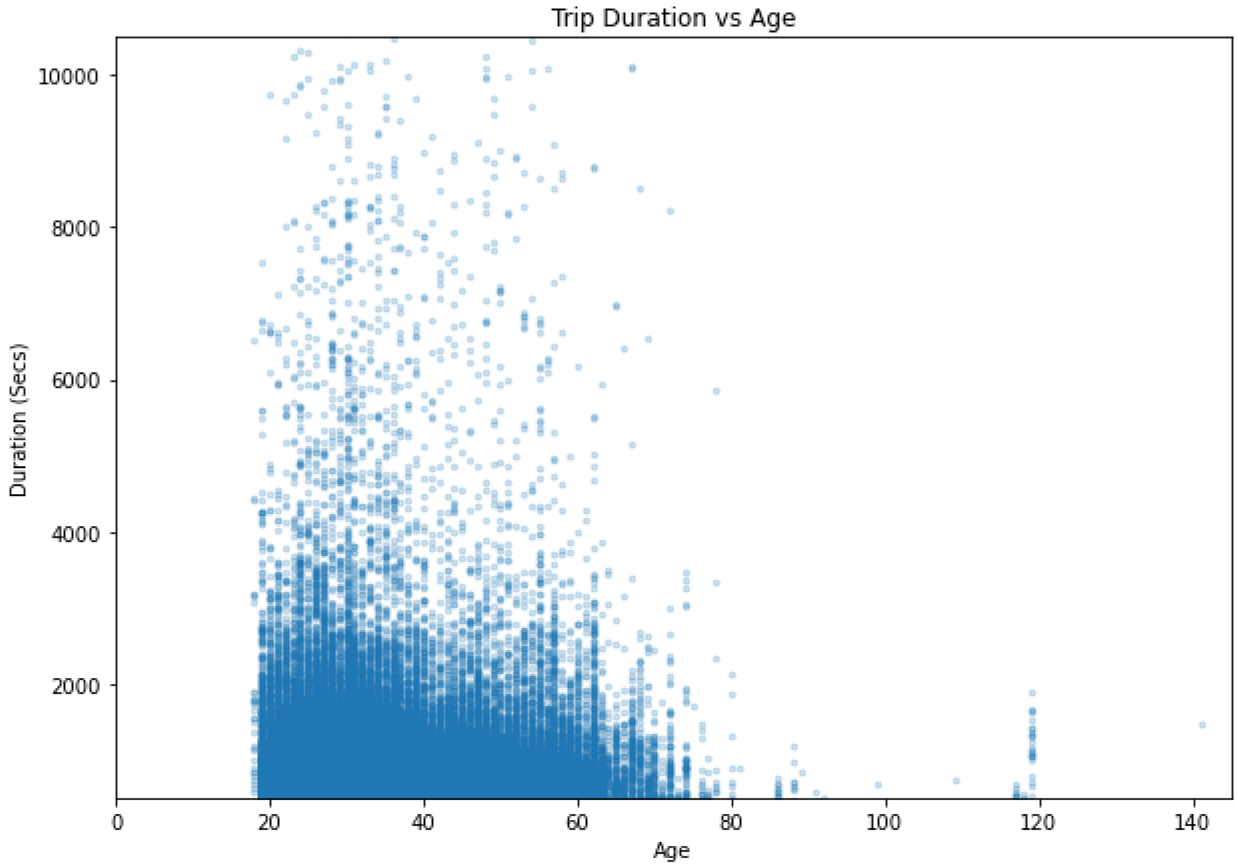
```
plt.figure(figsize = [10, 7])
sns.boxplot(data = df, x = 'member_gender', y = 'duration_sec', color = base_color)
plt.ylim([0, 2000])
plt.title('Trip Duration vs Gender')
plt.xlabel('Gender')
plt.ylabel('Duration (Secs)')
plt.show()
```



Female and other gender have higher duration times than male.

