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Data Analysis:Communicate Data Findings

Table of Contents

1.Introduction

2.Data wrangling process

```
    a.Data gathering

    b.Data Assessing

         i.Quality Issues

         ii.Tidiness Issues

    c.Data Cleaning
          i.Define

          ii.Code

          iii.Test
```

1. Exploratory Data Analysis

   I. Univariate Visualization

II. Bivariate Visualization

III. Multivariate Visualization

1. Conclusion

1. Introduction

In this project I will be doing data analysis of Bay Wheels's trip dataset of the year 2017. Bay Wheel's Dataset cover the three major regions San Francisco,San Jose and East Bay where the trips begin and end as well(It can be intra or inter region trips).

The data consist of bike rides from FY2017. The attributes include the trip start/end time, start/end station, duration in seconds as well as additional information such as user type.

The main purpose of doing analysis is to find out the trends and some useful information. On the basis of those trends we can get business insights visually.

To do data analysis I will follow the ideal way of data preprocessing, data visualization and the documentation. Atlast I would end with a proper story telling in a new notebook with suitable visualizations like Univariate, Bivarite and Multivariate.

2.Data Wrangling Process

Data Gathering

The data is downloaded from the given link:https://www.fordgobike.com/system-data

In [1]:
```
#importing necessary libraries
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style="darkgrid")
import os
```

In [2]:
```
#read csv
df_trip=pd.read_csv("2017-fordgobike-tripdata.csv")
```

Data Assessing

Visual Assessment

In [3]:
```
#assess data
df_trip
```

Out[3]:

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

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_stati
519695	435	2017-06-28 10:00:54.5280	2017-06-28 10:08:10.4380	81	Berry St at 4th St	
519696	431	2017-06-28 09:56:39.6310	2017-06-28 10:03:51.0900	66	3rd St at Townsend St	
519697	424	2017-06-28 09:47:36.3470	2017-06-28 09:54:41.1870	21	Montgomery St BART Station (Market St at 2nd St)	
519698	366	2017-06-28 09:47:41.6640	2017-06-28 09:53:47.7150	58	Market St at 10th St	
519699	188	2017-06-28 09:49:46.3770	2017-06-28 09:52:55.3380	25	Howard St at 2nd St	

519700 rows × 13 columns

Programmatic Assessment

In [4]:

```
#another way of Assessment
df_trip.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 519700 entries, 0 to 519699
Data columns (total 13 columns):
 #   Column                   Non-Null Count   Dtype  
---  ------                   --------------   -----  
 0   duration_sec             519700 non-null  int64  
 1   start_time               519700 non-null  object 
 2   end_time                 519700 non-null  object 
 3   start_station_id         519700 non-null  int64  
 4   start_station_name       519700 non-null  object 
 5   start_station_latitude   519700 non-null  float64
 6   start_station_longitude  519700 non-null  float64
 7   end_station_id           519700 non-null  int64  
 8   end_station_name         519700 non-null  object 
 9   end_station_latitude     519700 non-null  float64
```

```
 10  end_station_longitude    519700 non-null  float64
 11  bike_id                  519700 non-null  int64
 12  user_type                519700 non-null  object
dtypes: float64(4), int64(4), object(5)
memory usage: 51.5+ MB
```

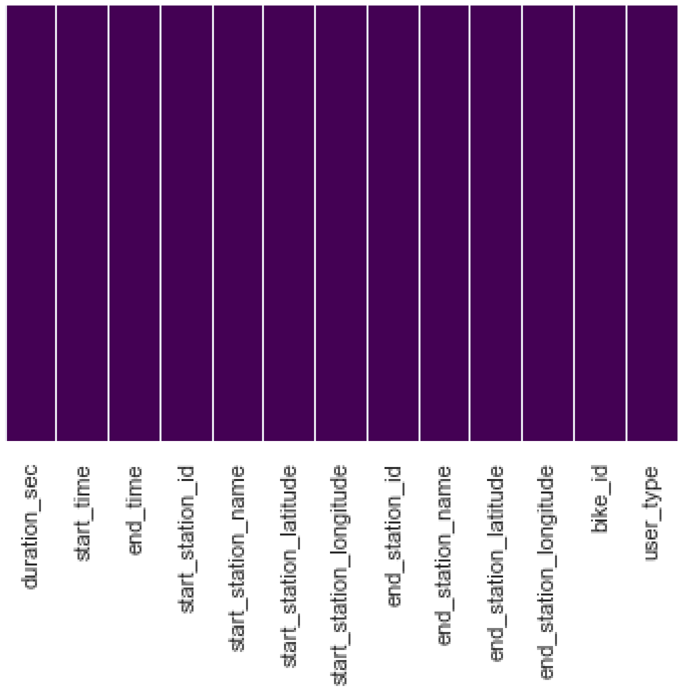
In [5]:
```
#check for missing values
df_trip.isna().sum()
```

Out[5]:
```
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
dtype: int64
```

Visually Check for missing values in the dataset

In [6]:
```
#heatmap
sns.heatmap(df_trip.isna(), yticklabels=False,cbar=False,cmap='viridis'
)
```

Out[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x18eba79c208>
```



As we can see that there is no missing values in the dataset by graphically as well as statistically

In [7]:
```
#check for duplicates
sum(df_trip.duplicated())
```

Out[7]: 0

Quality Issues:

1.Data type of start_time,end_time is object type.

Tidiness Issues

1. start_time and end_time having date in same column it must be separated in two different columns for date.

Data Cleaning

In [8]:
```
#make a copy od dataset before cleaning
df_trip_clean = df_trip.copy()
```

Define

Data type of start_time,end_time is object type it must be datetime.

Code

In [9]:
```
#using for loop to deeal with two columns at a time while correcting da
ta type
for col in ["start_time", "end_time"]:
    df_trip_clean[col] = pd.to_datetime(df_trip_clean[col])
```

Test

In [10]:
```
#test
df_trip_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 519700 entries, 0 to 519699
Data columns (total 13 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             519700 non-null  int64
 1   start_time               519700 non-null  datetime64[ns]
```

```
 2   end_time                 519700 non-null  datetime64[ns]
 3   start_station_id         519700 non-null  int64
 4   start_station_name       519700 non-null  object
 5   start_station_latitude   519700 non-null  float64
 6   start_station_longitude  519700 non-null  float64
 7   end_station_id           519700 non-null  int64
 8   end_station_name         519700 non-null  object
 9   end_station_latitude     519700 non-null  float64
 10  end_station_longitude    519700 non-null  float64
 11  bike_id                  519700 non-null  int64
 12  user_type                519700 non-null  object
dtypes: datetime64[ns](2), float64(4), int64(4), object(3)
memory usage: 51.5+ MB
```

make day,month in individual columns

In [11]:
```
#fucntion for indivisaul day
#for start_time
def day(name,name2):
    df_trip_clean[name] = name2.dt.day

day('start_day',df_trip_clean.start_time)
```

In [12]:
```
#for end_time
day('end_day',df_trip_clean.end_time)
```

In [13]:
```
#fucntion for indivisaul month
def month(name,name2):
    df_trip_clean[name] = name2.dt.month

month('start_month',df_trip_clean.start_time)
```

In [14]:
```
#for end_time
month('end_month',df_trip_clean.end_time)
```

In [15]:
```
#Test the changes you made in your dataset
```

```
df_trip_clean.head()
```

Out[15]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitu
0	80110	2017-12-31 16:57:39.654	2018-01-01 15:12:50.245	74	Laguna St at Hayes St	37.7764
1	78800	2017-12-31 15:56:34.842	2018-01-01 13:49:55.617	284	Yerba Buena Center for the Arts (Howard St at ...	37.7848
2	45768	2017-12-31 22:45:48.411	2018-01-01 11:28:36.883	245	Downtown Berkeley BART	37.8703
3	62172	2017-12-31 17:31:10.636	2018-01-01 10:47:23.531	60	8th St at Ringold St	37.7745
4	43603	2017-12-31 14:23:14.001	2018-01-01 02:29:57.571	239	Bancroft Way at Telegraph Ave	37.8688

Make a new column containing the start station names on the bais of longitude

In [16]:

```
#the start station names are given very raw manner
#separate start regions on the basis of longitude to make analysis easy

arr = df_trip_clean["start_station_longitude"].tolist()
#list of stations names
start_station=[]
for long in arr:
    if long > (-122.5) and long  < (-122.33):
        start_station.append('San Francisco')
    elif long  >= (-122.33) and long < (-122.1):
        start_station.append('East Bay')
    elif long  >= (-122.1) and long  < (-121.8):
        start_station.append('San Jose')
```

```
    else:
        start_station.append('Unknown')
```

In [17]:

```
#to dataframe
df_name = pd.DataFrame({'col':start_station})
df_name.head()
```

Out[17]:

	col
0	San Francisco
1	San Francisco
2	East Bay
3	San Francisco
4	East Bay

In [18]:

