Ford Gobike Data Exploration

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Preliminary Wrangling

This document explores a dataset containing the trip data of the fordgo bike.

In [1]:
```
# Run this cell if you encounter errors with seaborn later on
#!pip install --upgrade seaborn
```

In [2]:
```
import os
import requests
import csv
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt

import warnings
warnings.simplefilter("ignore")

%matplotlib inline
```

In [3]:
```
ford_gobike_url = 'https://video.udacity-data.com/topher/2020/October/5f91cf38_201902-ford

# Checking to make sure the file has not already been downloaded in a previous session
if not os.path.isfile('201902-fordgobike-tripdata.csv'):
    response = requests.get(ford_gobike_url, 'lxml')
    with open('201902-fordgobike-tripdata.csv', 'wb') as file:
        file.write(response.content)
```

In [4]:
```
df = pd.read_csv('201902-fordgobike-tripdata.csv')
df.head()
```

Out[4]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitude	start_station_l
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	-12
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	-12
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	-12
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	-12
4	1585	2019-02-28 23:54:18.5490	2019-03-01 00:20:44.0740	7.0	Frank H Ogawa Plaza	37.804562	-12

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
duration_sec               183412 non-null int64
start_time                 183412 non-null object
end_time                   183412 non-null object
start_station_id           183215 non-null float64
start_station_name         183215 non-null object
start_station_latitude     183412 non-null float64
start_station_longitude    183412 non-null float64
end_station_id             183215 non-null float64
end_station_name           183215 non-null object
end_station_latitude       183412 non-null float64
end_station_longitude      183412 non-null float64
bike_id                    183412 non-null int64
user_type                  183412 non-null object
member_birth_year          175147 non-null float64
member_gender              175147 non-null object
bike_share_for_all_trip    183412 non-null object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

In [6]:
```
#changing data type of start_time and end_time to datetime.
df.start_time = pd.to_datetime(df.start_time)
df.end_time = pd.to_datetime(df.end_time)
```

In [7]:
```
df.bike_share_for_all_trip = (df.bike_share_for_all_trip == 'Yes')
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
duration_sec               183412 non-null int64
start_time                 183412 non-null datetime64[ns]
end_time                   183412 non-null datetime64[ns]
start_station_id           183215 non-null float64
start_station_name         183215 non-null object
start_station_latitude     183412 non-null float64
start_station_longitude    183412 non-null float64
end_station_id             183215 non-null float64
end_station_name           183215 non-null object
end_station_latitude       183412 non-null float64
end_station_longitude      183412 non-null float64
bike_id                    183412 non-null int64
user_type                  183412 non-null object
member_birth_year          175147 non-null float64
member_gender              175147 non-null object
bike_share_for_all_trip    183412 non-null bool
dtypes: bool(1), datetime64[ns](2), float64(7), int64(2), object(4)
memory usage: 21.2+ MB
```

In [9]:
```
df.describe()
```

Out[9]:

	duration_sec	start_station_id	start_station_latitude	start_station_longitude	end_station_id	end_station_latitu
count	183412.000000	183215.000000	183412.000000	183412.000000	183215.000000	183412.000(
mean	726.078435	138.590427	37.771223	-122.352664	136.249123	37.7714

	duration_sec	start_station_id	start_station_latitude	start_station_longitude	end_station_id	end_station_latitu
std	1794.389780	111.778864	0.099581	0.117097	111.515131	0.0994
min	61.000000	3.000000	37.317298	-122.453704	3.000000	37.3172
25%	325.000000	47.000000	37.770083	-122.412408	44.000000	37.7704
50%	514.000000	104.000000	37.780760	-122.398285	100.000000	37.7810
75%	796.000000	239.000000	37.797280	-122.286533	235.000000	37.7973
max	85444.000000	398.000000	37.880222	-121.874119	398.000000	37.8802

What is the structure of your dataset?

There are 183,412 records with 16 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.

Out of the 16 features, 9 are numerical, 2 are datetime, 4 are object type and 1 is boolean.

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

I'm most interested in figuring out how the trip duration is dependent on the other features in this dataset.

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

I expect that trip duration will be dependent on the start and end stations since more crowded places should receive more rides so some stations should be taking longer times for their rides to end.
I also think user type, birth year and the time and day when the trip starts (start_time) should also affect trip duration.

In [10]:

```
def get_start_hour(timestamp_obj):
    return timestamp_obj.hour

df['start_hour'] = df.start_time.apply(get_start_hour)
```

```
hours = [i for i in range(24)]
cat_hours = pd.api.types.CategoricalDtype(categories = hours, ordered=True)
df.start_hour = df.start_hour.astype(cat_hours)
```

In [11]:

```
def get_start_day(timestamp_obj):
    return timestamp_obj.day_name()

df['start_day'] = df.start_time.apply(get_start_day)
days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
day_cat = pd.api.types.CategoricalDtype(categories = days, ordered = True)
df.start_day = df.start_day.astype(day_cat)
```

In [12]:

```
cols = ['duration_sec', 'start_station_id', 'end_station_id', 'member_birth_year', 'user_t
df[cols].head()
```

Out[12]:

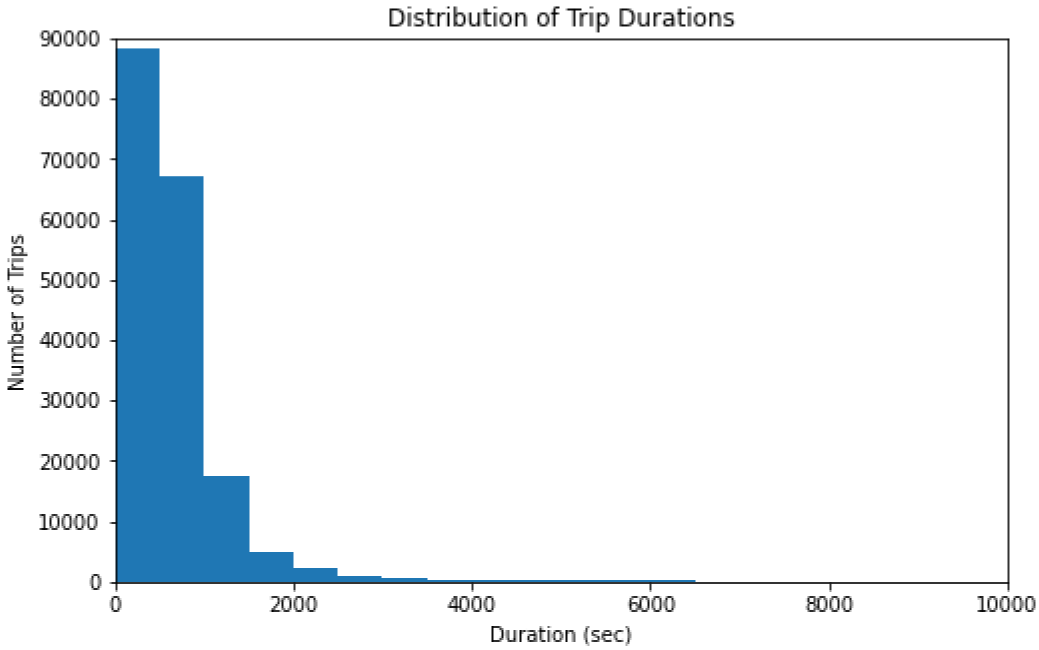
	duration_sec	start_station_id	end_station_id	member_birth_year	user_type	start_hour	start_day
0	52185	21.0	13.0	1984.0	Customer	17	Thursday
1	42521	23.0	81.0	NaN	Customer	18	Thursday
2	61854	86.0	3.0	1972.0	Customer	12	Thursday
3	36490	375.0	70.0	1989.0	Subscriber	17	Thursday
4	1585	7.0	222.0	1974.0	Subscriber	23	Thursday

Univariate Exploration

I'll start by looking at the distribution of the main variable of interest: duration_sec.

In [13]:

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

plt.figure(figsize=[8, 5])
plt.hist(data = df, x = 'duration_sec', bins = bins)
plt.title('Distribution of Trip Durations')
plt.xlabel('Duration (sec)')
plt.ylabel('Number of Trips')
plt.xlim(left = 0, right = 10000)
plt.ylim(top = 90000);
```



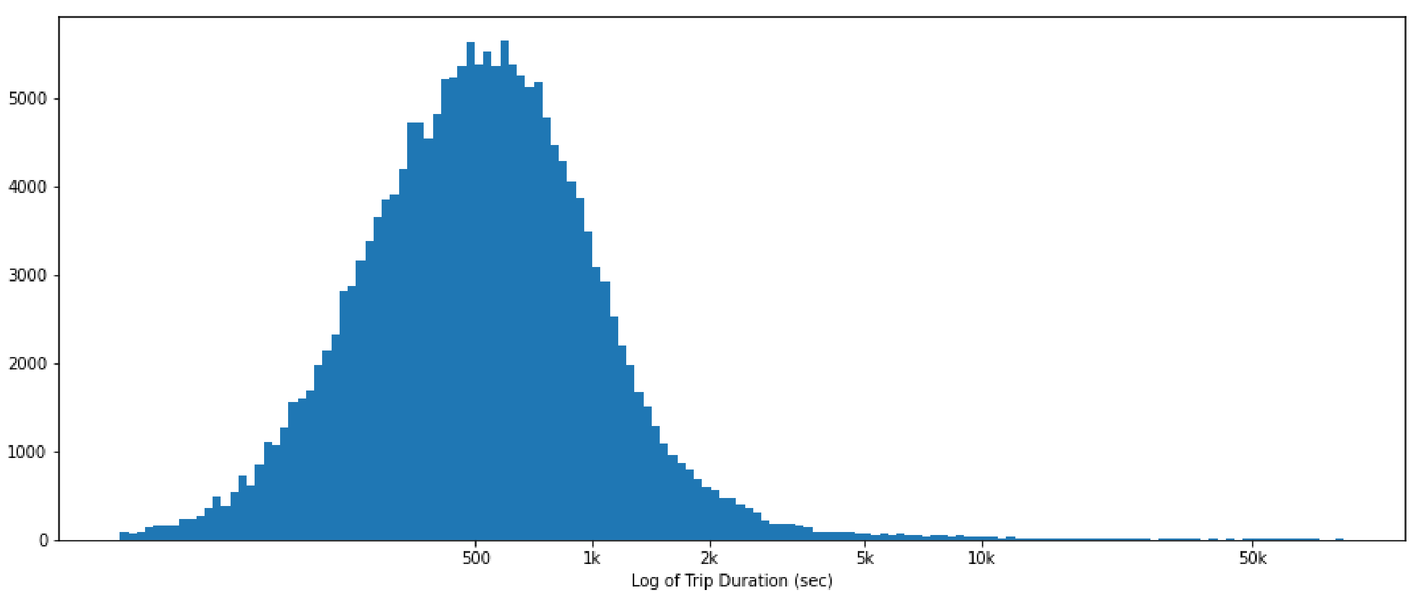
Let's try to visualize it using log scale

In [14]:

```
def log_transform(data, inverse = False):
    if not inverse:
        return np.log(data)
    else:
        return np.e ** data
```

In [15]:

```
# Plotting frequency of the log of duration_sec
plt.figure(figsize = (15, 6))
df['log_duration'] = log_transform(df.duration_sec)

bin_size = .05
bins = np.arange(df.log_duration.min(), df.log_duration.max() + bin_size, bin_size)
ticks = log_transform([500, 1000, 2000, 5000, 10000, 50000])
labels = [500, '1k', '2k', '5k', '10k', '50k']

plt.hist(data = df, x = 'log_duration', bins = bins)
plt.xlabel('Log of Trip Duration (sec)')
plt.xticks(ticks, labels);
```

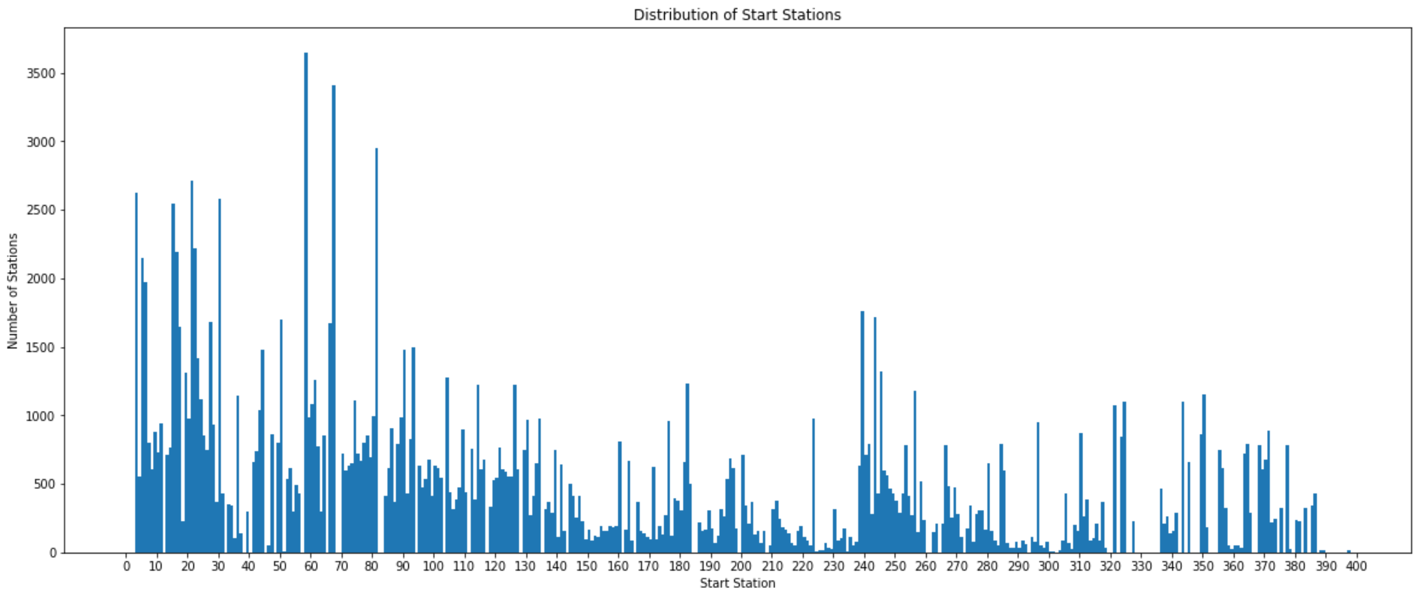


Using the log-transform of the trip's duration gives us a distribution we can more easily understand and relate with, a right-skewed normal distribution, with most of the trips les than 2000 seconds, and the most trips taking around 400 - 700 seconds

Now let us look at other features like the start and end station id, birth year, user type and start_hour

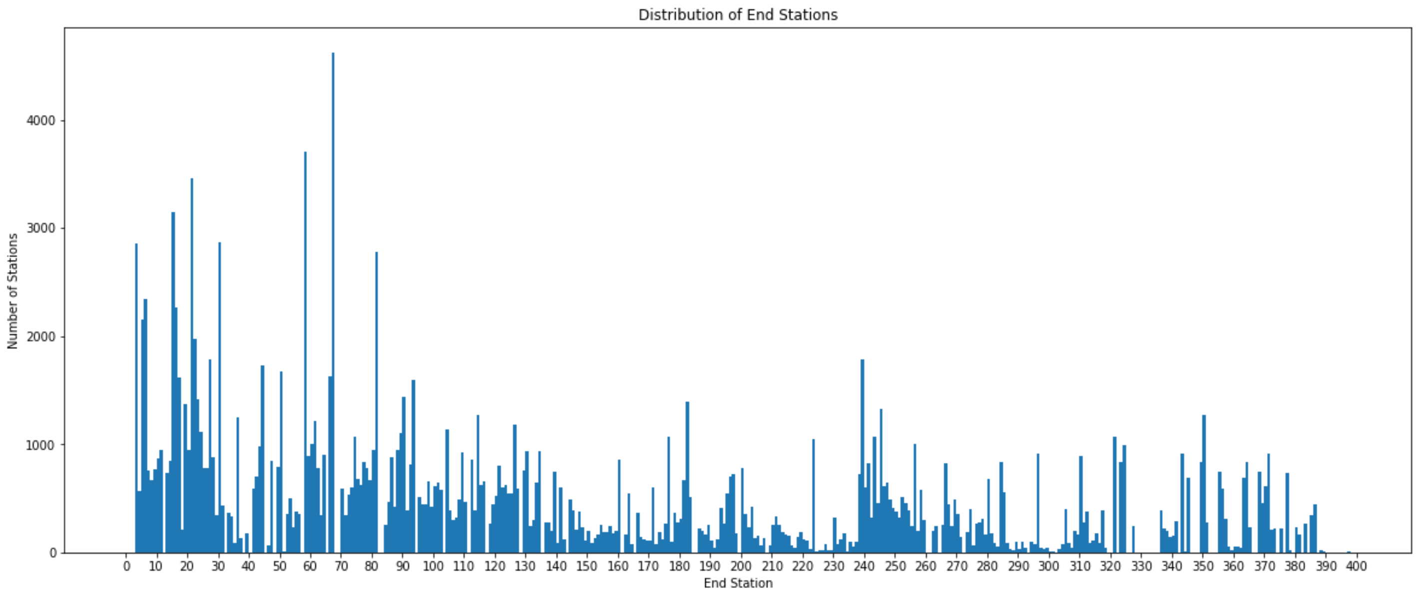
In [16]:

```
# Plotting start station id distribution.
binsize = 1
bins = np.arange(0, df['start_station_id'].astype(float).max()+binsize, binsize)

plt.figure(figsize=[20, 8])
plt.xticks(range(0, 401, 10))
plt.hist(data = df.dropna(), x = 'start_station_id', bins = bins)
plt.title('Distribution of Start Stations')
plt.xlabel('Start Station')
plt.ylabel('Number of Stations');
```



In [17]:

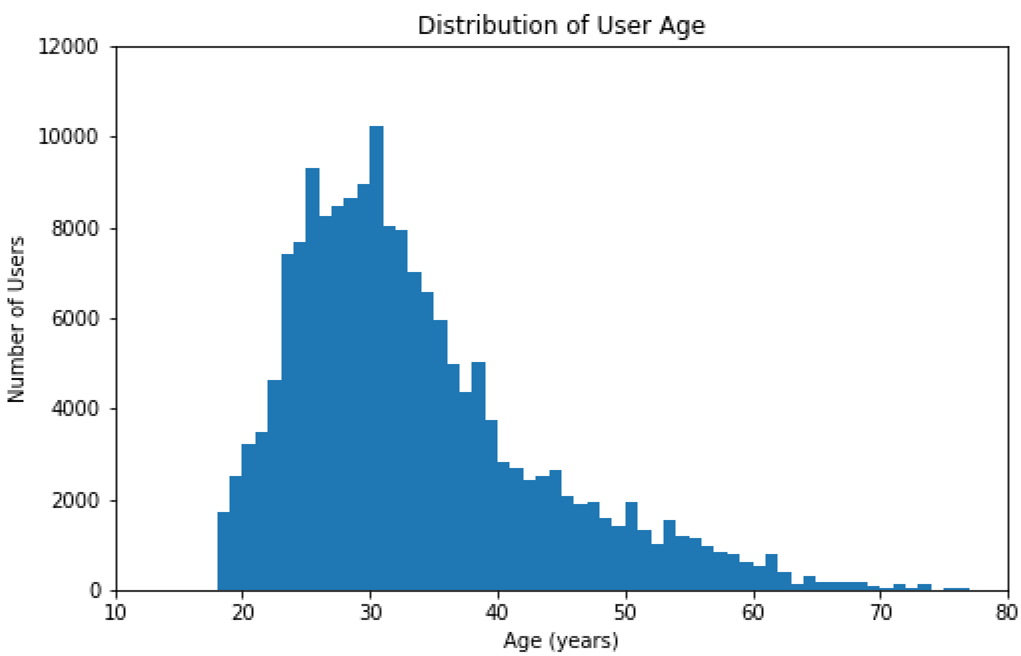
```
# Plotting end station id distribution.
binsize = 1
bins = np.arange(0, df['end_station_id'].astype(float).max()+binsize, binsize)