Duration and Age

In [47]:
```
plt.figure(figsize=[10,7])
plt.scatter(df['member_age'], df['duration_sec'], alpha = 0.2, marker = '.' )
plt.axis([0, 145, 500, 10500])
plt.title('Trip Duration vs Age')
plt.xlabel('Age')
plt.ylabel('Duration (Secs)')
plt.show()
```

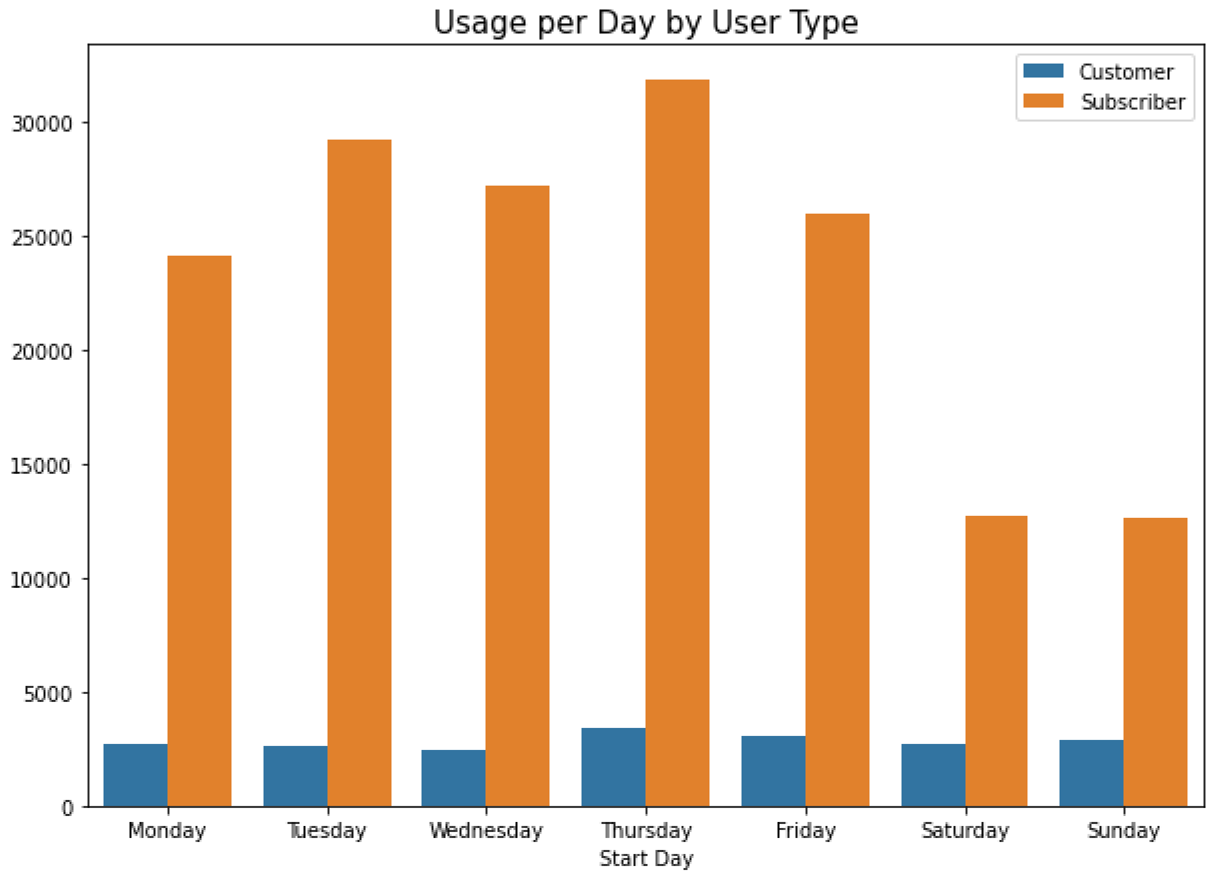


A large concentration of riders are aged between 18 and 70 years with most having trip duration between 0 and 2000 seconds. From the plot, we can see that as age increases more riders have less trip durations.

Usage by User Type

In [48]:

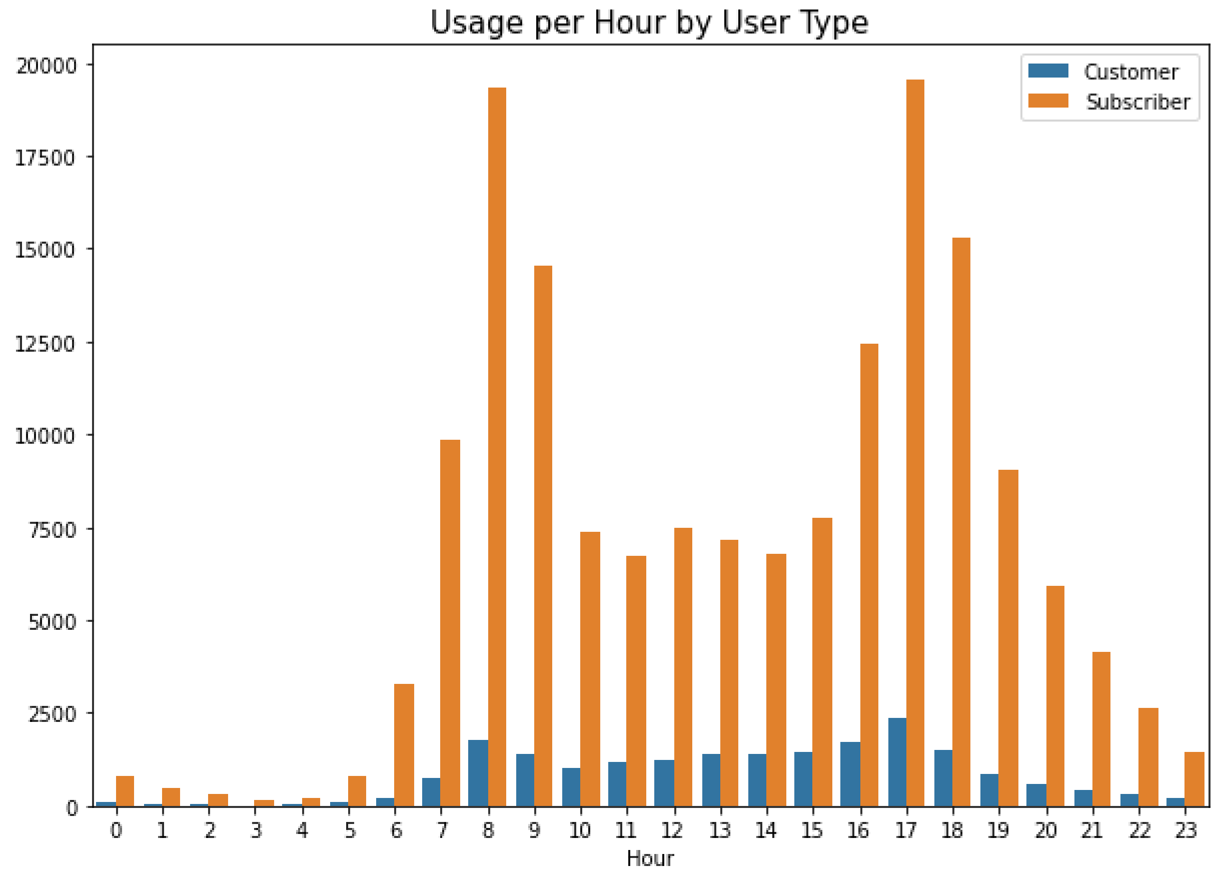
```
plt.figure(figsize=(10,7))
plt.title('Usage per Day by User Type', fontsize=15)
chart = sns.countplot(data=df, x='start_day', order=day_labels, hue='user_type')

chart.set(xlabel='Start Day', ylabel = '')

# Remove title of legend
plt.gca().legend().set_title('');
```



Both customers and subscribers have highest number of rides on Thursday. For suscribers, less rides are taken during the weekend.

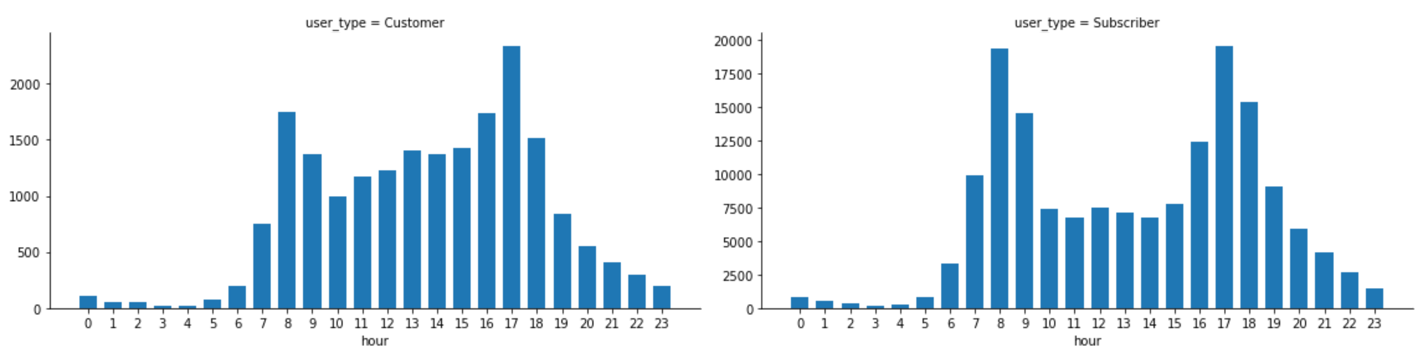
In [49]:

```
plt.figure(figsize=(10,7))
plt.title('Usage per Hour by User Type', fontsize=15)
chart = sns.countplot(data=df, x='hour', order = order_hour, hue='user_type')

chart.set(xlabel='Hour', ylabel = '')

# Remove title of legend
plt.gca().legend().set_title('');
```