```
#add to station mae column to main dataset
df_trip_clean['start_name']=df_name['col']
df_trip_clean.head()
```

Out[18]:

	duration_sec	start_time	end_time	start_station_id	start_station_name	start_station_latitu
0	80110	2017-12-31 16:57:39.654	2018-01-01 15:12:50.245	74	Laguna St at Hayes St	37.7764
1	78800	2017-12-31 15:56:34.842	2018-01-01 13:49:55.617	284	Yerba Buena Center for the Arts (Howard St at ...	37.7848
2	45768	2017-12-31 22:45:48.411	2018-01-01 11:28:36.883	245	Downtown Berkeley BART	37.8703
3	62172	2017-12-31 17:31:10.636	2018-01-01 10:47:23.531	60	8th St at Ringold St	37.7745
4	43603	2017-12-31 14:23:14.001	2018-01-01 02:29:57.571	239	Bancroft Way at Telegraph Ave	37.8688

Drop Unused Columns From Dataset

In [19]:
```
#remove few  columns
#as I am keeping my analysis out of end Station so keep only start stat
ion names(newly created col only)
df_trip_clean.drop(['start_station_name','end_station_name','start_stat
ion_id','end_station_id'],axis=1,inplace=True)
```

In [20]:
```
df_trip_clean.head()
```

Out[20]:

	duration_sec	start_time	end_time	start_station_latitude	start_station_longitude	end_stati
0	80110	2017-12-31 16:57:39.654	2018-01-01 15:12:50.245	37.776435	-122.426244	
1	78800	2017-12-31 15:56:34.842	2018-01-01 13:49:55.617	37.784872	-122.400876	
2	45768	2017-12-31 22:45:48.411	2018-01-01 11:28:36.883	37.870348	-122.267764	
3	62172	2017-12-31 17:31:10.636	2018-01-01 10:47:23.531	37.774520	-122.409449	
4	43603	2017-12-31 14:23:14.001	2018-01-01 02:29:57.571	37.868813	-122.258764	

In [21]:
```
#Save File as csv
df_trip_clean.to_csv("df_trip_clean.csv",index=False)
```

3. Exploratory Data Analysis(EDA)

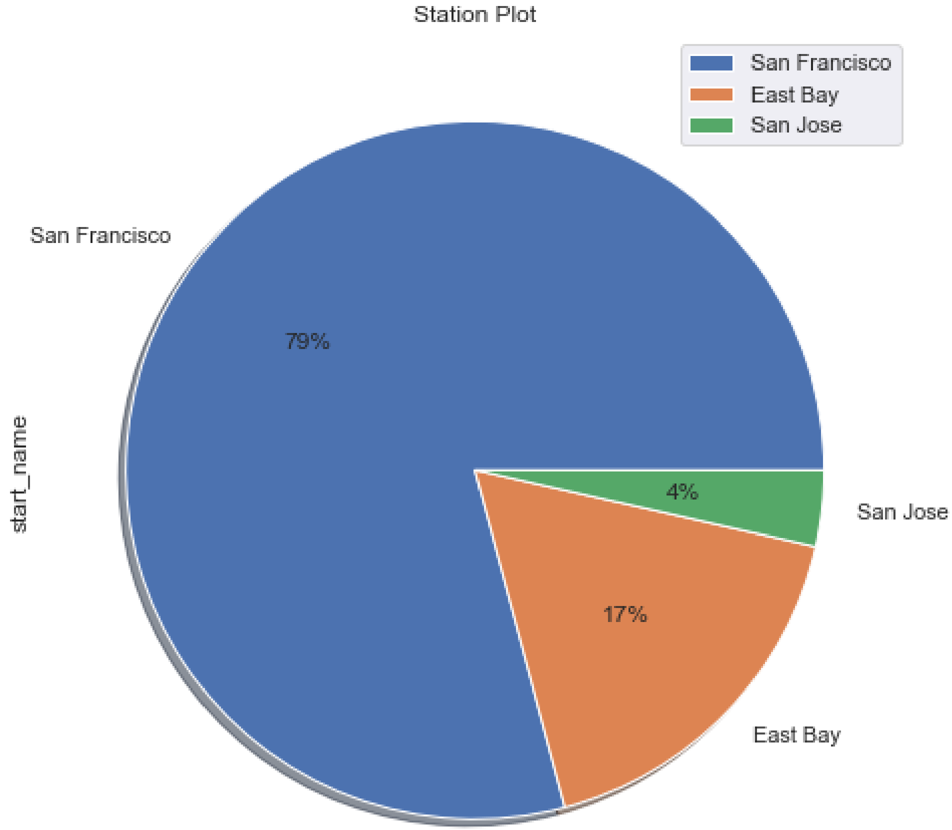
Univariate visualization

so we are in the EDA phase and in this section we will be exploring the single variable using plots and insights will be given

Feature Name: Statrt station

In [22]:
```
#pie chart for categorical data
df_trip_clean['start_name'].value_counts().plot(kind='pie',figsize=(8,8
), autopct='%1.0f%%', shadow=True,legend=True,title='Station Plot')
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x18ebb3dcb70>
```



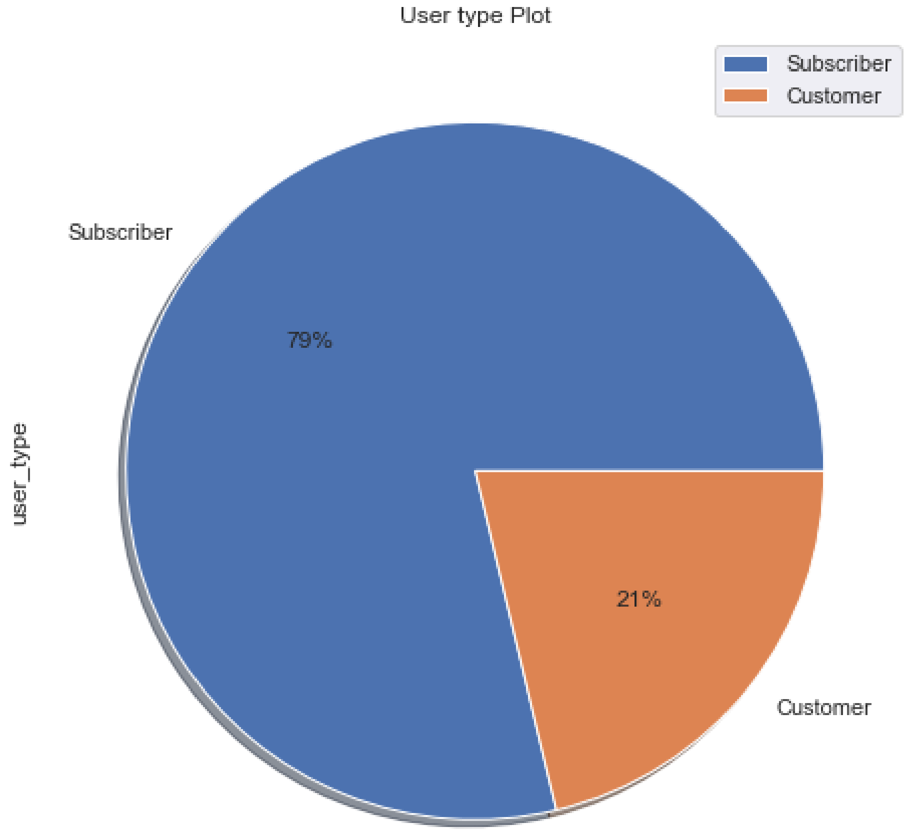
Analysis:

Well, this pie chart gives a rough idea about the percentage for the initial bookings in each region. And, we can clearly see that San Francisco has most bookings followed by East Baya and then San Jose.

Feature Name: User type

In [23]:
```
#pie chart for categorical data
df_trip_clean['user_type'].value_counts().plot(kind='pie',figsize=(8,8
), autopct='%1.0f%%',shadow=True, legend=True,title='User type Plot')
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x18ebb2f3a58>



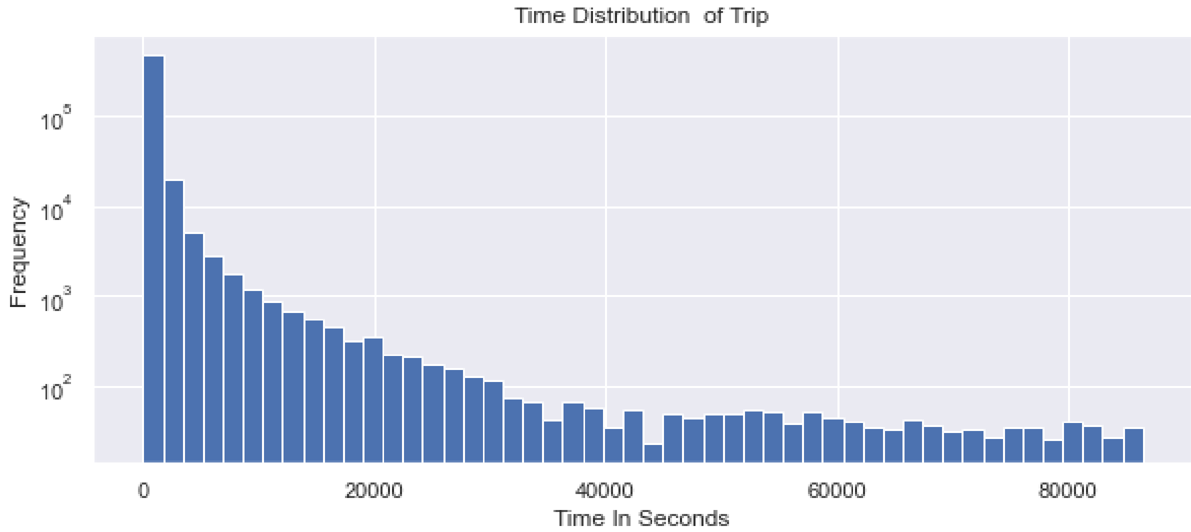
Analysis:

Pie chart gives better intuition while plotting less categorical features. Here we can visualize that around 4/5 of total bike bookings are done by subscribers and only 1/5th is done by casual customers. But, in further analysis we will see the relationships between more features.