plt.figure(figsize=[20, 8])
plt.xticks(range(0, 401, 10))
plt.hist(data = df.dropna(), x = 'end_station_id', bins = bins)
plt.title('Distribution of End Stations')
plt.xlabel('End Station')
plt.ylabel('Number of Stations');
```



We can see that some stations in this dataset see more activity than others.

In [18]:

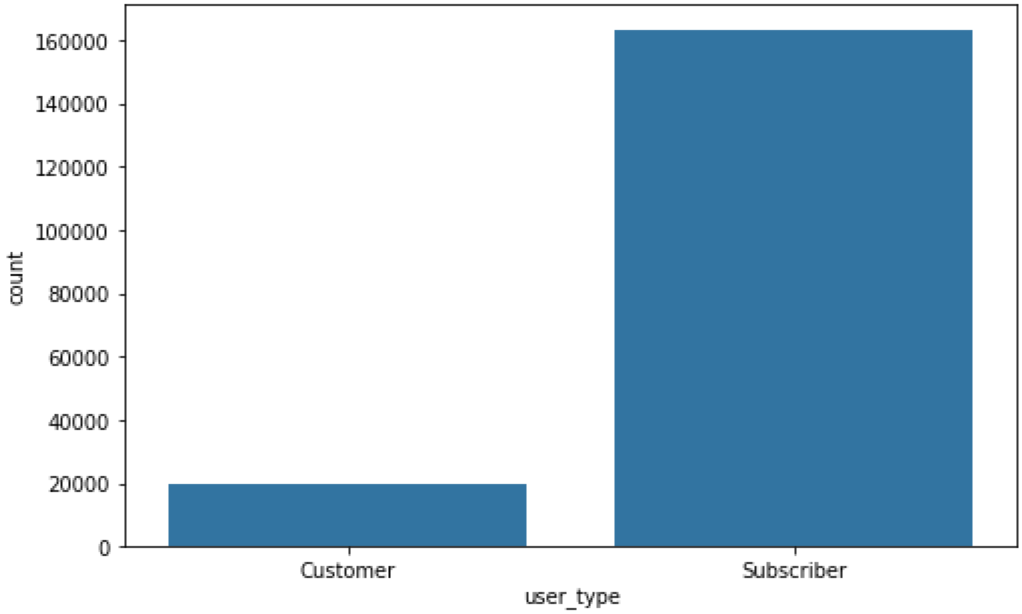
```
# Plotting the distribution of user age, derived from member's birth year.
binsize = 1
bins = np.arange(0, df['member_birth_year'].astype(float).max()+binsize, binsize)
tick = [1939, 1949, 1959, 1969, 1979, 1989, 1999, 2009]
label = [2019 - i for i in tick]

plt.figure(figsize=[8, 5])
plt.hist(data = df.dropna(), x = 'member_birth_year', bins = bins)
plt.axis([1939, 2009, 0, 12000])
plt.xticks(tick, label)
plt.gca().invert_xaxis()
plt.title('Distribution of User Age')
plt.xlabel('Age (years)')
plt.ylabel('Number of Users');
```



We can see from the distribution of the age of users that most users are between 20 to 45 years old.

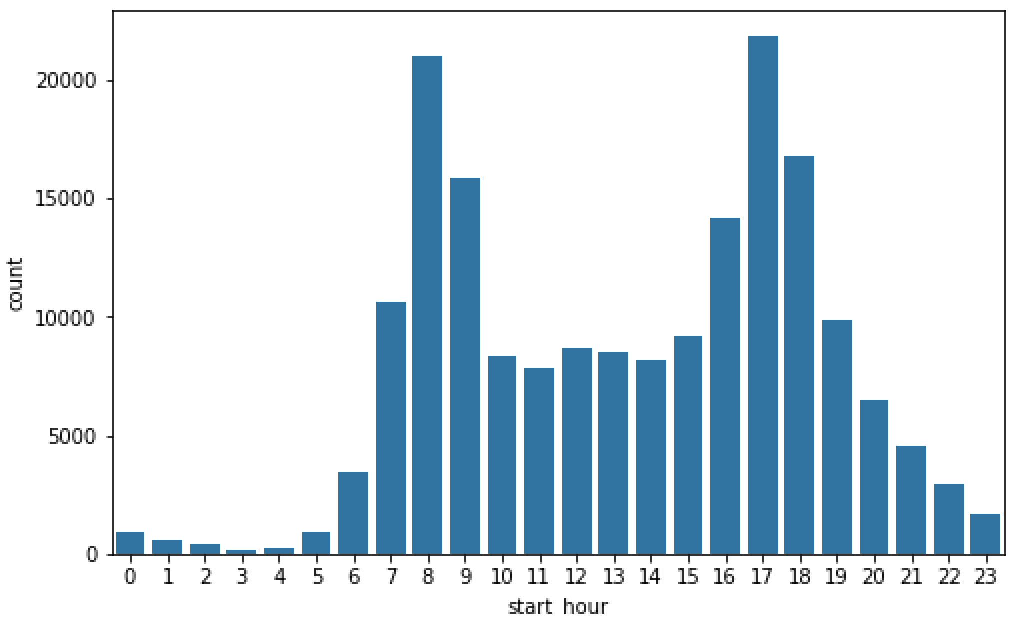
In [19]:

```
# plotting types of users on bar.
plt.figure(figsize=[8,5])
sb.countplot(x = 'user_type', data = df, color=sb.color_palette()[0]);
```



In [20]:

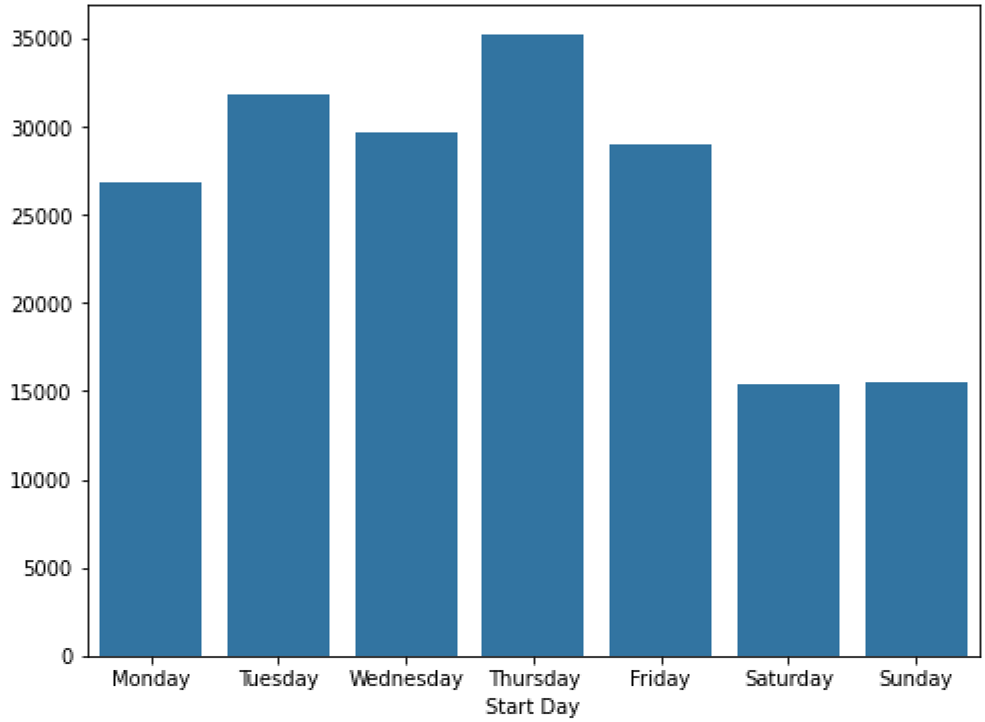
```
# plotting the hour the trip starts.
plt.figure(figsize=[8,5])
sb.countplot(x = 'start_hour', data = df, color=sb.color_palette()[0]);
```



Exploring the start_day feature

In [21]:

```
# Plotting the frequency distribution of the start_day feature
plt.figure(figsize = (8, 6))
day_count = df['start_day'].value_counts(sort = False)
sb.barplot(x = day_count.index, y = day_count.values, order = days, color=sb.color_palette
plt.xlabel('Start Day')
plt.show()
```



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

The trip duration takes a wide range of values and is highly skewed to the right. Transforming it into a log scale and plotting it shows that most rides took between 400-700 seconds to complete.

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 determined the age of the users by subtracting the birth year of the users from 2019.

Wrangling was carried out on the start_time variable, to obtain the hour at which the bike ride began. This was to enable us ask questions like

> "Does the time when the bike ride starts play a part in how long the ride will take?"

The distribution of hours at which bike rides start is bimodal, with peak periods at 8AM and 5PM. This coincides closely with the open and close of working hours. After 5PM, the number of rides keep decreasing up till 3AM in the morning, where it is at its lowest.

Rides during the weekends were less frequent than during weekdays. It would be interesting to observe how this feature and the hour of the day interact.

Start station and end station IDs were also plotted to get insight regarding traffic at certain stations.

Bivariate Exploration

Let us take a look at the relationship between the 2 numerical variables, trip duration and age.

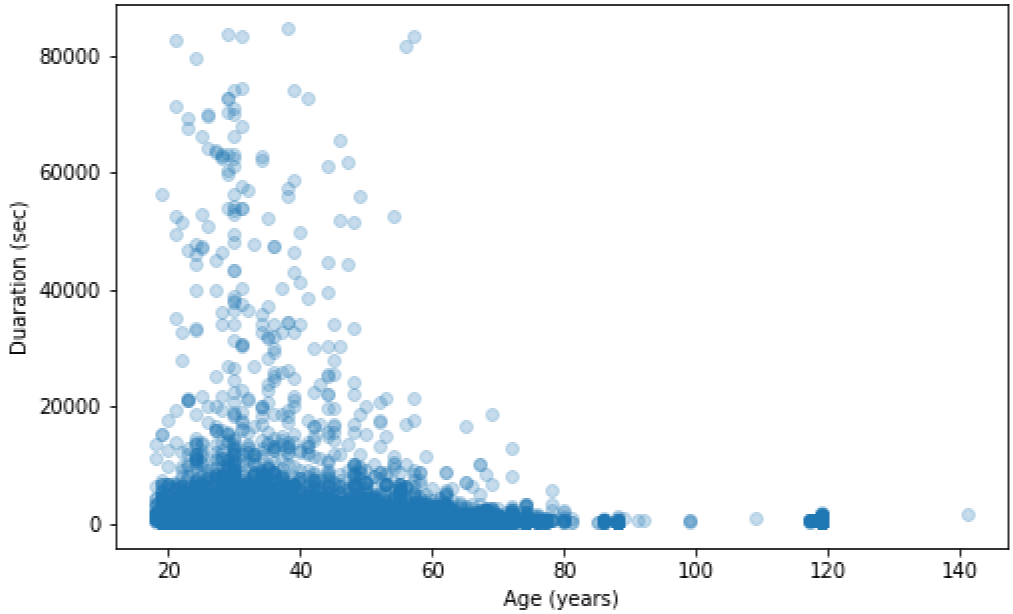
In [22]:

```
df['user_age'] = 2019 - df['member_birth_year']
```

In [23]:

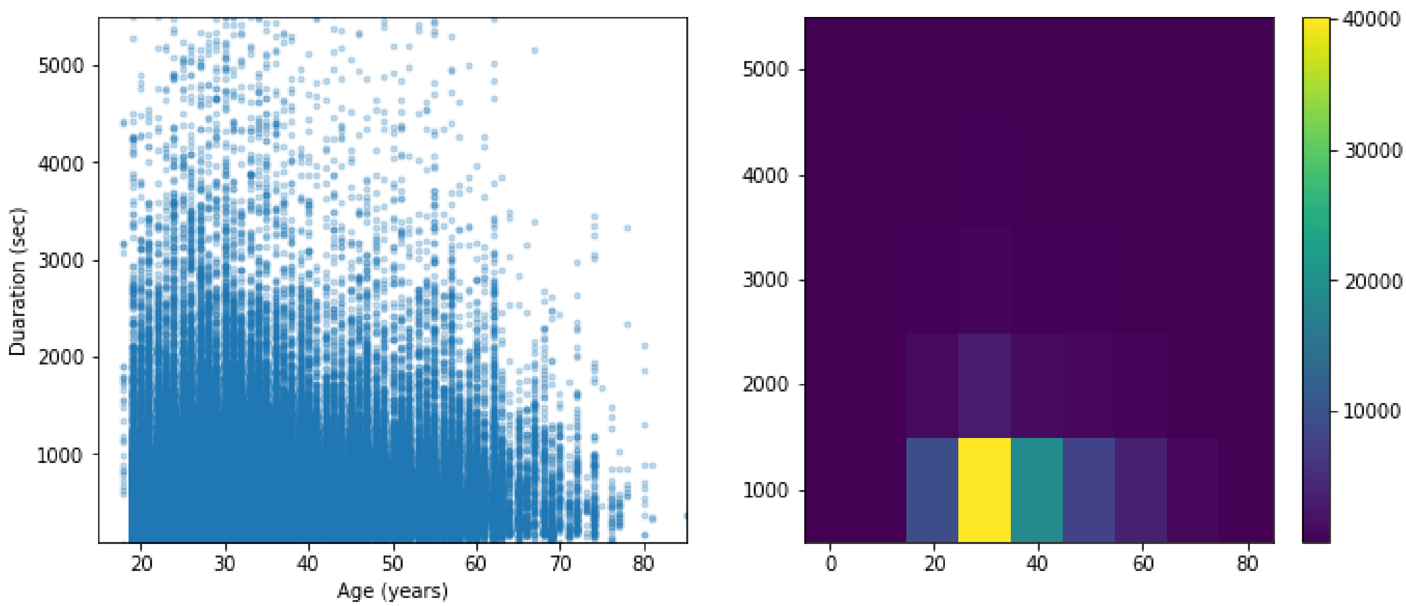
```
plt.figure(figsize=[8,5])
```

```
plt.scatter(df.user_age, df.duration_sec, alpha = 0.25 )
#plt.axis([-5, 145, 500, 10500])
plt.xlabel('Age (years)')
plt.ylabel('Duaration (sec)');
```



As most of the durations are below 5000 and age is below 80, lets crop the plot to reflect those values.

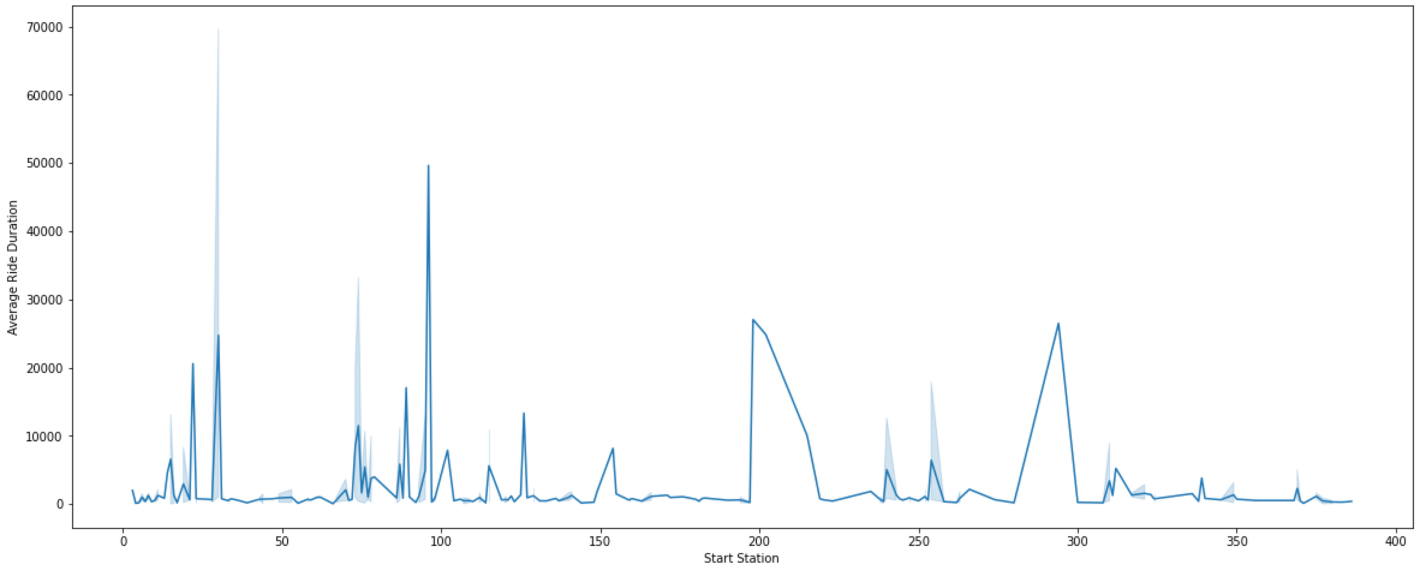
In [24]:
```
plt.figure(figsize=[12,5])

plt.subplot(1, 2, 1)
plt.scatter(df.user_age, df.duration_sec, alpha = 0.25, marker = '.' )
plt.axis([15, 85, 100, 5500])
plt.xlabel('Age (years)')
plt.ylabel('Duaration (sec)')