Both customers and subscribers have their highest number of rides at peak hours

In [50]:
```
# facetting histograms of start_hour against user_type
bin_edges = np.arange(-0.5, 23.5+1, 1)
g = sns.FacetGrid(data = df, col = 'user_type', height=4, aspect=2, sharey=False)
g.map(plt.hist, "hour", bins = bin_edges, rwidth = 0.7);
plt.xticks(np.arange(0, 23+1, 1));
```



Facetting was sone to further break down customers and subsribers and same results were observed.

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?

Trip duration and age have a negative relationship. Males tend to have less trip duration than females and others, subscribers tend to have less duration than customers.

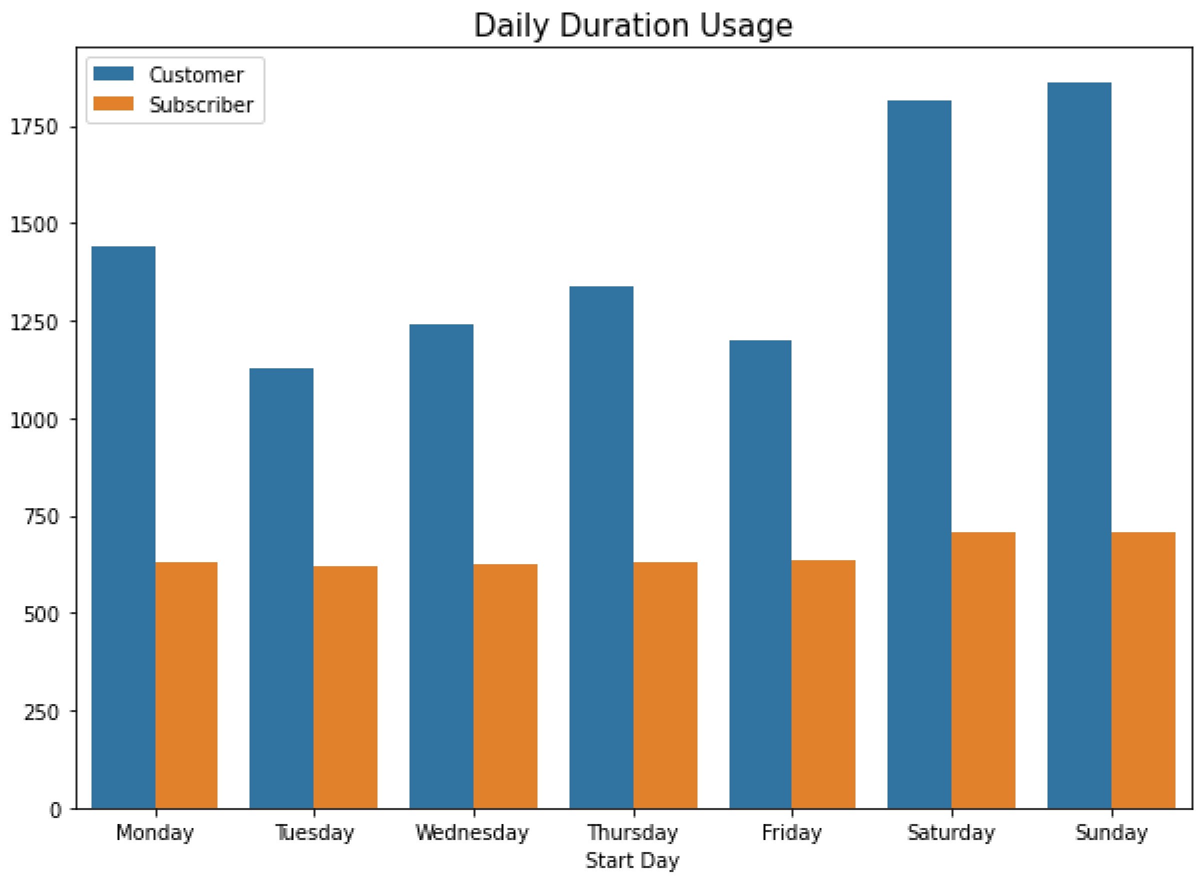
Did you observe any interesting relationships between the other features (not the main feature(s) of interest)?