Feature name: Duration

In [24]:
```
#histogram for continuous or numerical data
plt.figure(figsize=(10,4))
df_trip_clean['duration_sec'].plot(kind='hist',bins=50)
plt.yscale('log')
plt.xlabel('Time In Seconds')
plt.title('Time Distribution  of Trip')
```

Out[24]:
```
Text(0.5, 1.0, 'Time Distribution  of Trip')
```



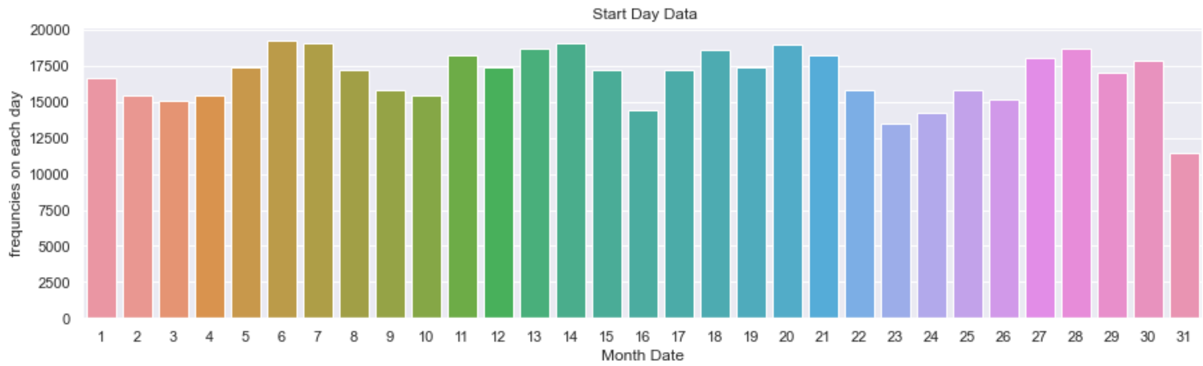
Analysis:

After Visualizing trip duration I came to know that trips are done for less than a minute and for a day as well. so less than minute sort of trips done by children, or free trails provided by the company.

Feature Name: Start Day

In [25]:
```
start_day_count=df_trip_clean.groupby('start_day')['bike_id'].count()
```

In [26]:
```
#bar plot for discete value of numeric.
x=[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26
,27,28,29,30,31]
plt.figure(figsize=(15,4))
sns.barplot(x=x,y=start_day_count)
#plt.yscale('log')
plt.xlabel('Month Date')
plt.ylabel('frequncies on each day')
plt.title(" Start Day Data")
plt.show()
```



Analysis:

This the clearly visible that there is periodically drop in trips around every 8th day of the month.

Feature Name : Start Month

In [27]:
```
#count plot for numerical sort of data.
```

```
fig, ax = plt.subplots(figsize = (20,5))
sns.countplot(x = df_trip_clean["start_month"],  palette = "viridis")
plt.xlabel('Month')
plt.ylabel('Frequencies per month')
plt.title("Start month Data")
plt.show()
```

Analysis:

The trend shows that the bookings are done only from June to December month.October has highest number of bookings.

Feature Name: End Month

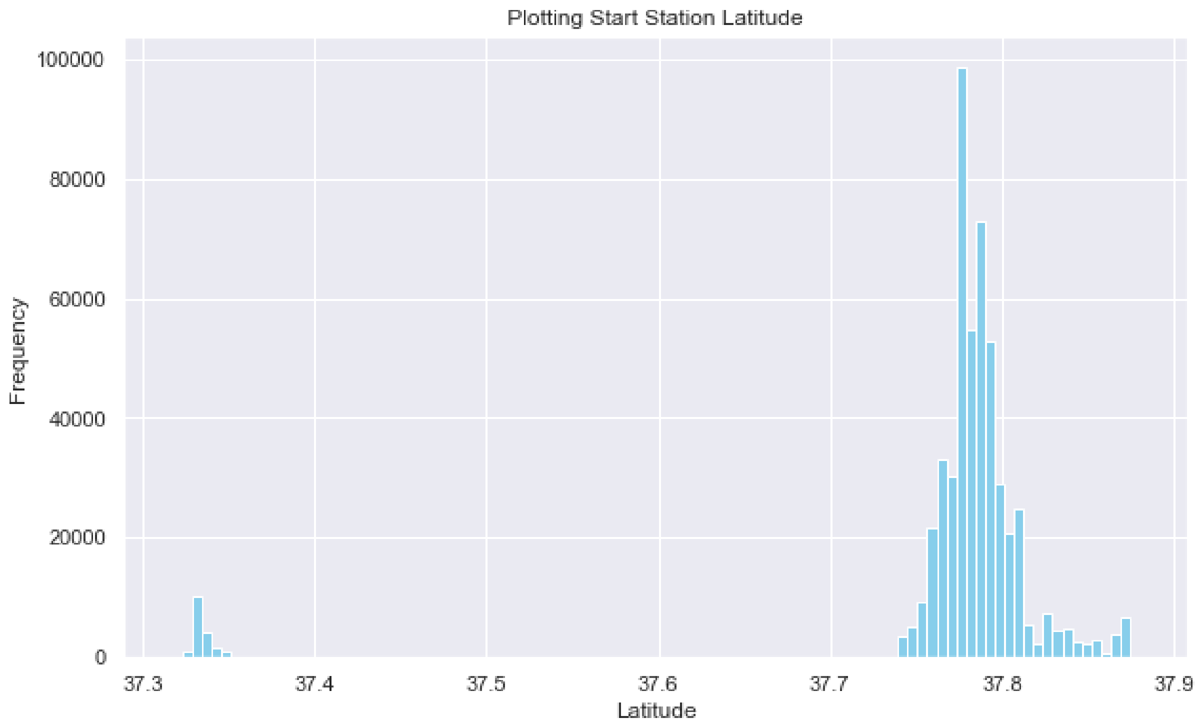
In [28]:
```
#count plot for numeric sort of data.
fig, ax = plt.subplots(figsize = (20,5))
sns.countplot(x = df_trip_clean["end_month"],  palette = "viridis")
plt.xlabel('Month')
plt.ylabel('Frequencies per month')
plt.title("Start month Data")
plt.show()
```

Analysis:

So, This is related to start month bookings are done only June to December. But what we see that end booking in January it is because of the bookings at end of the December month.

Feature Name: End station Latitude

In [29]:
```
#histogram for continuous data
plt.figure(figsize=(10,6))
df_trip_clean['start_station_latitude'].plot(kind='hist',bins=100,color
='skyblue')
plt.title(' Plotting Start Station Latitude ')
plt.xlabel("Latitude")
plt.show()
```



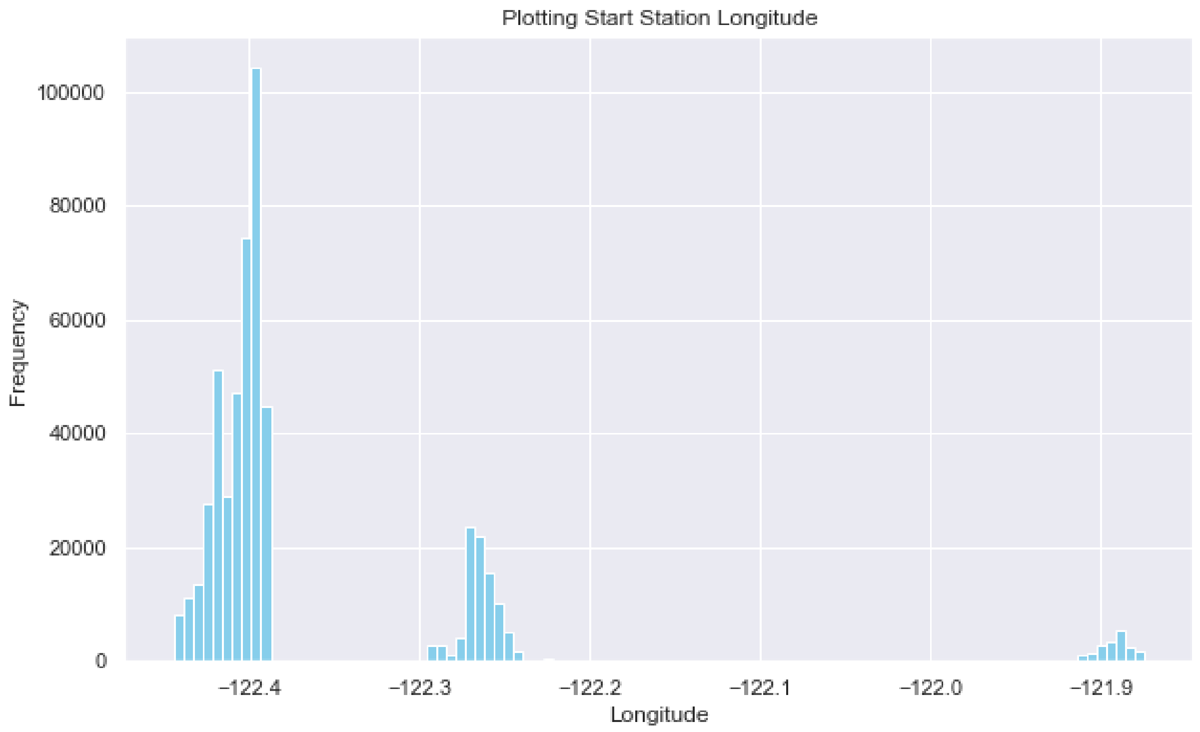
Analysis:

Analysing Latitude alone would not give the idea about starting stations of trips. So i would be doing bivariate as well as multi variate to see the visualization to differentiate bwtween the stations.