plt.subplot(1, 2, 2)
bins_y = np.arange(500, 5500+1, 1000)
bins_x = np.arange(-5, 85+1, 10)
plt.hist2d(df.user_age, df.duration_sec, bins = [bins_x, bins_y])
plt.colorbar(ticks=[10000, 20000, 30000, 40000]);
```

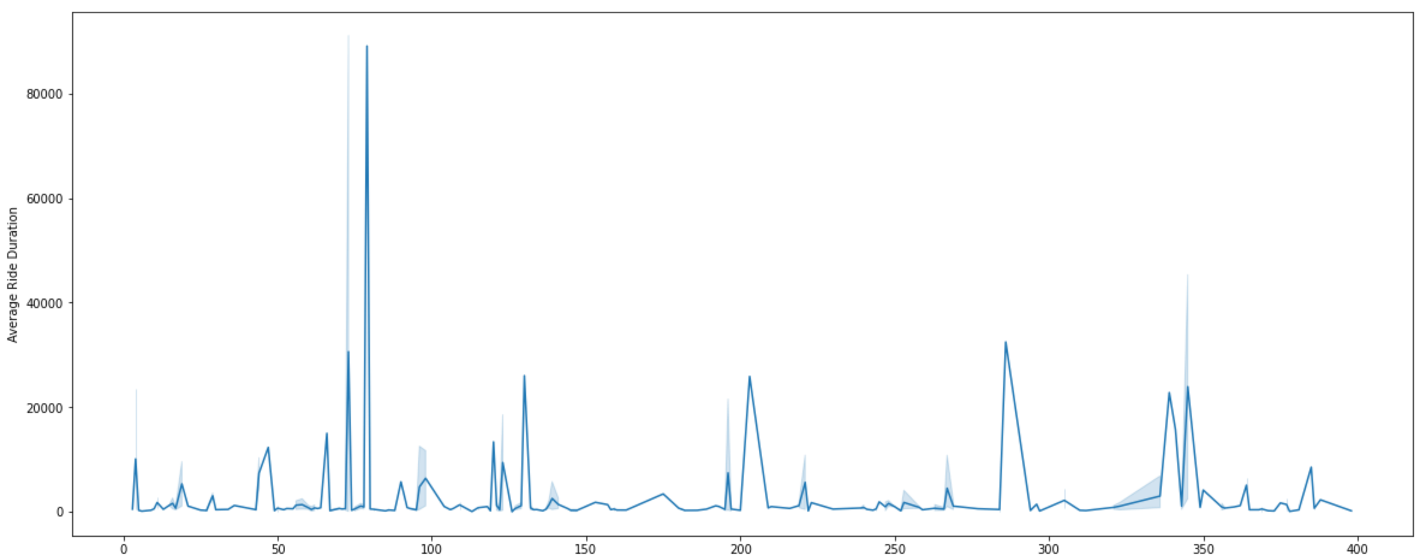


By looking at the heatmap, we see that users of bikes aged between 20 and 45 tend to take the longest time completing their rides.

Now let us explore the trip's duration dependence on start station and end station.

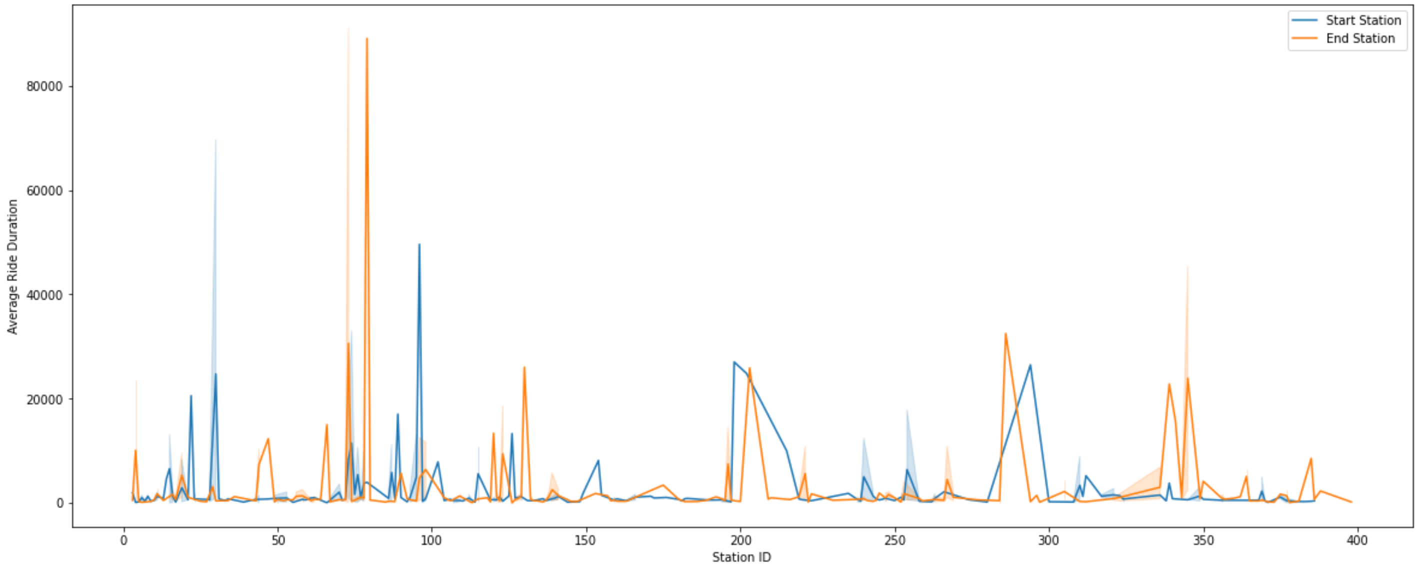
In [25]:
```
td = df.groupby('start_station_id').sum()['duration_sec'].reset_index().sort_values('start
no_of_rides = df['start_station_id'].value_counts().reset_index().sort_values('index')
average_ride_duration = td.duration_sec / no_of_rides.start_station_id

plt.figure(figsize = [20, 8])
sb.lineplot(x = df['start_station_id'].sort_values(), y = average_ride_duration)
plt.xlabel('Start Station')
plt.ylabel('Average Ride Duration');

td = df.groupby('end_station_id').sum()['duration_sec'].reset_index().sort_values('end_sta
no_of_rides = df['end_station_id'].value_counts().reset_index().sort_values('index')
average_ride_duration = td.duration_sec / no_of_rides.end_station_id

plt.figure(figsize = [20, 8])
sb.lineplot(x = df['end_station_id'].sort_values(), y = average_ride_duration)
plt.xlabel('End Station')
plt.ylabel('Average Ride Duration');
```





In [26]:
```
# Calculating the average duration of trips for each start station
start_td = df.groupby('start_station_id').sum()['duration_sec'].reset_index().sort_values
start_no_of_rides = df['start_station_id'].value_counts().reset_index().sort_values('index
average_start_ride_duration = start_td.duration_sec / start_no_of_rides.start_station_id
# Calculating the average duration of trips for each end station
end_td = df.groupby('end_station_id').sum()['duration_sec'].reset_index().sort_values('end
```

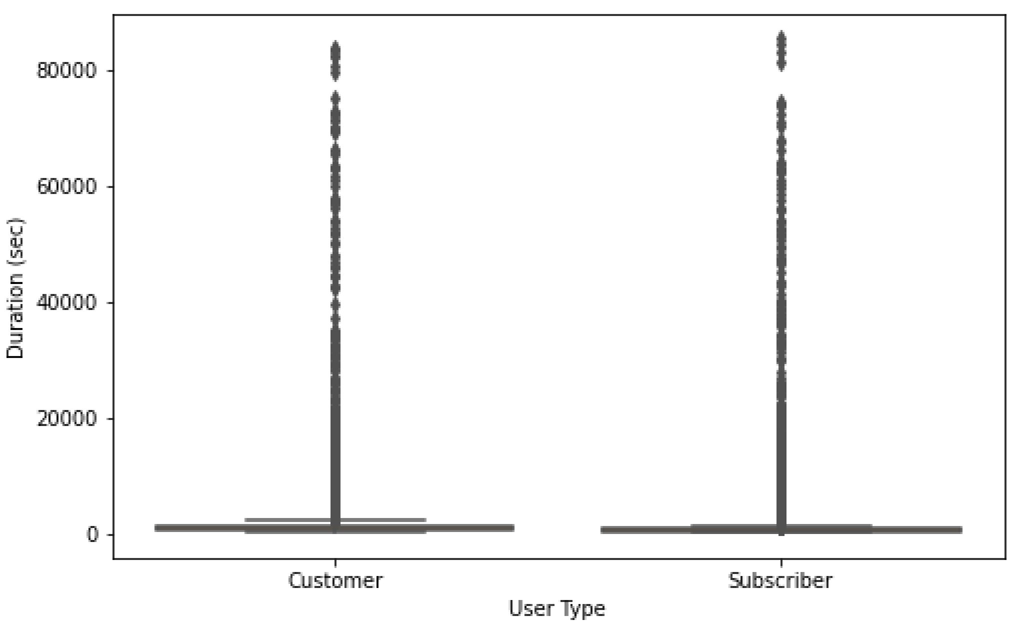
```
end_no_of_rides = df['end_station_id'].value_counts().reset_index().sort_values('index')
average_end_ride_duration = end_td.duration_sec / end_no_of_rides.end_station_id

# Superimposing the two averages on a single plot
plt.figure(figsize = [20, 8])
sb.lineplot(x = df['start_station_id'].sort_values(), y = average_start_ride_duration, col
sb.lineplot(x = df['end_station_id'].sort_values(), y = average_ride_duration, color = sb.
plt.xlabel('Station ID')
plt.ylabel('Average Ride Duration')
plt.legend();
```



By looking at these plots you can see that the average trip duration for some station as start station is higher and for some stations as end station is higher. By this we can see what stations result in starting of longer trips and what stations comes end of longer trips.

Now let us explore the dependency of trip durations on member type.

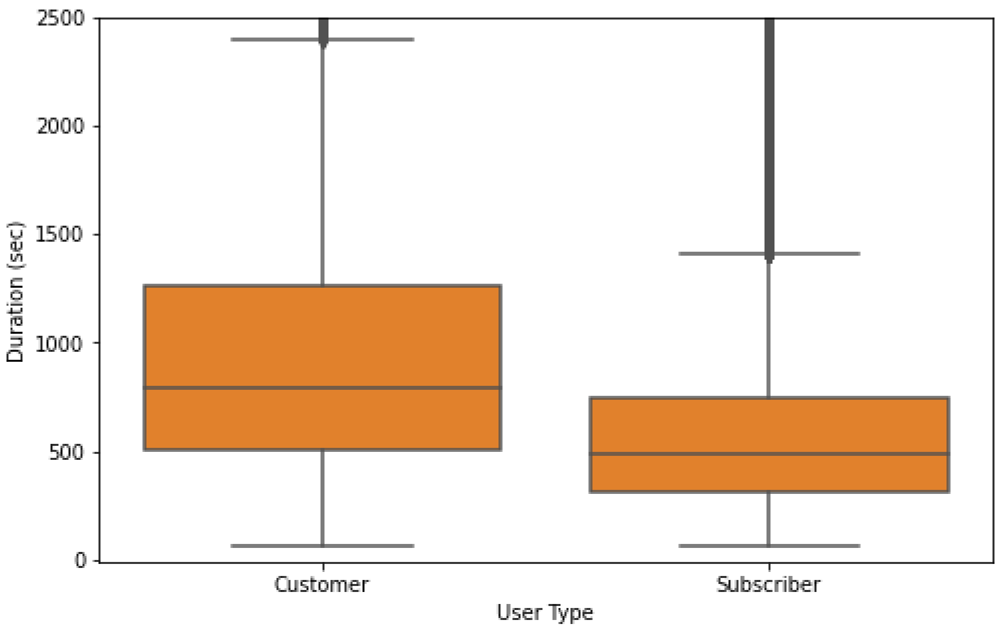
In [27]:
```
plt.figure(figsize = [8, 5])
base_color = sb.color_palette()[1]
sb.boxplot(data = df, x = 'user_type', y = 'duration_sec', color = base_color)
plt.xlabel('User Type')
plt.ylabel('Duration (sec)');
```



As we can see, values are vey widespread to see a box plot, so lets trim duration to max 2500 sec to get clearer picture.

In [28]:

```
plt.figure(figsize = [8, 5])
base_color = sb.color_palette()[1]
sb.boxplot(data = df, x = 'user_type', y = 'duration_sec', color = base_color)
plt.ylim([-10, 2500])
plt.xlabel('User Type')
plt.ylabel('Duration (sec)');
```

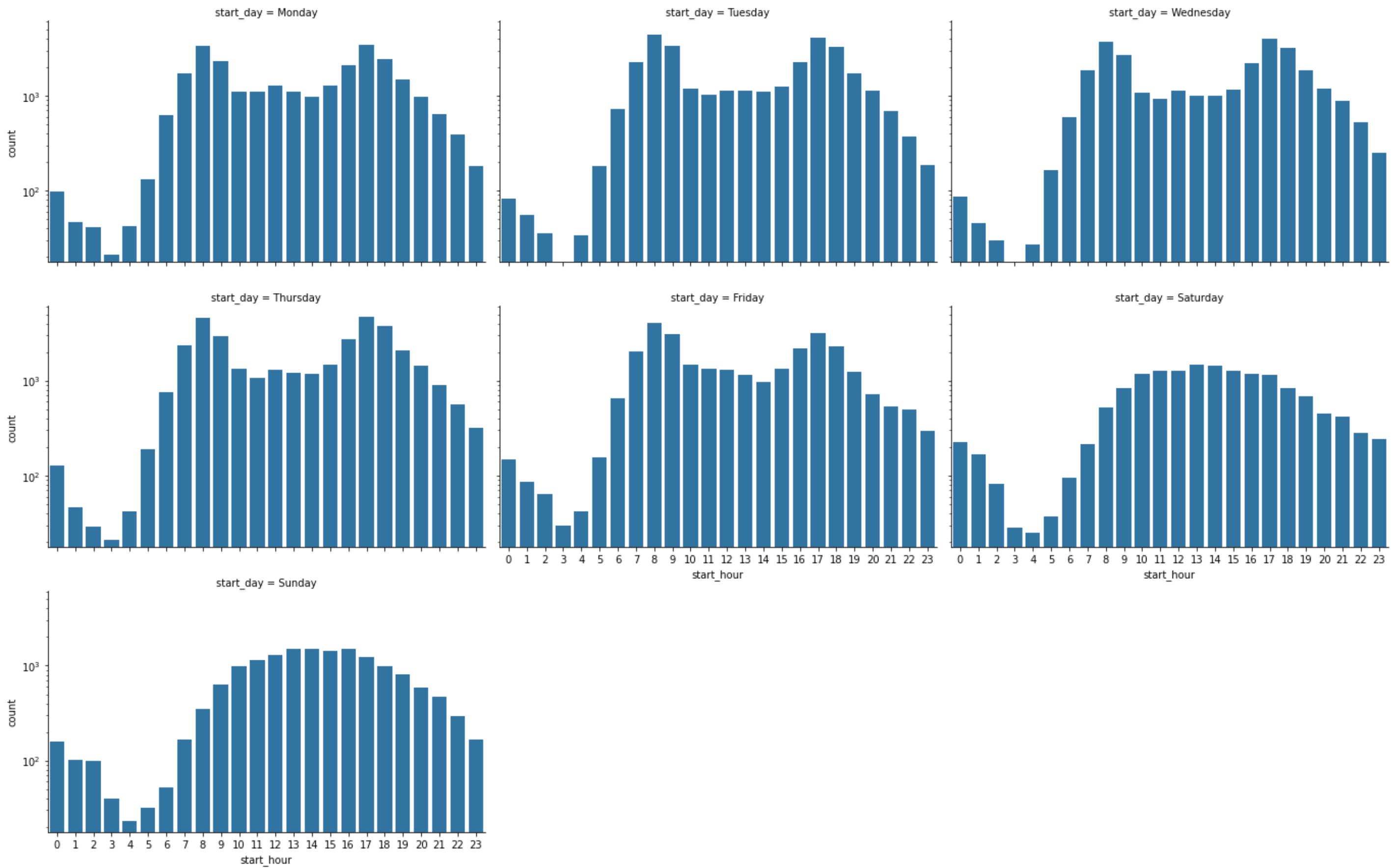


Here we can see that higher percentage of customers are taking longer trips then compared to subscribers.

Let us now explore relationships among the features

In [29]:

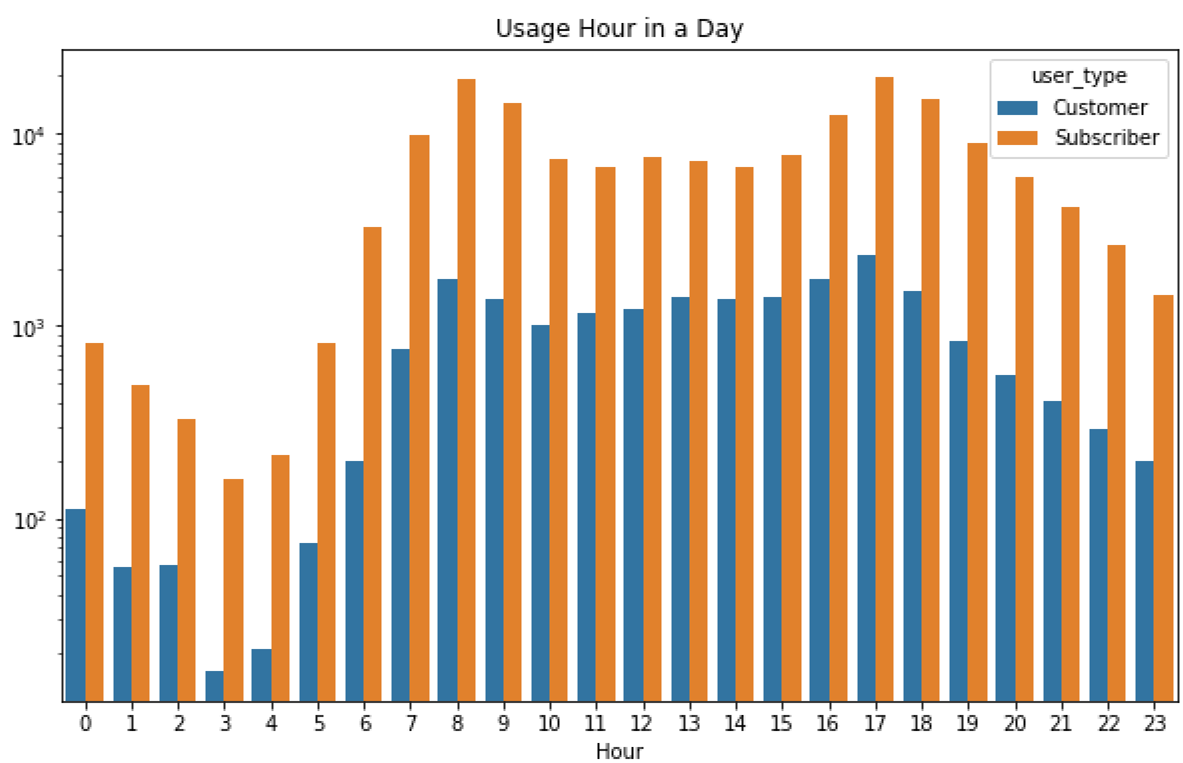
```
# Plotting start_day against start hour
g = sb.FacetGrid(data = df, col = 'start_day', height = 4, aspect = 1.6, col_wrap = 3)
g.map(sb.countplot, 'start_hour')
plt.yscale('log');
```



We observed a bimodal distribution of rides during weekdays with peak periods at 8AM and 5PM. However, on weekends, peak period is around 1-2PM, and it is not bimodal.

In [30]:

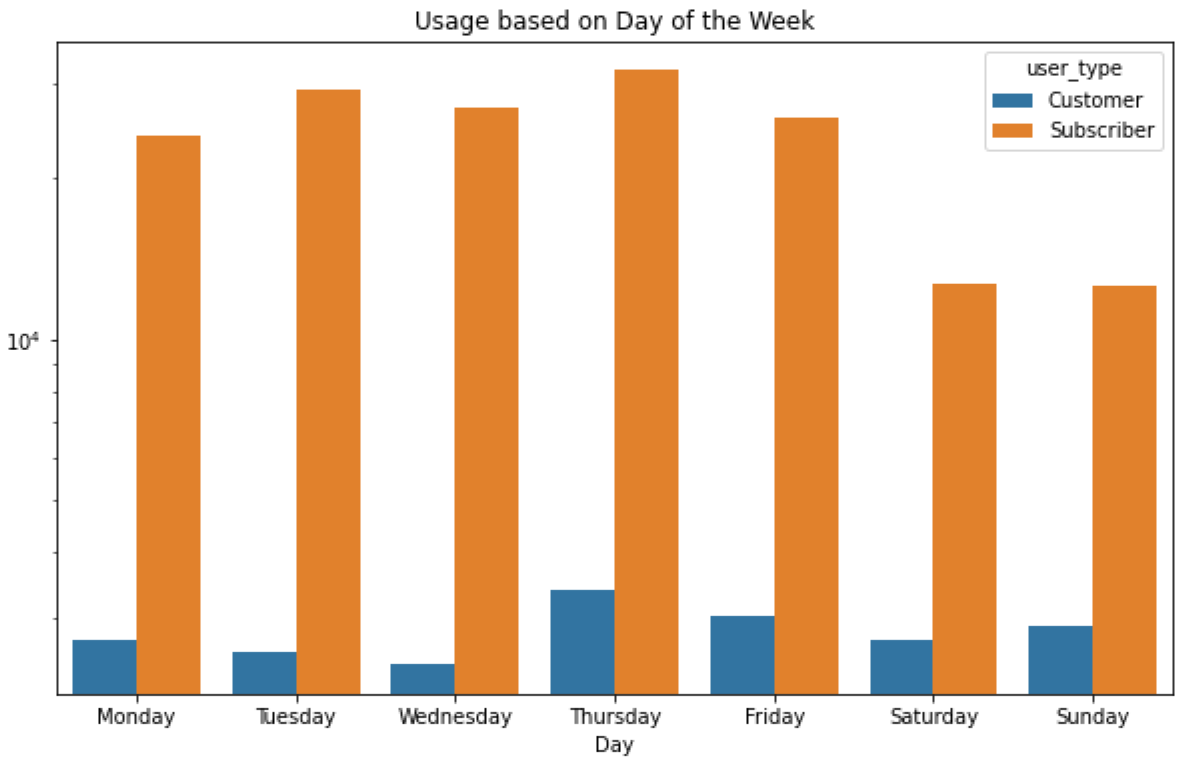
```
plt.figure(figsize=(10,6))
plt.title('Usage Hour in a Day')
chart = sb.countplot(data=df, x='start_hour', hue='user_type')
plt.yscale('log')

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



Both set of users seem to use the service most around peak periods.

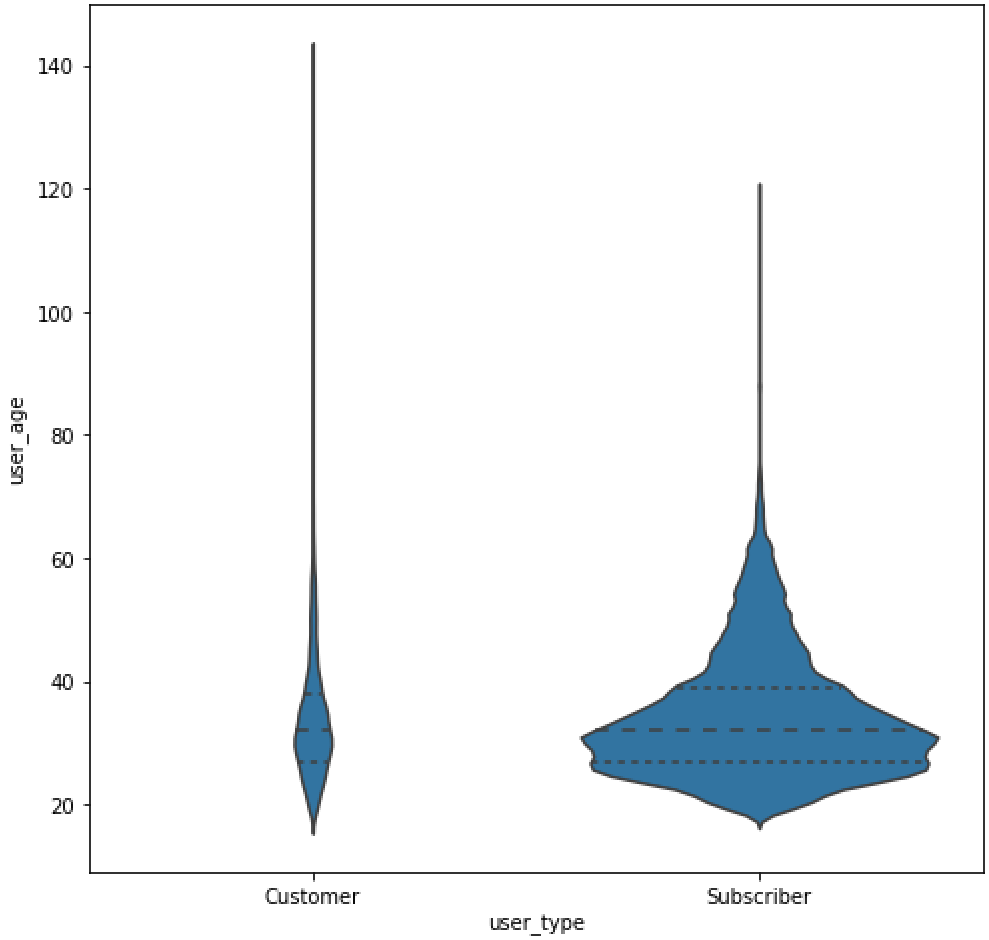
In [31]:

```
plt.figure(figsize=(10,6))
plt.title('Usage based on Day of the Week')
chart = sb.countplot(data=df, x='start_day', hue='user_type')
plt.yscale('log')

chart.set(xlabel='Day', ylabel='');
```



In [32]:

```
plt.figure(figsize = (8,8))

sb.violinplot(data = df, x = 'user_type', y = 'user_age', inner = 'quartile', scale = 'cou
```



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?

- We found out that the trips with the longest durations are usually taken by relatively younger users between the ages of 20 and 45.
- Also, while the start and station are too many to be looked at in detail, we notice that while the average duration of rides for most stations are similarly low, it is particularly high for some stations.
- Rides taken during weekdays were on average observed to take longer than rides on weekends.
- Customers were also observed to, on average, take rides that lasted longer than rides taken by subscribers

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

We observed a bimodal distribution of rides during weekdays with peak periods at 8AM and 5PM. However, on weekends, peak period is around 1-2PM, and it is not bimodal.

Multivariate Exploration

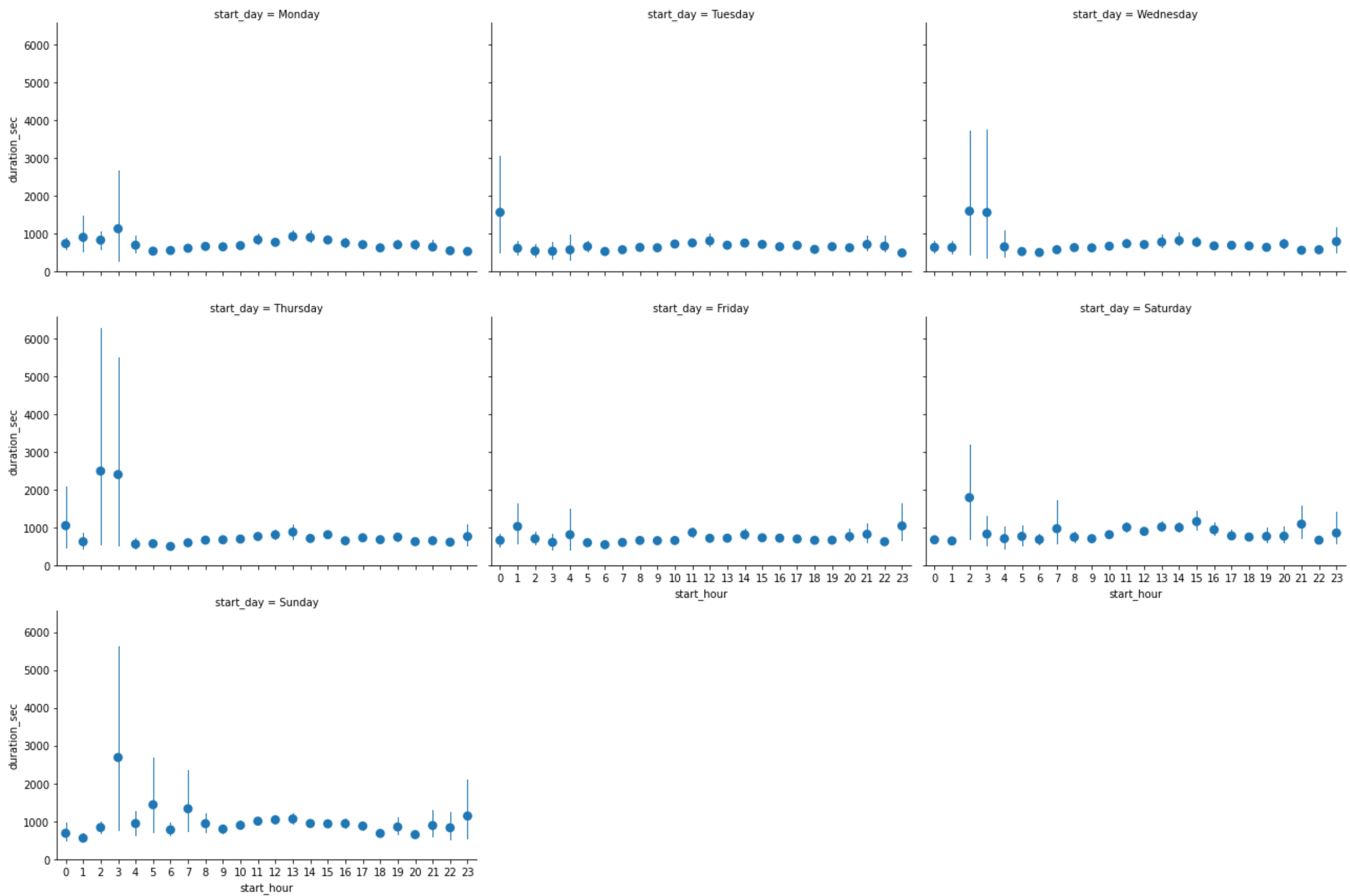
The main thing I want to explore in this part of the analysis is how the time and day of the week jointly influences the duration of the ride.

Other relationships I will investigate include:

- trip's duration, user's age, and user type
- trip's duration, time of the day, and user type
- user's age, user type and time of the day

In [33]:

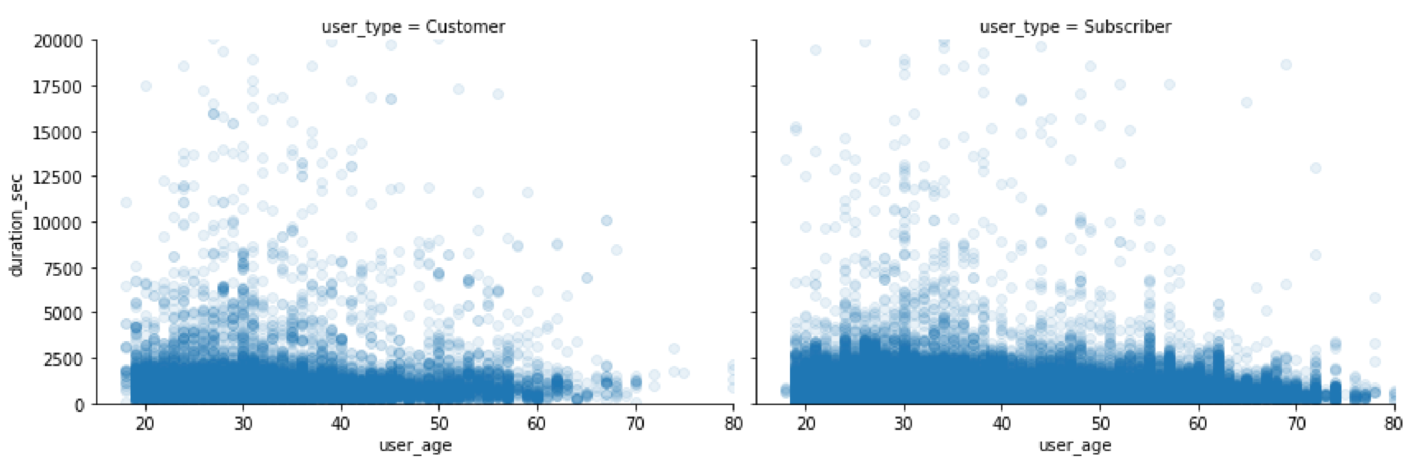
```python
g = sb.FacetGrid(data = df, col = 'start_day', col_wrap = 3, size = 4, aspect = 1.5)
g.map(sb.pointplot, 'start_hour', 'duration_sec', join = False, errwidth = 1);
```



There seems to be significant variance in the average duration of rides that start early in the morning, between 12 and 3AM.
Duration of rides for the rest of the day are fairly consistent.

In [34]:

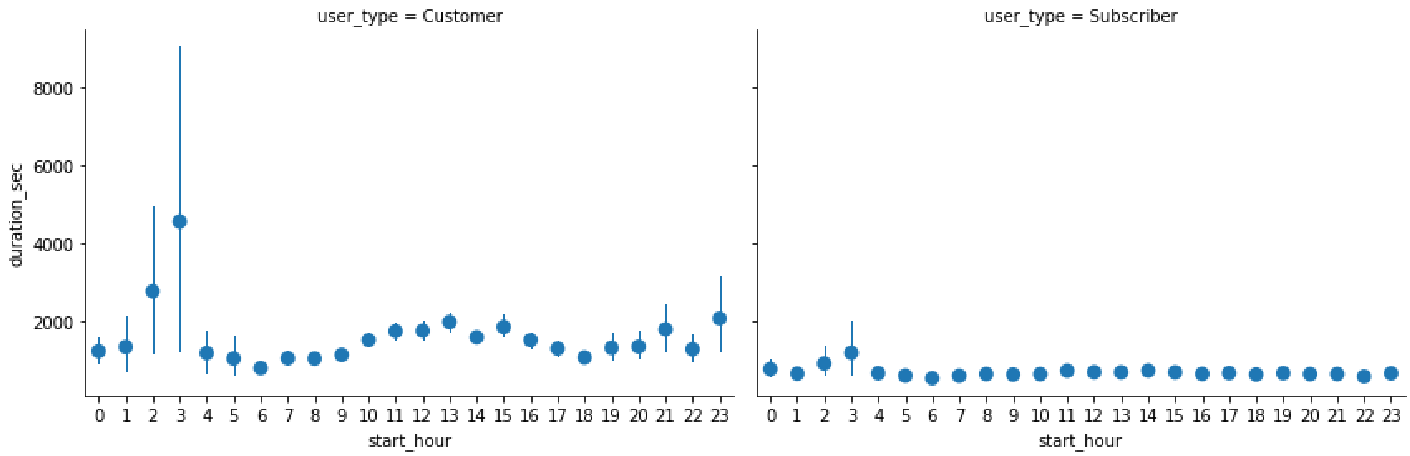
```python
g = sb.FacetGrid(data = df, col = 'user_type', size = 4, aspect = 1.5)
g.map(plt.scatter, 'user_age', 'duration_sec', alpha = .1)
plt.axis((15, 80, 0, 20000));
```



While customers and subscribers are showing similar trends for age and trip duration, there is a slight tilt to higher age for subscribers. Above 60 years, more users are subscibers than customers, and they tend to go on rides that don't take too long.

In [35]:

```
# Plotting user type against start hour
g = sb.FacetGrid(data = df, col = 'user_type', size = 4, aspect = 1.5)
g.map(sb.pointplot, 'start_hour', 'duration_sec', join = False, errwidth = 1);
```



In [36]:

```
df.groupby('user_type').describe()
```

Out[36]:

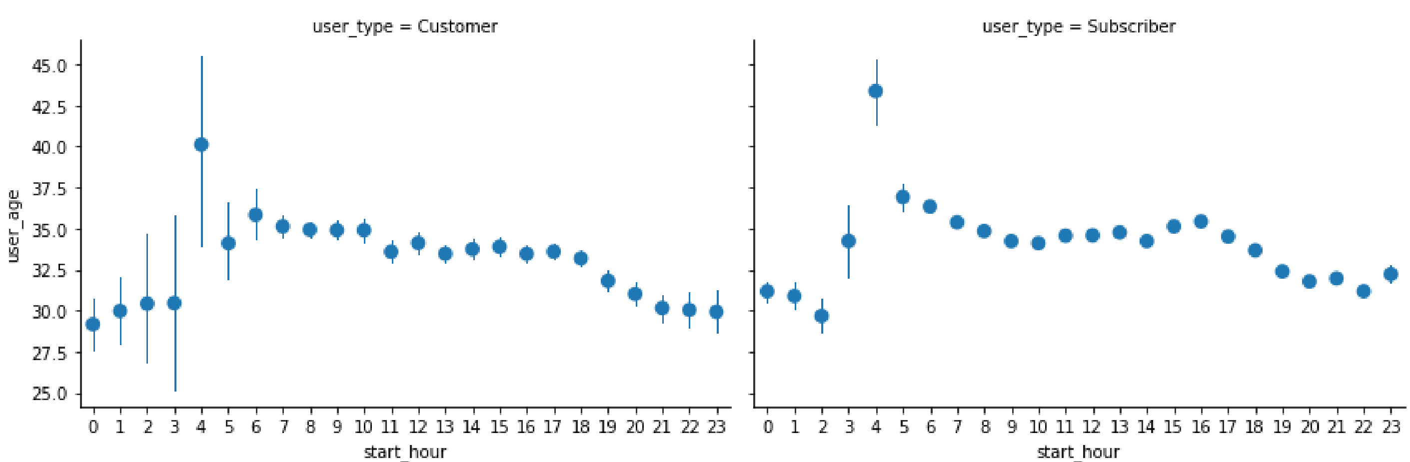
								bike_id		duration_sec	...	sta
	count	mean	std	min	25%	50%	75%	max	count	mean	...	
user_type												
Customer	19868.0	4225.550181	1817.784966	11.0	2861.0	4860.0	5474.0	6644.0	19868.0	1432.465019	...	-122.
Subscriber	163544.0	4502.956226	1642.243173	11.0	3892.0	4964.0	5505.0	6645.0	163544.0	640.263678	...	-122.

2 rows × 88 columns

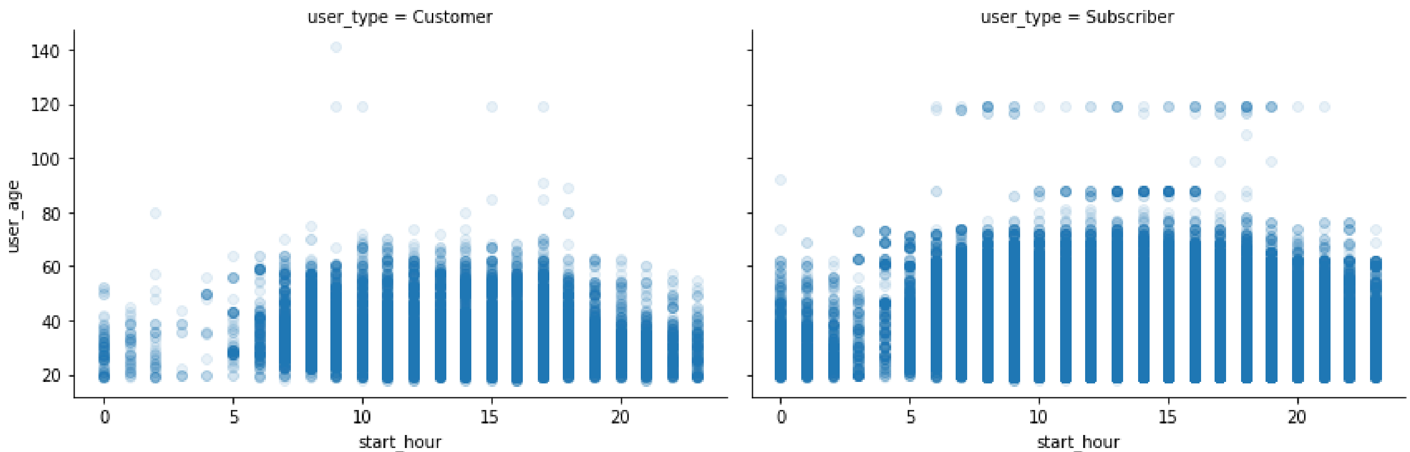
From the charts above, we see that there is moderate variation in the duration of rides by subscribers, typically less than 750s. However, most of the variance observed in the duration of rides stem from customers, where there are a lot more rides that take extremely long amounts of time.

In [37]:

```
g = sb.FacetGrid(data = df, col = 'user_type', size = 4, aspect = 1.5)
g.map(sb.pointplot, 'start_hour', 'user_age', join = False, errwidth = 1);
```



In [38]:
```
g = sb.FacetGrid(data = df, col = 'user_type', size = 4, aspect = 1.5)
g.map(plt.scatter, 'start_hour', 'user_age', alpha = .1);
```



The charts seem to suggest that more younger people make use of the bike riding system late at night and early in the morning. However from 4AM where we notive a spike in the average age of both user types, the age of the users is slightly higher than usual, until around 5PM when it starts to decline again.

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?

- From the multivariate analysis of start day, start hour and duration_sec, we observe that the longest trips tend to start in the early hours of the morning, typically before 6AM.
- Also, customers tend to have the longest trip durations, with a peak at 3AM in the morning. On the other hand, the average ride duration for subscribers is quite low when compared to that of the customers, and is quite similar across the hours of the day.

Were there any interesting or surprising interactions between features?

- There are generally more older subscribers than customers.
- The average age of users using the bike sharing service is at its highest at 4AM, for both user types.