It was interesting to see that Saturday and Sunday had the highest trip durations across week days despite being the days with the least number of trips.

Multivariate Exploration

In [51]:

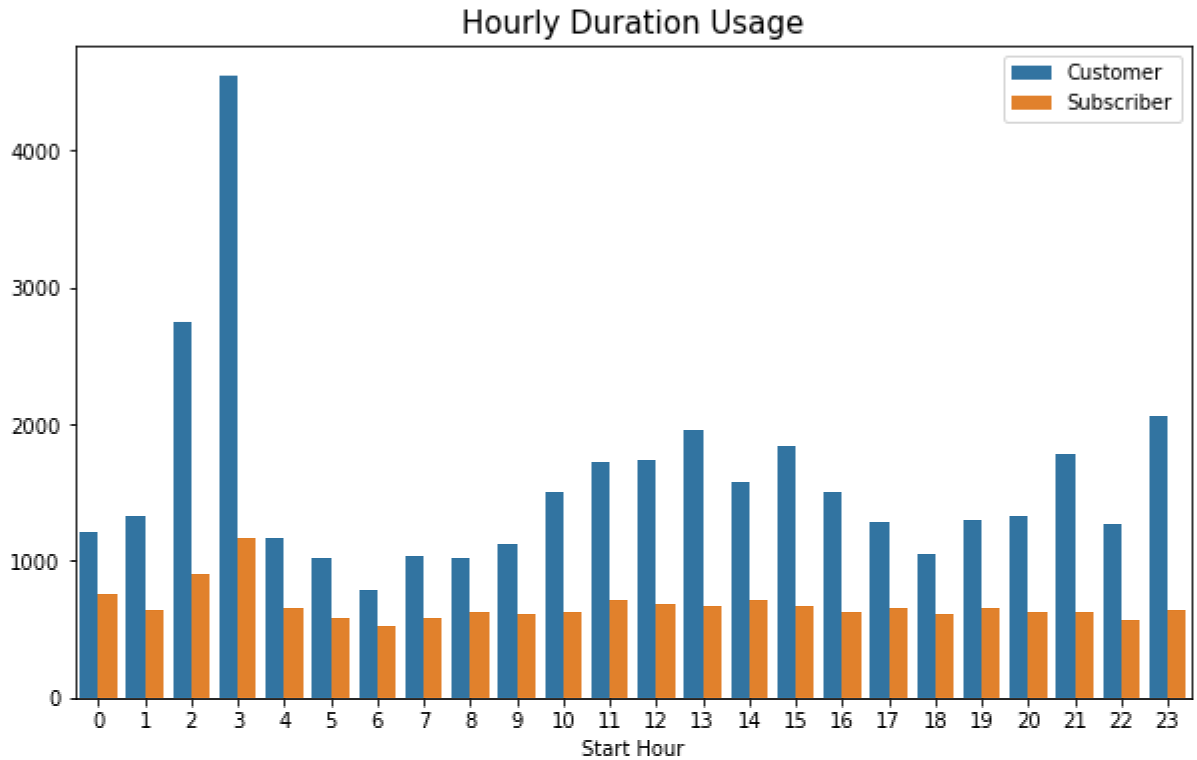
```
plt.figure(figsize=(10,7))
plt.title('Daily Duration Usage', fontsize=15)
chart = sns.barplot(data=df, x='start_day', y='duration_sec', order=day_labels, hue='user_

chart.set(xlabel='Start Day', ylabel='')

# Remove legend title
plt.gca().legend().set_title('');
```



Customers used this service on weekdays and weekends for longer durations. We see an almost steady pattern in duration for subscribers. This is interesting seeing as we have more subscribers than customers.