Feature Name: Start Station longitude

In [30]:
```
#histogram for continuous data
plt.figure(figsize=(10,6))
df_trip_clean['start_station_longitude'].plot(kind='hist',bins=100,colo
r='skyblue')
```

```
plt.title(' Plotting Start Station Longitude ')
plt.xlabel("Longitude")
plt.show()
```



Analysis:

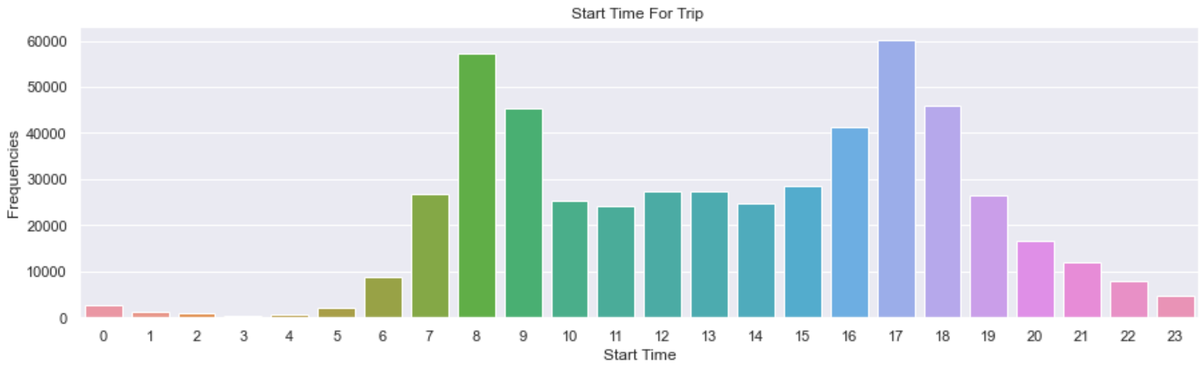
Wow! Great visualization of longitude with respect to the start stations. The locations are differentiable now and we can recognize then clearly. But we can't identify the names still. While doing Bivariate or multivariate, names will be clear and certain.

Feature Name: Start Time

In [31]:
```
start_hours=df_trip_clean.start_time.dt.hour
```

In [32]:
```
#count plot for dicrete data
plt.figure(figsize=(15,4))
ax=sns.countplot(start_hours)
ax.set_title('Start Time For Trip ')
ax.set_ylabel('Frequencies')
ax.set_xlabel('Start Time')
```

Out[32]: Text(0.5, 0, 'Start Time')



Analysis:

This is very important feature to analyse with respecct to business. We can see the traffic time when people start their trips. In the morning 8 am to 9 am and in the evening 4 pm to 6 pm the traffic is high. we could add more offers and facilities at this time to attract the casual customers and subscribers.

Bivariate visualization

Quantitative Variables Vs Quantitative Variables

Feature Names:Start Longitude and Start Longitude

In [33]:
```
#a new dataframe
log_lat=df_trip_clean[['start_station_latitude','start_station_longitud
e']]
```

In [34]:
```
#groupby
log_lat.groupby(['start_station_latitude','start_station_longitude']).c
ount().reset_index()
```

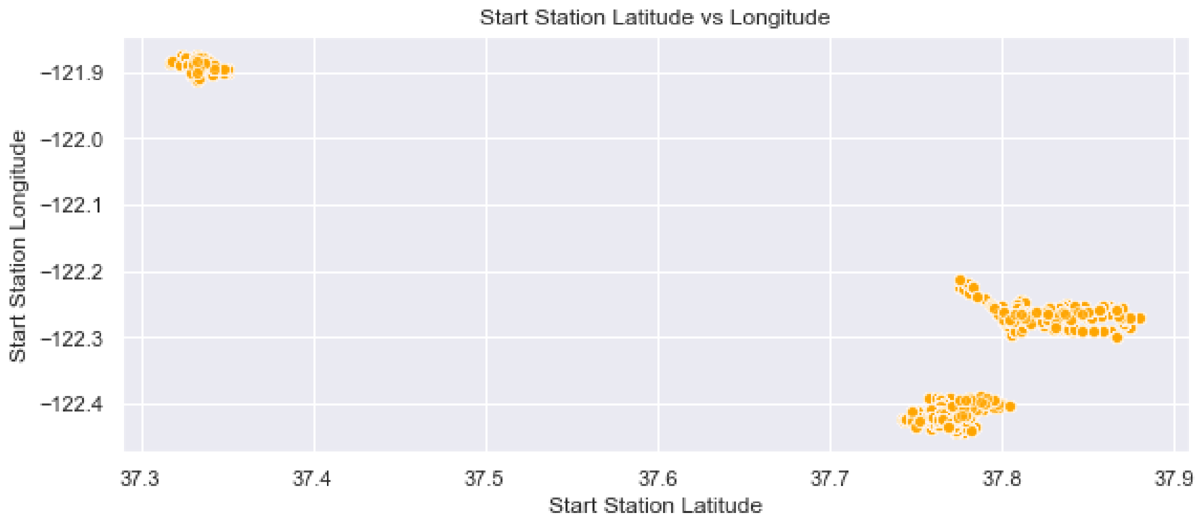
Out[34]:

	start_station_latitude	start_station_longitude
0	37.317298	-121.884995
1	37.318450	-121.883172
2	37.322980	-121.887931
3	37.323678	-121.874119
4	37.325998	-121.877120
...	...	...
267	37.871719	-122.273068
268	37.872355	-122.266447
269	37.873792	-122.268618
270	37.874014	-122.283019
271	37.880222	-122.269592

272 rows × 2 columns

In [35]:
```
#scatterplots for two continuous data
plt.figure(figsize=(10,4))
ax=sns.scatterplot(x=log_lat.start_station_latitude,y=log_lat.start_sta
tion_longitude,color="orange",alpha=.7)
ax.set_xlabel("Start Station Latitude")
ax.set_ylabel("Start Station Longitude")
ax.set_title("Start Station Latitude vs Longitude")
```

Out[35]: Text(0.5, 1.0, 'Start Station Latitude vs Longitude')



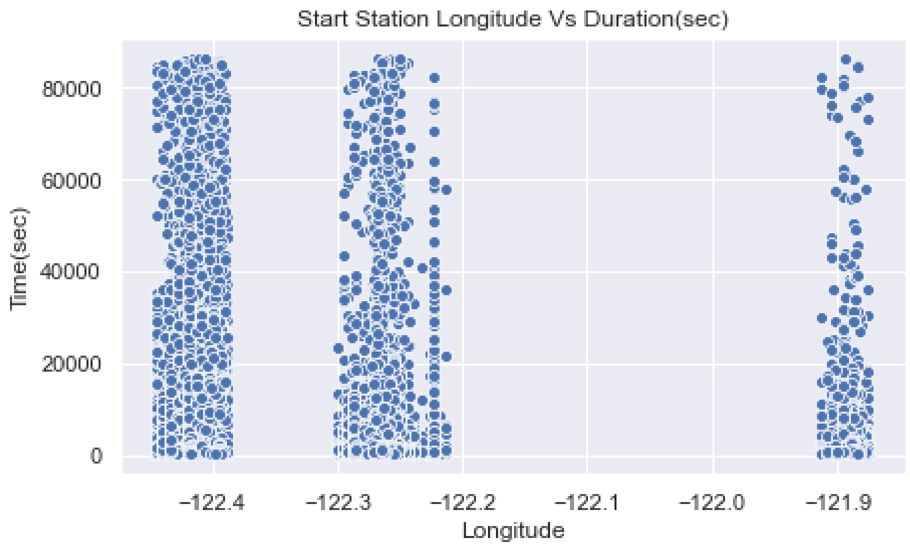
Analysis:

So, It's time to visualization be two features at a time. Now earlier we see longitude and latitue indivisually but while aggregating into one, our visualization becomes more clear about the Start Stations.

Feature Name: Start Station Longitude and Duration

In [36]:
```
#scatterplots for two continuous data
plt.figure(figsize=(7,4))
ax=sns.scatterplot(x='start_station_longitude',y="duration_sec", data=d
f_trip_clean)
ax.set_title('Start Station Longitude Vs Duration(sec)')
ax.set_ylabel('Time(sec)')
ax.set_xlabel('Longitude')
```

Out[36]: Text(0.5, 0, 'Longitude')



Analysis:

Visualizing Trip Duration and Longitude gives an idea about the time taken in each region. The longitude -122.4 has quite dense distribution of time(sec), it shows people from this area rents the bike for more time.

Feature Name: Start Day And Start Month

In [37]:
```
#new dataframe
new_month_day=df_trip_clean[['start_day','start_month','bike_id']]
```

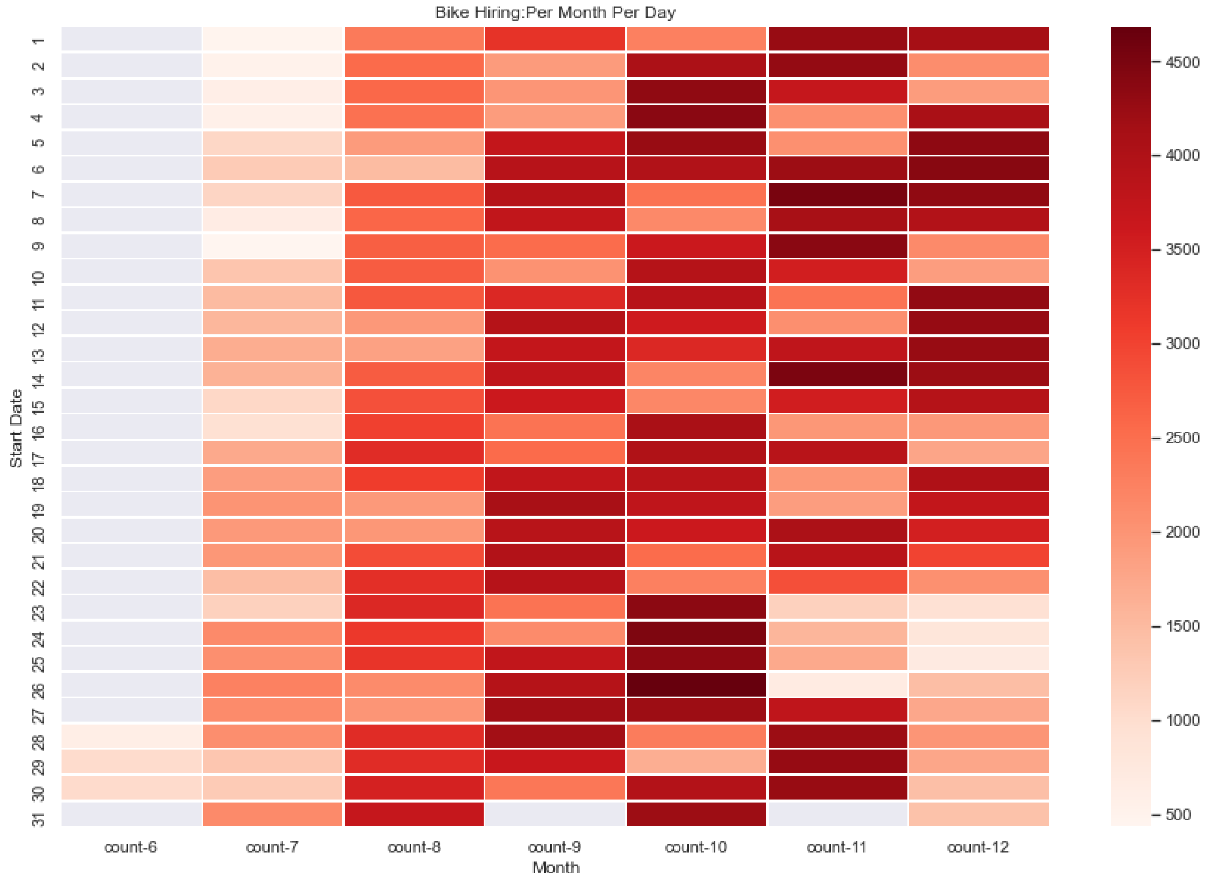
In [38]:
```
#groupby
new_month_day=new_month_day.groupby(['start_day', 'start_month'])['bike_id'].size().to_frame(name = 'count').reset_index()
```

In [39]:
```
#to pivot table
```

```
new_month_day=new_month_day.pivot('start_day','start_month')
```

In [40]:
```
#heatmap for two discrete data
plt.figure(figsize=(15, 10));
ax=sns.heatmap(new_month_day,cmap="Reds",linewidths=.5)
ax.set_title('Bike Hiring:Per Month Per Day')
ax.set_xlabel('Month')
ax.set_ylabel('Start Date')
```

Out[40]:
```
Text(111.5, 0.5, 'Start Date')
```



Analysis:

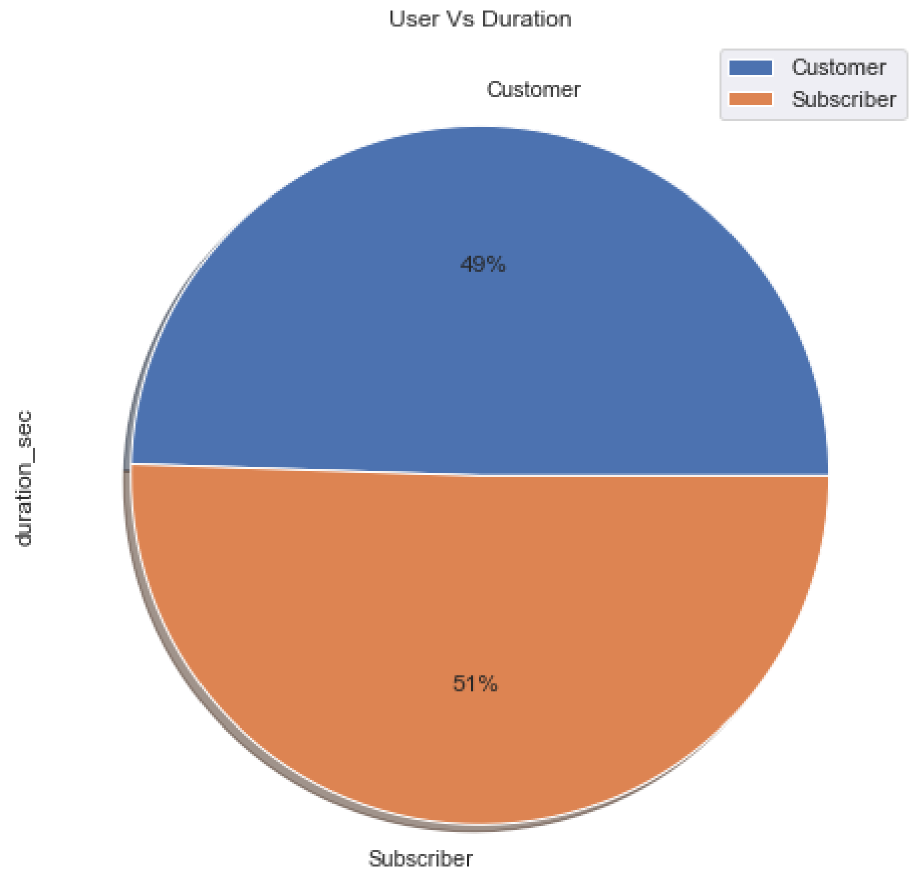
This gives the idea about the trend the way bikes are got hired. The heatmap shows the frequncy of hiring bike every day per month. Darker the colour more is the frequncy. We can see that every month excluding June has a fix trend. There is continuous hiring for 5 days and then drop for 2 days.

Quantitative Variables Vs Qualitative Variables

Feature Names: User_type and duration_sec

In [41]:

```
#pie chart for two categorical data
df_trip_clean.groupby('user_type')['duration_sec'].sum().plot(kind='pie',figsize=(8,8), shadow=True,autopct='%1.0f%%', legend=True,title='User Vs Duration')
plt.show()
```

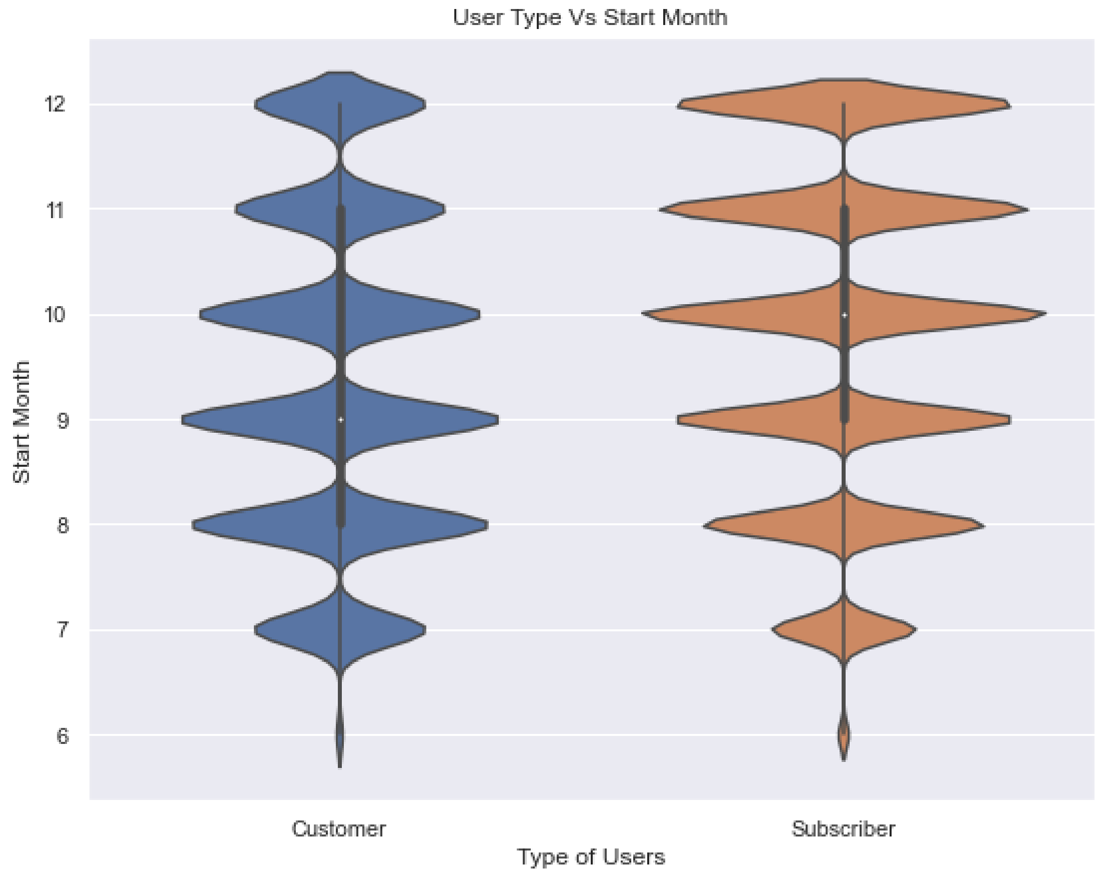


Analysis:

This visualization is very interesting because as saw earlier that only 1/5th of customers are contributing in total hiring but here we can see that their contribution in hiring a bike with respect to time is almost equal to the Subscribers.

Feature Names: User Type and Start Month

In [42]:
```
#violin plot for onre categorical and one numeric
fig, ax = plt.subplots(figsize =(9, 7))
ax=sns.violinplot(x='user_type',y='start_month',data=df_trip_clean)
ax.set_title('User Type Vs Start Month')
ax.set_ylabel('Start Month')
ax.set_xlabel('Type of Users')
plt.show()
```



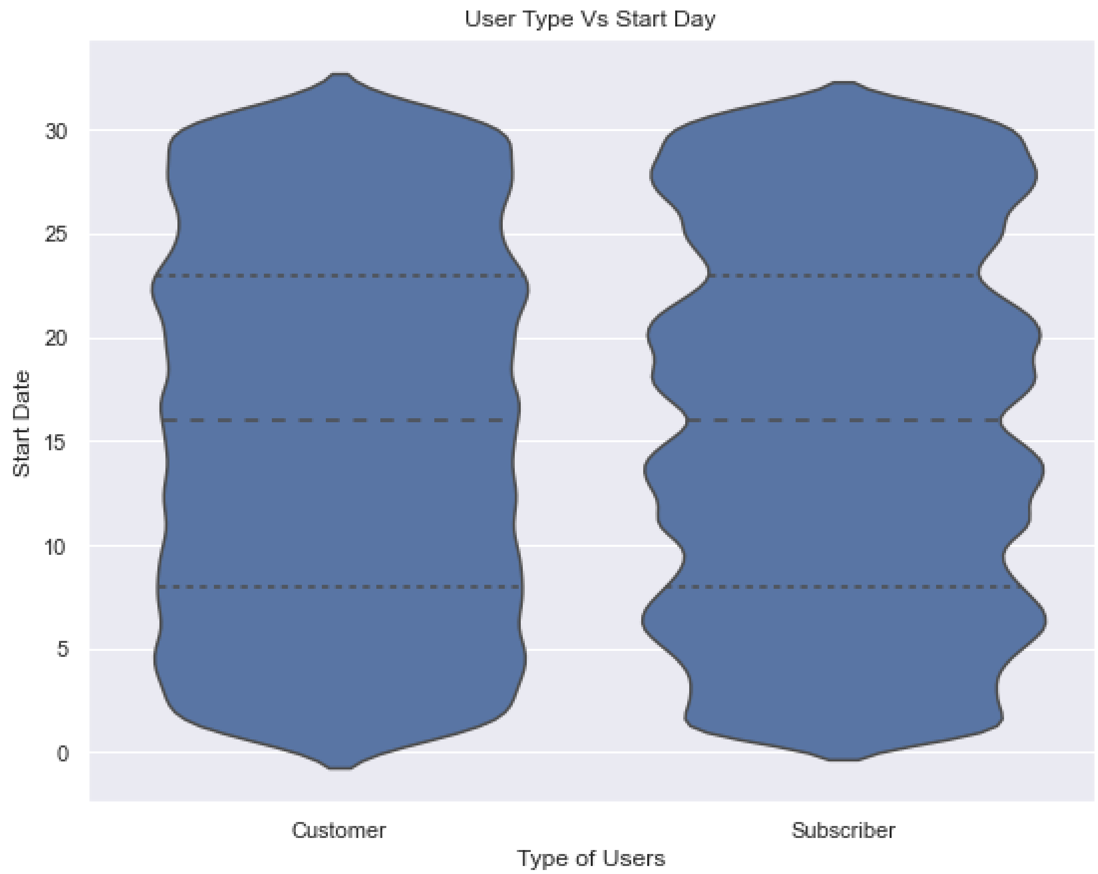
Analysis:

Now will see the type of users are renting bike in the particular month. Casual customers hire the bike moslty in the month of august to October while Subscribers hire the bike frequently from September to December.

Feature Names: User Type Vs Start Day

In [43]:

```
#violin plot for onre categorical and one numeric
fig, ax = plt.subplots(figsize =(9, 7))
ax=sns.violinplot(data=df_trip_clean, x='user_type', y='start_day', col
or=sns.color_palette()[0],inner='quartile')
ax.set_title('User Type Vs Start Day')
ax.set_ylabel('Start Date')
ax.set_xlabel('Type of Users')
plt.show()
```



Analysis:

There is a trend while hiring the bike with respect to Subscribers whereas Customers' hiring seems to be linear

Feature Names:Start Month and Start Name(Station Name)

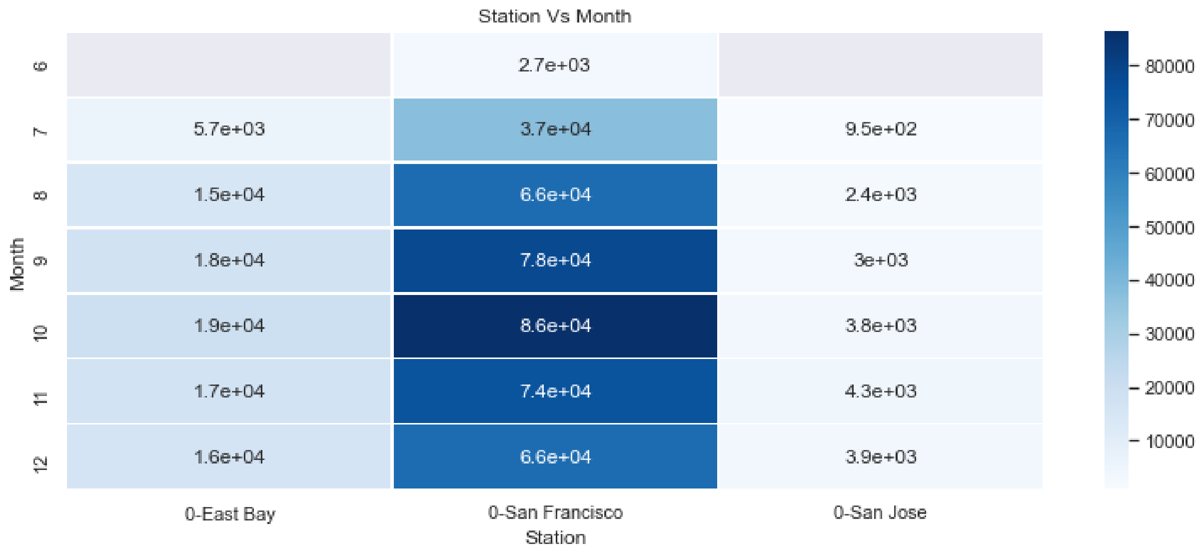
In [44]:
```
#copy to new dataframe
df=df_trip_clean[['start_month','start_name','bike_id']].copy()
```

```
#groupby
df=df.groupby(['start_month','start_name']).size().reset_index()
```

In [45]:
```
#to pivot table
df=df.pivot('start_month','start_name')
```

In [46]:
```
#heat map for one numeric and one categorical data
plt.figure(figsize=(13, 5));
ax=sns.heatmap(df,cmap="Blues",linewidths=.5,annot=True)
ax.set_title('Station Vs Month')
ax.set_xlabel('Station')
ax.set_ylabel('Month')
```

Out[46]: Text(93.5, 0.5, 'Month')



Analysis:

Main finding of this plot is that San Francisco has more registerd Customers and Subscribers which leads to the highest hiring of the bikes in each month. For San Francisco and East Bay

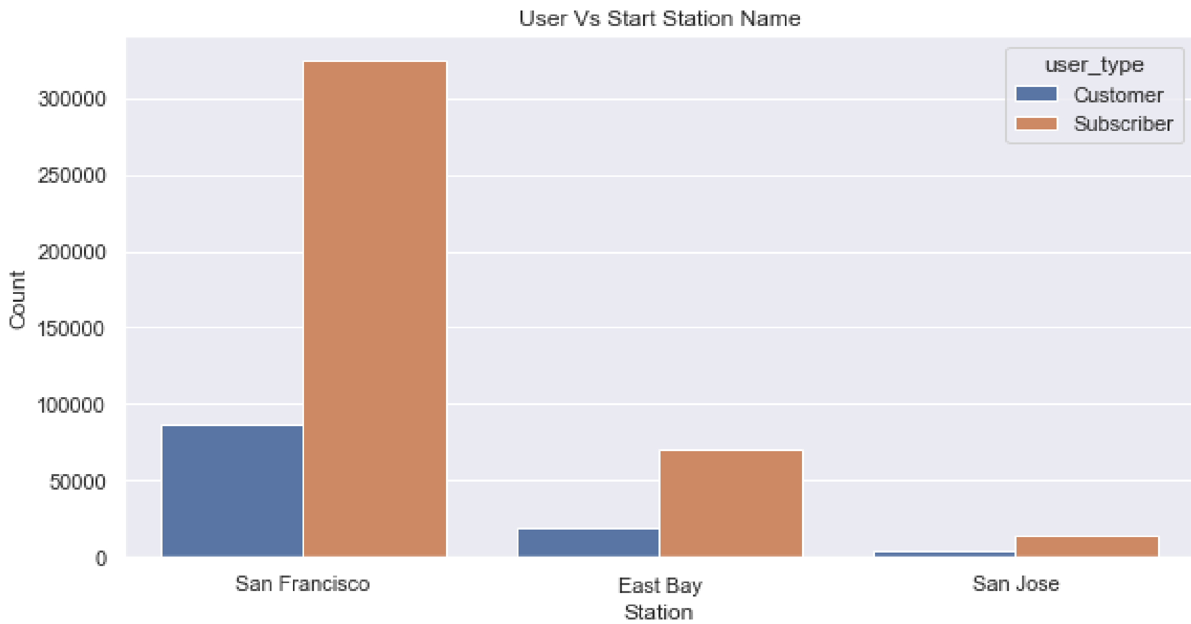
October is the highest hiring month, and for San jose November adds more audience.

Qualitative Variables Vs Qualitative Variables

Feature Names: User Type and Start Name(station name)

In [47]:
```
#countplot for two categorical data
fig, ax = plt.subplots(figsize =(10, 5))
ax=sns.countplot(x="start_name",hue='user_type',data=df_trip_clean)
ax.set_title('User Vs Start Station Name')
ax.set_xlabel('Station')
ax.set_ylabel('Count')
```

Out[47]: `Text(0, 0.5, 'Count')`



Analysis:

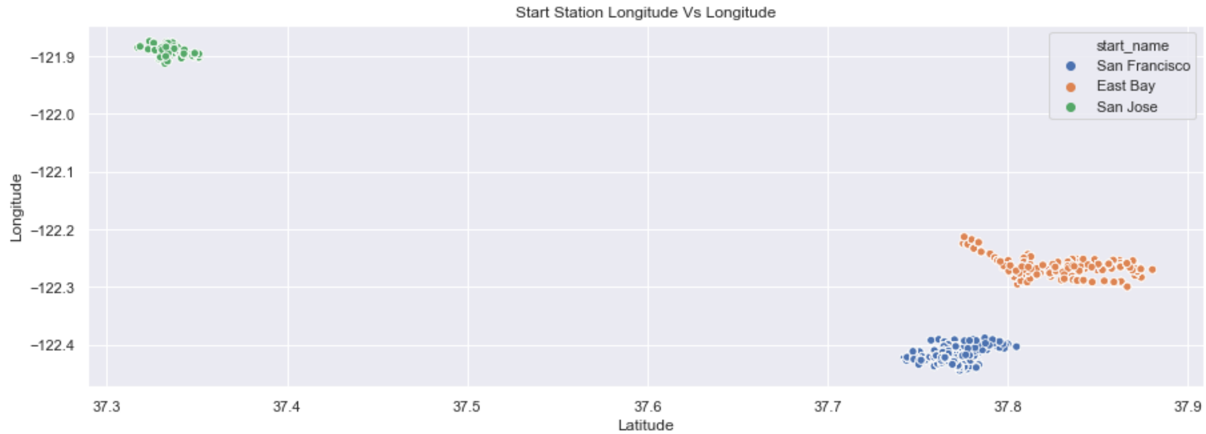
Categorizing Users on the basis of Regions. San Francisco has most users , followed by East Bay and then San Jose. Now User type has same trend as total user counts.

Multivariate Visualization

Feature Names: Start Latitude , Start Longitude and Start Station Name

In [48]:
```
#scatter plot for multivariate visualization of two numeric and one cat
egorical
plt.figure(figsize=(15,5))
ax=sns.scatterplot(x='start_station_latitude',y="start_station_longitud
e", data=df_trip_clean,hue='start_name')
ax.set_title('Start Station Longitude Vs Longitude')
ax.set_ylabel('Longitude')
ax.set_xlabel('Latitude')
```

Out[48]:
```
Text(0.5, 0, 'Latitude')
```



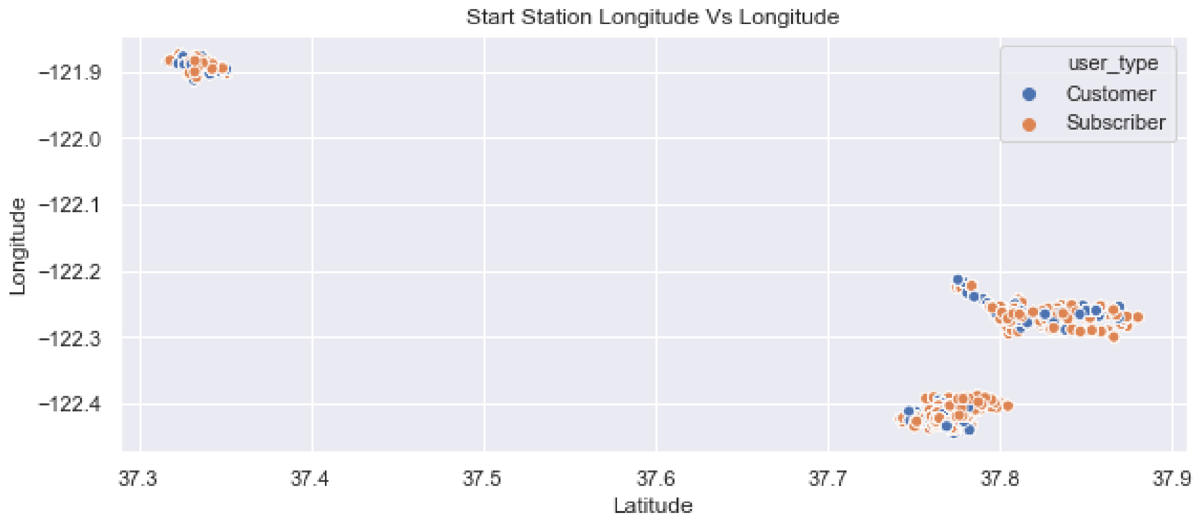
Analysis:

As i mentioned while visualizing univariate that the multivariate plot will give better regionwise classification of start stations. and here we can easily differentiate after adding third feature as the regions.

Feature Names: Start Longitude, Start Latitude and User Type

In [49]:
```
#scatter plot for multivariate visualization of two numeric and one cat
egorical
plt.figure(figsize=(10,4))
ax=sns.scatterplot(x='start_station_latitude',y="start_station_longitud
e", data=df_trip_clean,hue='user_type')
ax.set_title('Start Station Longitude Vs Longitude')
ax.set_ylabel('Longitude')
ax.set_xlabel('Latitude')
```

Out[49]:
```
Text(0.5, 0, 'Latitude')
```



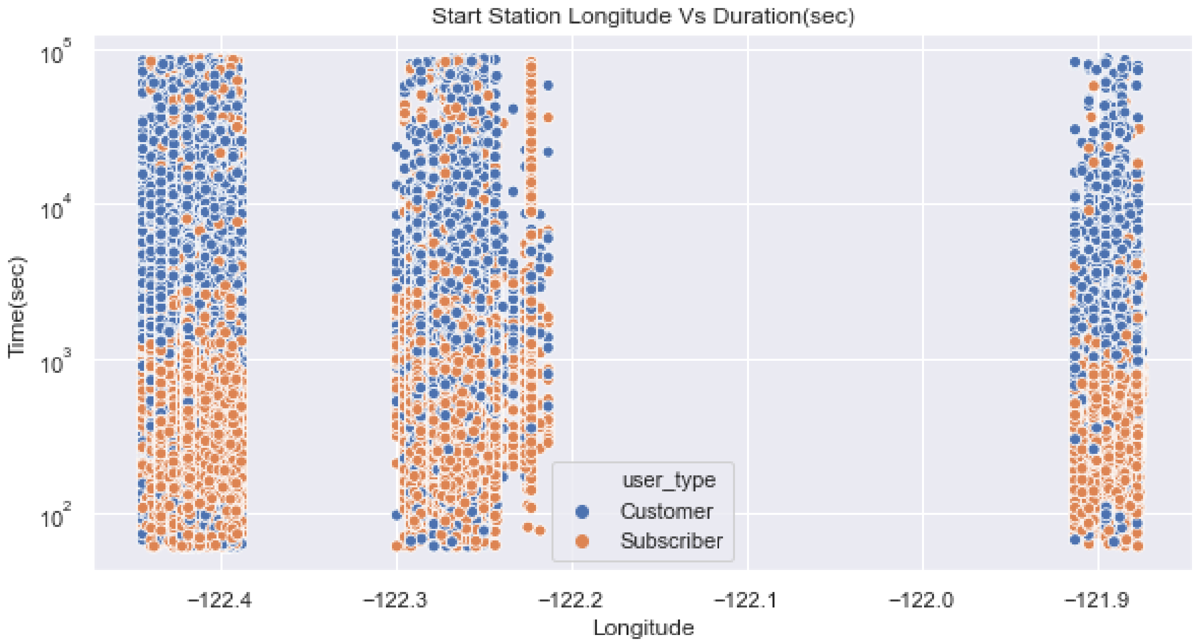
Analysis:

Sometimes Bivariate visualization gives better analysis than multivariate. The previous Plot(User Vs Station name) gives better idea of the distribution of the users regionwise.

Feature Names: Start Station LOngitude Duration and Customers

In [50]:
```
#scatter plot for two numeric and one categorical
plt.figure(figsize=(10,5))
ax=sns.scatterplot(x='start_station_longitude',y="duration_sec", data=d
f_trip_clean,hue='user_type')
plt.yscale('log')
ax.set_title('Start Station Longitude Vs Duration(sec)')
ax.set_ylabel('Time(sec)')
ax.set_xlabel('Longitude')
```

Out[50]: `Text(0.5, 0, 'Longitude')`



Analysis:

It's a great Visualization that gives the idea in which region a particular type of user has more trip time. we can see that customers hire bikes for more time as compared to subscirbers and that is why being in less count Customers adds more time trip and hence benefits the company.

Feature Name:Start Month Start day And User type

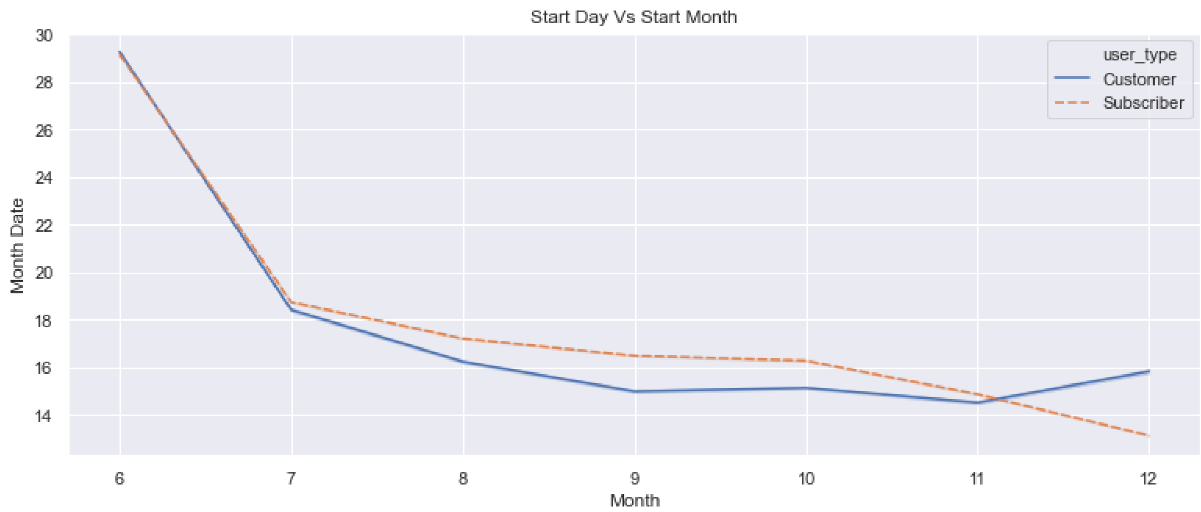
In [51]:

```
#visulaize three features using lineplot
plt.figure(figsize=(13,5))
ax = sns.lineplot(x="start_month", y='start_day', hue="user_type",
                  style="user_type", ci=68, data=df_trip_clean)

ax.set_title('Start Day Vs Start Month')
ax.set_ylabel('Month Date')
ax.set_xlabel('Month')
```

Out[51]:

```
Text(0.5, 0, 'Month')
```



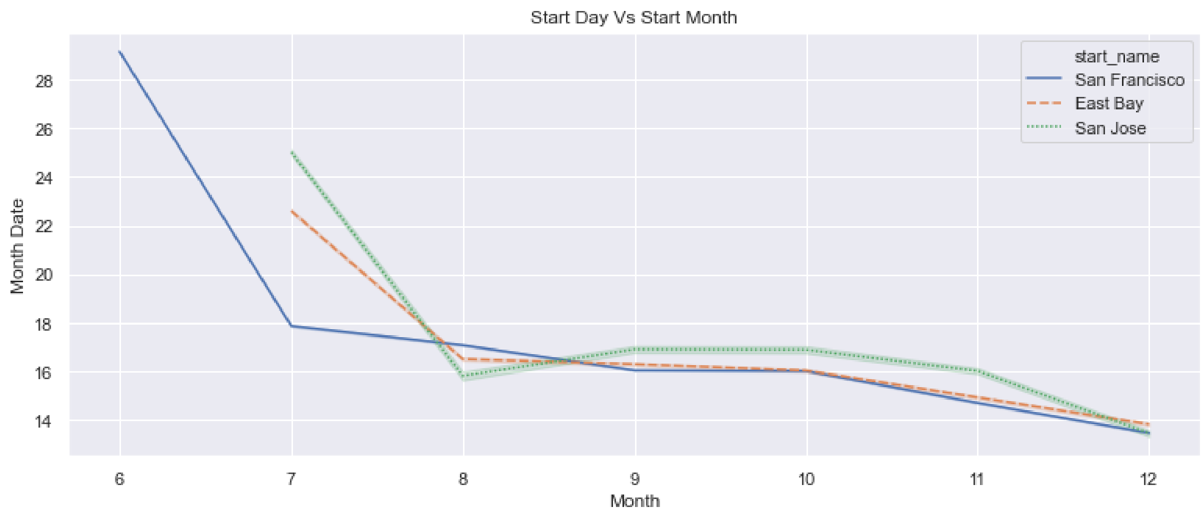
Analysis:

The line plot shows how users are hiring bikes per day per month.

Feature Name:Start Month Start day And Start Station

In [52]:
```
#visulaize three features using lineplot
plt.figure(figsize=(13,5))
ax = sns.lineplot(x="start_month", y='start_day', hue="start_name",
                  style="start_name", ci=68, data=df_trip_clean)
ax.set_title('Start Day Vs Start Month')
ax.set_ylabel('Month Date')
ax.set_xlabel('Month')
```

Out[52]: Text(0.5, 0, 'Month')



Analysis:

The line plot shows how users are hiring bikes per day per month in the particular region.

References:

https://stackoverflow.com/questions/52080991/display-percentage-above-bar-chart-in-matplotlib
https://matplotlib.org/3.1.1/gallery/pie_and_polar_charts/pie_features.html

https://stackoverflow.com/questions/22341271/get-list-from-pandas-dataframe-column#:~:text=7%20Answers&text=Pandas%20DataFrame%20columns%20are%20Pandas,it%2

https://stackoverflow.com/questions/42406233/how-to-add-title-to-seaborn-boxplot

https://matplotlib.org/3.2.2/api/_as_gen/matplotlib.pyplot.scatter.html

https://seaborn.pydata.org/generated/seaborn.heatmap.html

https://stackoverflow.com/questions/10373660/converting-a-pandas-groupby-output-from-series-to-dataframe

https://stackoverflow.com/questions/18695605/python-pandas-dataframe-to-dictionary

https://stackoverflow.com/questions/42049147/convert-list-to-pandas-dataframe-column

4.Conclusion

This is not the end though, I would polish some visualizations for the better story telling in the next notebook. I will follow a proper way of story telling so that anybody can get attached to it and understands in better way.