In [52]:

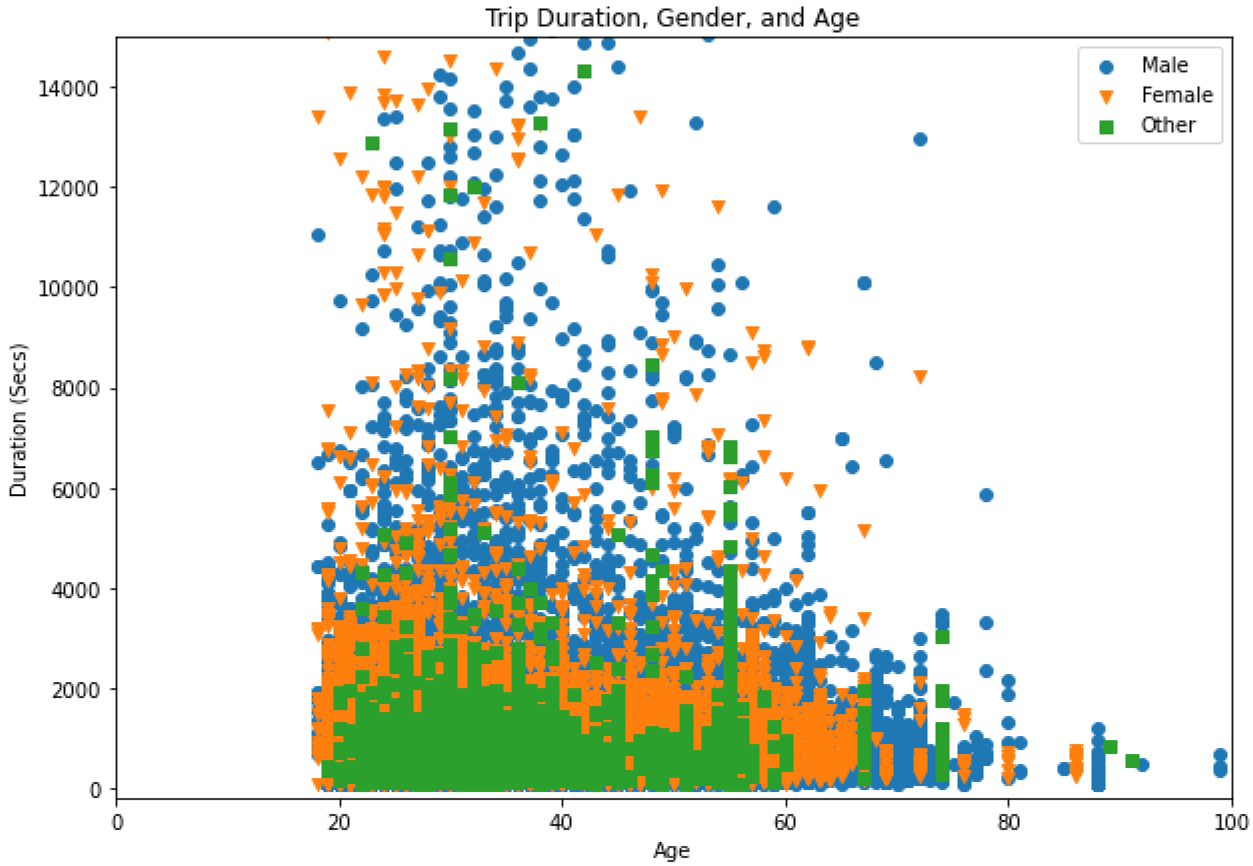
```
plt.figure(figsize=(10,6))
plt.title('Hourly Duration Usage', fontsize=15)
chart = sns.barplot(data=df, x='hour', y='duration_sec', hue='user_type', ci=None)

chart.set(xlabel='Start Hour', ylabel='')

# Remove legend title
plt.gca().legend().set_title('');
```



Per hours, subscribers also generally have a longer duration. It's quite interesting however that 2am and 3am have the highest duration times for both customers and subscribers.

In [53]:

```
shapes = [['Male', 'o'],['Female', 'v'],['Other', 's']]
plt.figure(figsize=(10,7))
for gender, shape in shapes:
    df_gender = df[df['member_gender'] == gender]
    plt.scatter(df_gender['member_age'], df_gender['duration_sec'], marker = shape, alpha=
plt.legend(['Male','Female','Other'])
plt.axis([0, 100, -200, 15000 ])
plt.title('Trip Duration, Gender, and Age')
plt.xlabel('Age')
plt.ylabel('Duration (Secs)')
plt.show()
```



All three genders show similar relationship per age and duration

In [ ]: