ford_bike_exploration

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1 Ford GoBike Sysytem Data Exploration

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This report details the data wrangling as well as an exploratory analysis on the 2017- March 2020 Bay Area Bike Share data.

1.2 Content

- Section **??**
- Section **??**
- Section **??**
- Section **??**

Preliminary Wrangling

[45]:
```
# import all packages and set plots to be embedded inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import csv
from math import sin, cos, sqrt, atan2, radians
from IPython.display import display
import os
from datetime import datetime
%matplotlib inline
```

Load in your dataset and describe its properties through the questions below. Try and motivate your exploration goals through this section.

[30]:
```
first_df = pd.read_csv('2017-fordgobike-tripdata.csv', dtype={'duration_sec':
↪'int','start_time':'str','end_time':'str','start_station_id':pd.
↪Int64Dtype(),'start_station_name':'str',
          'start_station_latitude':'float','start_station_longitude':
↪'float','end_station_id':pd.Int64Dtype(),
          'end_station_name':'str','end_station_latitude':
↪'float','end_station_longitude':'float',
```

```
          'bike_id':'int','user_type':'str'}, header=0,
                        parse_dates=['start_time','end_time'], na_values=['', '␣
 ↪'])
first_df.head()
```

[30]:

```
   duration_sec              start_time                end_time  \
0         80110 2017-12-31 16:57:39.654 2018-01-01 15:12:50.245
1         78800 2017-12-31 15:56:34.842 2018-01-01 13:49:55.617
2         45768 2017-12-31 22:45:48.411 2018-01-01 11:28:36.883
3         62172 2017-12-31 17:31:10.636 2018-01-01 10:47:23.531
4         43603 2017-12-31 14:23:14.001 2018-01-01 02:29:57.571

   start_station_id                                start_station_name  \
0                74                              Laguna St at Hayes St
1               284  Yerba Buena Center for the Arts (Howard St at ...
2               245                             Downtown Berkeley BART
3                60                               8th St at Ringold St
4               239                      Bancroft Way at Telegraph Ave

   start_station_latitude  start_station_longitude  end_station_id  \
0               37.776435              -122.426244              43
1               37.784872              -122.400876              96
2               37.870348              -122.267764             245
3               37.774520              -122.409449               5
4               37.868813              -122.258764             247

                                end_station_name  end_station_latitude  \
0  San Francisco Public Library (Grove St at Hyde...             37.778768
1                             Dolores St at 15th St             37.766210
2                            Downtown Berkeley BART             37.870348
3       Powell St BART Station (Market St at 5th St)             37.783899
4                          Fulton St at Bancroft Way             37.867789

   end_station_longitude  bike_id   user_type
0            -122.415929       96    Customer
1            -122.426614       88    Customer
2            -122.267764     1094    Customer
3            -122.408445     2831    Customer
4            -122.265896     3167  Subscriber
```

[27]:

```
files = os.listdir("./files/")
colums =␣
 ↪['duration_sec','start_time','end_time','start_station_id','start_station_name','start_stat
          ␣
 ↪'start_station_longitude','end_station_id','end_station_name','end_station_latitude',
            'end_station_longitude','bike_id','user_type']
tables = []
for file in files:
```

```
    with open("./files/" + file, 'r') as f_in:
        df = pd.read_csv(f_in, dtype={'duration_sec':'int','start_time':
↪'str','end_time':'str','start_station_id':pd.
↪Int64Dtype(),'start_station_name':'str',
          'start_station_latitude':'float','start_station_longitude':
↪'float','end_station_id':pd.Int64Dtype(),
          'end_station_name':'str','end_station_latitude':
↪'float','end_station_longitude':'float',
          'bike_id':'int','user_type':'str'}, header=0, usecols=colums,
                         parse_dates=['start_time','end_time'], na_values=['', '␣
↪'])
        tables.append(df)

set_df = pd.concat(tables, axis=0, ignore_index=True)

display(set_df.head(5))
```

```
   duration_sec              start_time                end_time  \
0         75284 2018-01-31 22:52:35.239 2018-02-01 19:47:19.824
1         85422 2018-01-31 16:13:34.351 2018-02-01 15:57:17.310
2         71576 2018-01-31 14:23:55.889 2018-02-01 10:16:52.116
3         61076 2018-01-31 14:53:23.562 2018-02-01 07:51:20.500
4         39966 2018-01-31 19:52:24.667 2018-02-01 06:58:31.053

   start_station_id                                start_station_name  \
0               120                                Mission Dolores Park
1                15  San Francisco Ferry Building (Harry Bridges Pl...
2               304                                Jackson St at 5th St
3                75                              Market St at Franklin St
4                74                                Laguna St at Hayes St

   start_station_latitude  start_station_longitude  end_station_id  \
0               37.761420              -122.426435             285
1               37.795392              -122.394203              15
2               37.348759              -121.894798             296
3               37.773793              -122.421239              47
4               37.776435              -122.426244              19

                                    end_station_name  end_station_latitude  \
0                          Webster St at O'Farrell St             37.783521
1  San Francisco Ferry Building (Harry Bridges Pl...             37.795392
2                                5th St at Virginia St             37.325998
3                                4th St at Harrison St             37.780955
4                                 Post St at Kearny St             37.788975

   end_station_longitude  bike_id   user_type
0            -122.431158     2765  Subscriber
```

```
1            -122.394203      2815     Customer
2            -121.877120      3039     Customer
3            -122.399749       321     Customer
4            -122.403452       617   Subscriber
```

[31]:
```python
final_df= pd.concat([first_df, set_df], axis=0, ignore_index=True)
final_df = final_df.sample(frac=.1)
```

[39]:
```python
print(final_df.shape)
final_df.info()
```

```
(579541, 13)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 579541 entries, 4018389 to 2056693
Data columns (total 13 columns):
duration_sec               579541 non-null int64
start_time                 579541 non-null datetime64[ns]
end_time                   579541 non-null datetime64[ns]
start_station_id           521877 non-null Int64
start_station_name         522050 non-null object
start_station_latitude     579541 non-null float64
start_station_longitude    579541 non-null float64
end_station_id             521724 non-null Int64
end_station_name           521896 non-null object
end_station_latitude       579541 non-null float64
end_station_longitude      579541 non-null float64
bike_id                    579541 non-null int64
user_type                  579541 non-null object
dtypes: Int64(2), datetime64[ns](2), float64(4), int64(2), object(3)
memory usage: 63.0+ MB
```

Before proceeding to exploration, there are some issues that need to be cleaned in the dataset. - Rows with null values should be dropped - Create new columns for the day of the week, month and time. - Calculate the distance for rides

[76]:
```python
##make a copy of the dataset for cleaning
final= final_df.copy()
```

[77]:
```python
##drop the rows with null and na values
final = final.dropna()
final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 512788 entries, 4018389 to 2056693
Data columns (total 13 columns):
duration_sec               512788 non-null int64
start_time                 512788 non-null datetime64[ns]
end_time                   512788 non-null datetime64[ns]
```

```
start_station_id           512788 non-null Int64
start_station_name         512788 non-null object
start_station_latitude     512788 non-null float64
start_station_longitude    512788 non-null float64
end_station_id             512788 non-null Int64
end_station_name           512788 non-null object
end_station_latitude       512788 non-null float64
end_station_longitude      512788 non-null float64
bike_id                    512788 non-null int64
user_type                  512788 non-null object
dtypes: Int64(2), datetime64[ns](2), float64(4), int64(2), object(3)
memory usage: 55.7+ MB
```

[78]:
```
##get columns for year, month, day of the week and the time the rides were␣
↪taken
final['year'] = final['start_time'].dt.year
final['ride_month']=final['start_time'].dt.strftime('%B')
final['day_of_week']=final['start_time'].dt.strftime('%a')
final['time_of_day']=final['start_time'].dt.hour


final.head()
```

[78]:
```
         duration_sec              start_time                end_time  \
4018389           474 2019-08-13 08:51:36.422 2019-08-13 08:59:30.860
4098528           639 2019-09-30 18:15:45.893 2019-09-30 18:26:25.075
2158951           613 2018-11-19 08:10:03.753 2018-11-19 08:20:17.733
1733102           657 2018-09-30 12:17:39.000 2018-09-30 12:28:36.870
4948310           488 2020-01-14 18:31:14.862 2020-01-14 18:39:23.071

         start_station_id                            start_station_name  \
4018389                 5    Powell St BART Station (Market St at 5th St)
4098528                80                         Townsend St at 5th St
2158951                30  San Francisco Caltrain (Townsend St at 4th St)
1733102               121                            Mission Playground
4948310                81                            Berry St at 4th St

         start_station_latitude  start_station_longitude  end_station_id  \
4018389               37.783899              -122.408445              90
4098528               37.775235              -122.397437              16
2158951               37.776598              -122.395282              15
1733102               37.759210              -122.421339              89
4948310               37.775880              -122.393170             114

                                     end_station_name  \
4018389                          Townsend St at 7th St
4098528                        Steuart St at Market St
2158951  San Francisco Ferry Building (Harry Bridges Pl...
```

```
1733102                        Division St at Potrero Ave
4948310                        Rhode Island St at 17th St

         end_station_latitude  end_station_longitude  bike_id   user_type  \
4018389             37.771058            -122.402717     1357  Subscriber
4098528             37.794130            -122.394430    12450    Customer
2158951             37.795392            -122.394203      603  Subscriber
1733102             37.769218            -122.407646     1072    Customer
4948310             37.764478            -122.402570    13036    Customer

         year ride_month day_of_week  time_of_day
4018389  2019     August         Tue            8
4098528  2019  September         Mon           18
2158951  2018   November         Mon            8
1733102  2018  September         Sun           12
4948310  2020    January         Tue           18
```

[79]:
```
### calculate distance of ride in km
dist=[]
def calculate_distance(row):
    R = 6373.0
    startlat = radians(row['start_station_latitude'])
    startlon = radians(row['start_station_longitude'])
    endlat = radians(row['end_station_latitude'])
    endlon = radians(row['end_station_longitude'])

    distlon = endlon - startlon
    distlat = endlat - startlat
    a = sin(distlat / 2)**2 + cos(startlat) * cos(endlat) * sin(distlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))
    distance = (R * c)*1000
    dist.append(distance)

final.apply(calculate_distance, axis=1)
final['distance'] = dist
```

[80]:
```
final['duration_min']= final['duration_sec'] / 60
final=final.sort_values(by=['duration_min'])
```

[81]:
```
final.head()
```

[81]:
```
         duration_sec               start_time                 end_time  \
5318343            60  2020-02-21 08:13:01.000  2020-02-21 08:14:02.000
3804507            60  2019-07-18 08:20:31.000  2019-07-18 08:21:31.000
5725615            60  2020-03-31 12:24:45.000  2020-03-31 12:25:45.000
2306334            61  2018-12-17 13:30:22.725  2018-12-17 13:31:23.769
3443369            61  2019-06-29 12:39:40.414  2019-06-29 12:40:41.984

         start_station_id                            start_station_name  \
```

```
5318343                309                                  San Jose City Hall
3804507                317                           San Salvador St at 9th St
5725615                513                        Alameda St at Henry Adams St
2306334                 15  San Francisco Ferry Building (Harry Bridges Pl...
3443369                104                                   4th St at 16th St

         start_station_latitude  start_station_longitude  end_station_id  \
5318343               37.337391              -121.886995             309
3804507               37.333955              -121.877349             317
5725615               37.768546              -122.404403             513
2306334               37.795392              -122.394203              16
3443369               37.767045              -122.390833             104

                     end_station_name  end_station_latitude  \
5318343            San Jose City Hall             37.337391
3804507     San Salvador St at 9th St             37.333955
5725615  Alameda St at Henry Adams St             37.768546
2306334        Steuart St at Market St            37.794130
3443369             4th St at 16th St             37.767045

         end_station_longitude  bike_id   user_type  year ride_month  \
5318343            -121.886995   174123  Subscriber  2020   February
3804507            -121.877349   376583  Subscriber  2019       July
5725615            -122.404403   276620  Subscriber  2020      March
2306334            -122.394430     3402  Subscriber  2018   December
3443369            -122.390833     3629  Subscriber  2019       June

        day_of_week  time_of_day    distance  duration_min
5318343         Fri            8    0.000000      1.000000
3804507         Thu            8    0.000000      1.000000
5725615         Tue           12    0.000000      1.000000
2306334         Mon           13  141.782938      1.016667
3443369         Sat           12    0.000000      1.016667
```

[112]:
```
final.describe()
```

[112]:
```
        duration_sec  start_station_id  start_station_latitude  \
count  506836.000000     506836.000000           506836.000000
mean      709.353077        133.327958               37.769917
std       590.246861        114.850229                0.098752
min        60.000000          3.000000               37.263310
25%       356.000000         39.000000               37.771058
50%       562.000000         93.000000               37.781010
75%       870.000000        204.000000               37.795393
max      5998.000000        521.000000               45.510000

       start_station_longitude  end_station_id  end_station_latitude  \
count            506836.000000   506836.000000         506836.000000
```

```
mean                 -122.355012      130.349423             37.770078
std                     0.134830      114.046448              0.098639
min                  -122.509071        3.000000             37.263310
25%                  -122.411901       33.000000             37.771058
50%                  -122.398295       93.000000             37.781074
75%                  -122.294837      200.000000             37.796248
max                   -73.570000      521.000000             45.510000

       end_station_longitude        bike_id            year    time_of_day  \
count          506836.000000  506836.000000   506836.000000  506836.000000
mean             -122.354315   11538.432453     2018.504719      13.508549
std                 0.134281   68082.390736        0.764607       4.761202
min              -122.509071      11.000000     2017.000000       0.000000
25%              -122.411306    1468.000000     2018.000000       9.000000
50%              -122.397405    2830.000000     2019.000000      14.000000
75%              -122.294837    5007.000000     2019.000000      17.000000
max               -73.570000  998430.000000     2020.000000      23.000000

            distance   duration_min
count  506836.000000  506836.000000
mean     1635.588920      11.822551
std      1009.173509       9.837448
min         0.000000       1.000000
25%       906.252026       5.933333
50%      1413.991319       9.366667
75%      2161.219922      14.500000
max      5999.995148      99.966667
```

[82]:
```
final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 512788 entries, 5318343 to 5237876
Data columns (total 19 columns):
duration_sec               512788 non-null int64
start_time                 512788 non-null datetime64[ns]
end_time                   512788 non-null datetime64[ns]
start_station_id           512788 non-null Int64
start_station_name         512788 non-null object
start_station_latitude     512788 non-null float64
start_station_longitude    512788 non-null float64
end_station_id             512788 non-null Int64
end_station_name           512788 non-null object
end_station_latitude       512788 non-null float64
end_station_longitude      512788 non-null float64
bike_id                    512788 non-null int64
user_type                  512788 non-null object
year                       512788 non-null int64
ride_month                 512788 non-null object
```

```
day_of_week                  512788 non-null object
time_of_day                  512788 non-null int64
distance                     512788 non-null float64
duration_min                 512788 non-null float64
dtypes: Int64(2), datetime64[ns](2), float64(6), int64(4), object(5)
memory usage: 79.2+ MB
```

[220]:
```
final.to_csv('gobike_master.csv',
                  index=False, encoding = 'utf-8')
```

1.2.1 Structure of the dataset

After data wrangling and joining multiple data files to get the coverage of 2017- March 2020, the dataset was very large. Hence I took a fractional sample of the entire dataset to work with and cleaned it. The final dataset has 512788 instances and 19 attributes.

1.2.2 Main feature(s) of interest in the dataset

From my initial inspection of the dataset, I can see that the duration of the ride, the distance, stations and the user type are the most interesting features in the dataset. I would like to investigate usage trends in the data for length of ride times, for distance of ride, for specific days of the week and for specific cities, and what kind of users are more common.

1.2.3 Features in the dataset that will help support the investigation into the feature(s) of interest

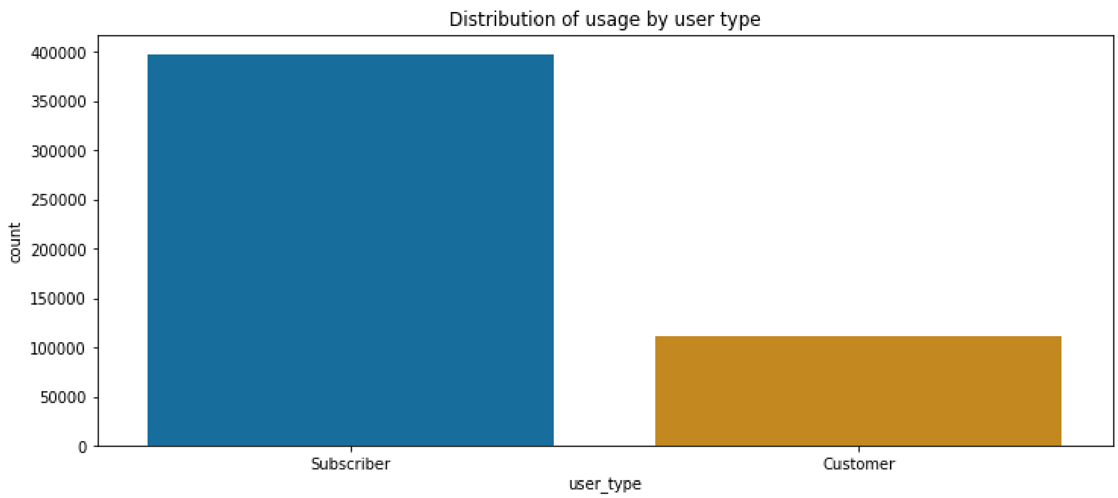
I will be utilizing the duration in seconds, the month, year, day of the week, the time the ride was taken, station names, distance of the rides and the user-types.

Univariate Exploration

In this section, distributions of individual variables are investigated and discussed.

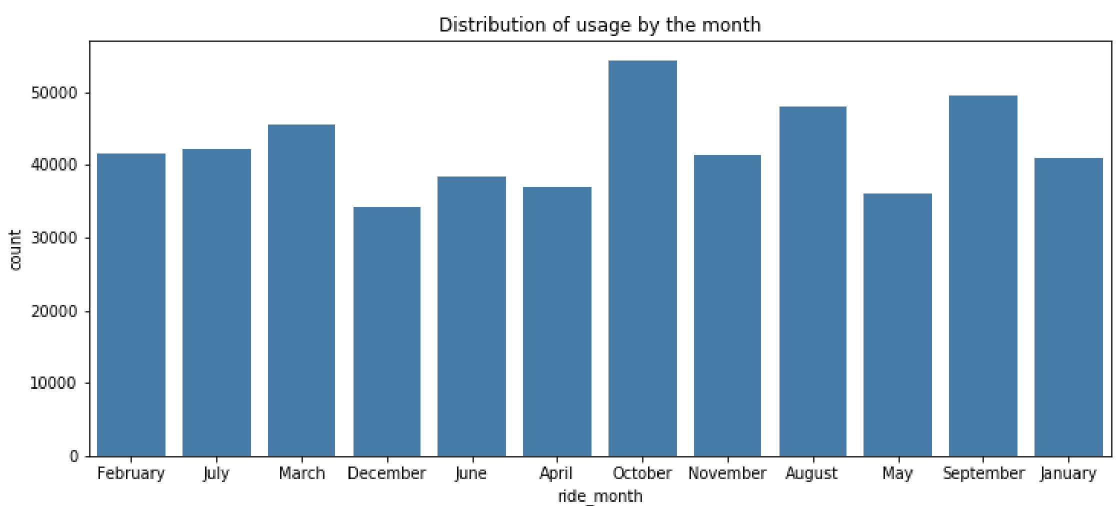
What are the usage trends in the data for different types of users, days, months and years?

[102]:
```
##plot distribution of user type
plt.figure(figsize=(12, 5))
sb.countplot(final['user_type'], palette = sb.color_palette('colorblind'))
plt.title("Distribution of usage by user type")
plt.show();
```



The plot above shows that most of the users of the bike share are actually subscribers. Next we will look at the distribution of the rides based on month, day of the week, times of the day and year.

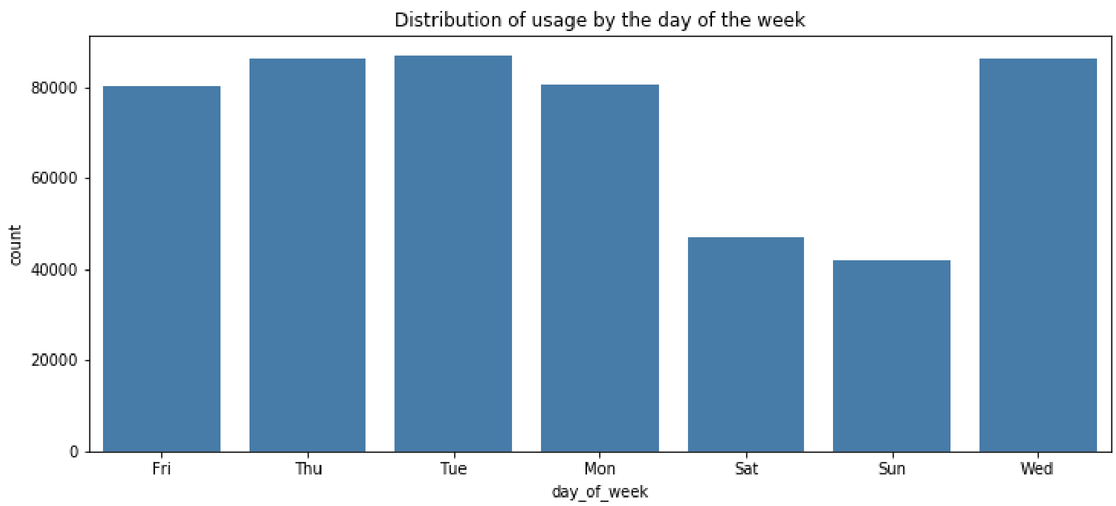
[103]:
```
#plot of distribution by month
plt.figure(figsize=(12, 5))
sb.countplot(final['ride_month'], color='#377eb8')
plt.title("Distribution of usage by the month")
plt.show();
```



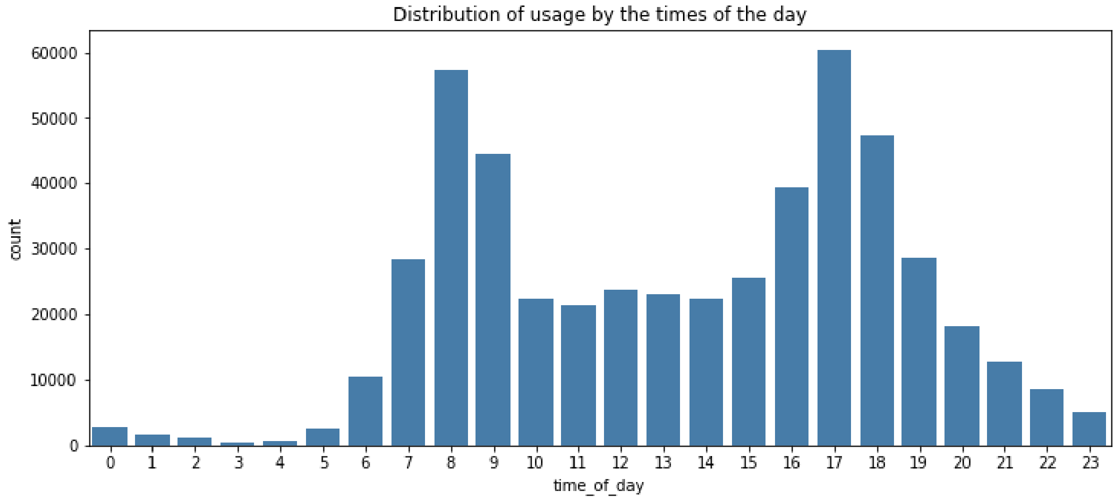
[104]:
```
final.day_of_week.value_counts()
```

[104]:
```
Tue    86877
Thu    86100
Wed    86066
Mon    80444
Fri    80123
Sat    46974
Sun    41899
Name: day_of_week, dtype: int64
```

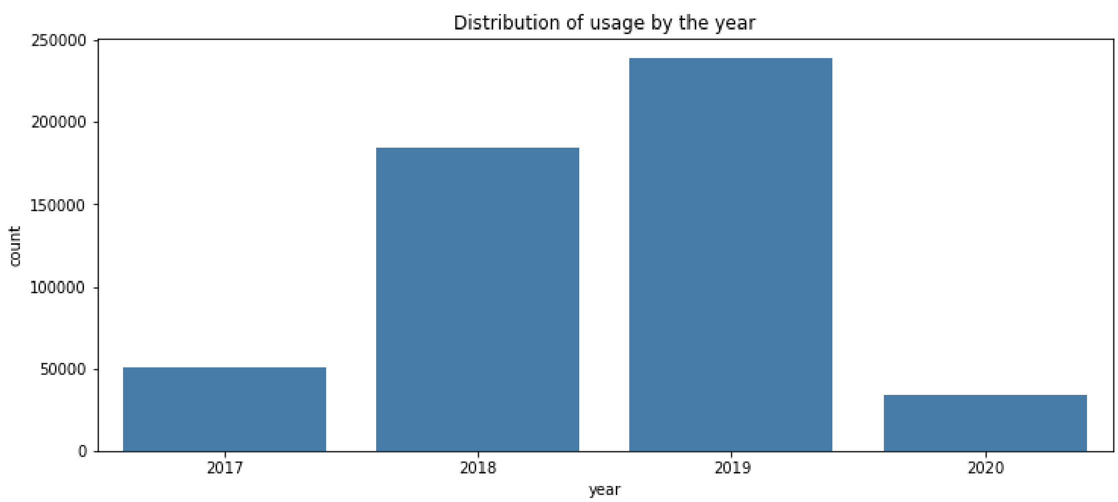
[99]:
```
#plot by day of the week
plt.figure(figsize=(12, 5))
sb.countplot(final['day_of_week'], color='#377eb8')
plt.title("Distribution of usage by the day of the week")
plt.show();
```



[100]:
```
#plot of distribution by the times
plt.figure(figsize=(12, 5))
sb.countplot(final['time_of_day'], color='#377eb8')
plt.title("Distribution of usage by the times of the day")
plt.show();
```



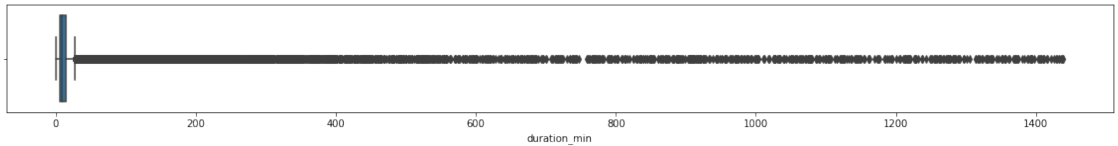
[101]:
```
#plot by year
plt.figure(figsize=(12, 5))
sb.countplot(final['year'], color='#377eb8')
plt.title("Distribution of usage by the year")
plt.show();
```



From the series of plots above, October had the highest number of bike share use, while December has the lowest, probably due to the cold weather. There is a high use of the service on midweek: Tuesdays, Wednesdays and Thursday than on the weekends. Next we see an obvious spike in use of the service at 7-9am and at 4-6pm, probably due to workgoers. 2019 also had the highest count of users than the other years. However, I will not pay too much mind to this as this dataset is just a sample of the entire dataset and 2020 also doesn't also have its full dataset included. Next we look at the distribution of trips by their duration and distance.

What are the average duration and distance for trips taken?

[84]:
```
plt.figure(figsize = [20, 2])
base_color = sb.color_palette()[0]
sb.boxplot(data=final, x='duration_min', color=base_color);
```

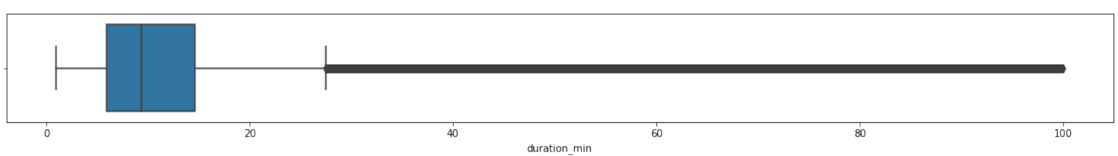


We see from the boxplot that the data is very skewed to the right, so we will look at the percentiles to spot outliers.

[85]:
```
final['duration_min'].describe(percentiles = [0.01, 0.05, 0.95, 0.99])
```

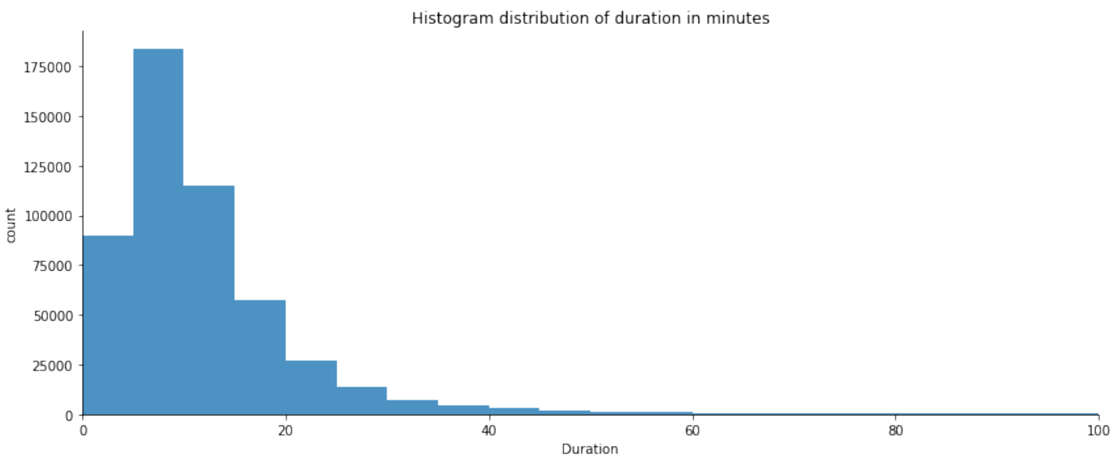
[85]:
```
count    512788.000000
mean         14.251144
std          38.214561
min           1.000000
1%            1.816667
5%            3.033333
50%           9.450000
95%          30.200000
99%          88.102167
max        1438.616667
Name: duration_min, dtype: float64
```

[86]:
```
#get rid of outliers
final = final.query('duration_min <= 100')

plt.figure(figsize = [20, 2])
base_color = sb.color_palette()[0]
sb.boxplot(data=final, x='duration_min', color=base_color);
```



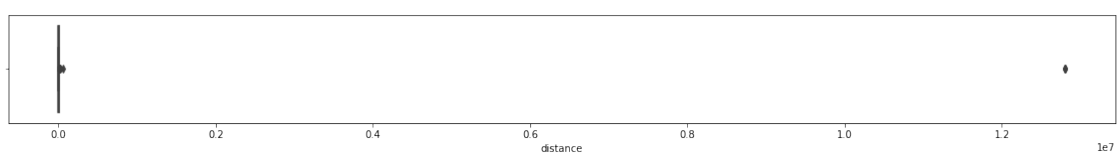
[87]:
```
#plot histogram
bin_size = 5
bins = np.arange(0, final.duration_min.max()+bin_size, bin_size)
color = sb.color_palette()[0]
```

```
fig, axes = plt.subplots(figsize = (12,5))
plt.hist(final.duration_min, bins = bins, color= color, alpha=0.8)
plt.title('Histogram distribution of duration in minutes')
plt.xlabel('Duration')
plt.ylabel('count')
plt.xlim(0,100)
sb.despine(fig)
plt.tight_layout();
```



The histogram shows that most trips are within the 5-10 minute range. Now we do the same process to visualize the distance distribution.

[106]:
```
#distance plot
plt.figure(figsize = [20, 2])
base_color = sb.color_palette()[0]
sb.boxplot(data=final, x='distance', color=base_color);
```



[105]:
```
final['distance'].describe(percentiles = [0.01, 0.05, 0.95, 0.99]) #view␣
↪percentiles
```

[105]:
```
count    5.084830e+05
mean     1.778278e+03
std      4.014350e+04
min      0.000000e+00
```

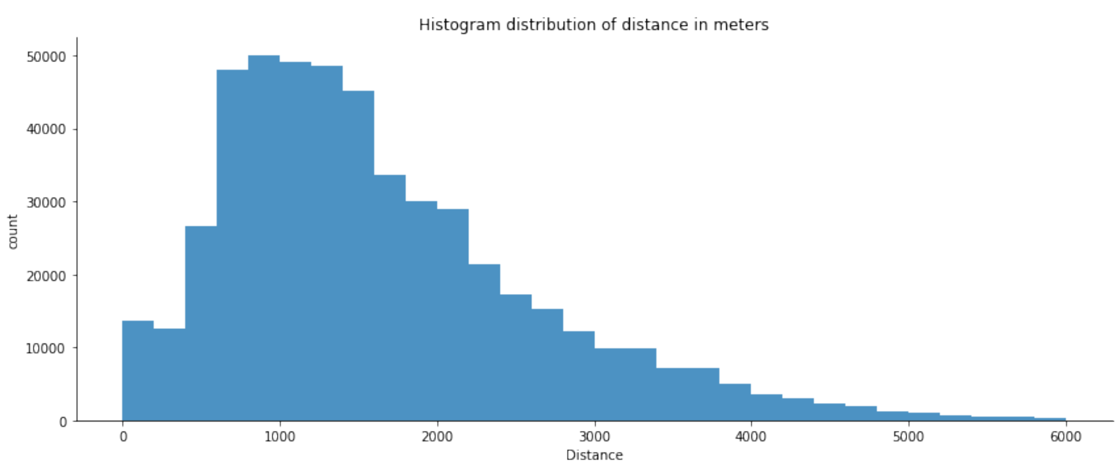
```
1%       0.000000e+00
5%       3.934297e+02
50%      1.413991e+03
95%      3.699192e+03
99%      4.939688e+03
max      1.280234e+07
Name: distance, dtype: float64
```

[107]:
```
final = final.query('distance <= 6000') #get rid of outliers
```

[219]:
```
final['distance'].describe()
```

[219]:
```
count    506836.000000
mean       1635.588920
std        1009.173509
min           0.000000
25%         906.252026
50%        1413.991319
75%        2161.219922
max        5999.995148
Name: distance, dtype: float64
```

[111]:
```
#distance histogram
bin_size = 200
bins = np.arange(0, final.distance.max()+bin_size, bin_size)
color = sb.color_palette()[0]
fig, axes = plt.subplots(figsize = (12,5))
plt.hist(final.distance, bins = bins, color= color, alpha=0.8);
plt.title('Histogram distribution of distance in meters')
plt.xlabel('Distance')
plt.ylabel('count')
sb.despine(fig)
plt.tight_layout();
```

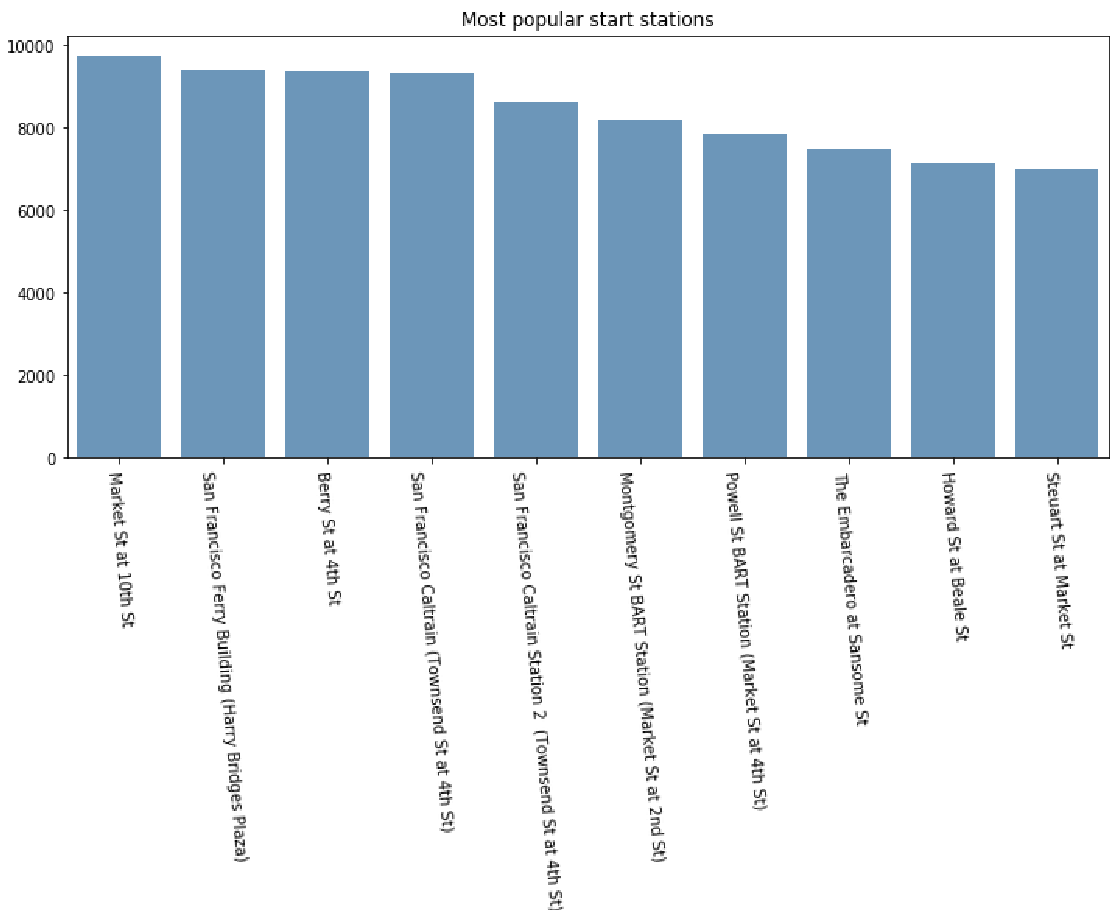


The histogram distribution of the trip distances above follows a normal distribution and it shows that most trips are between 600-1800 meters. Next, we look at the stations with the most number of trips leaving and arriving

What are the usage trends for incoming and outgoing trips at stations?

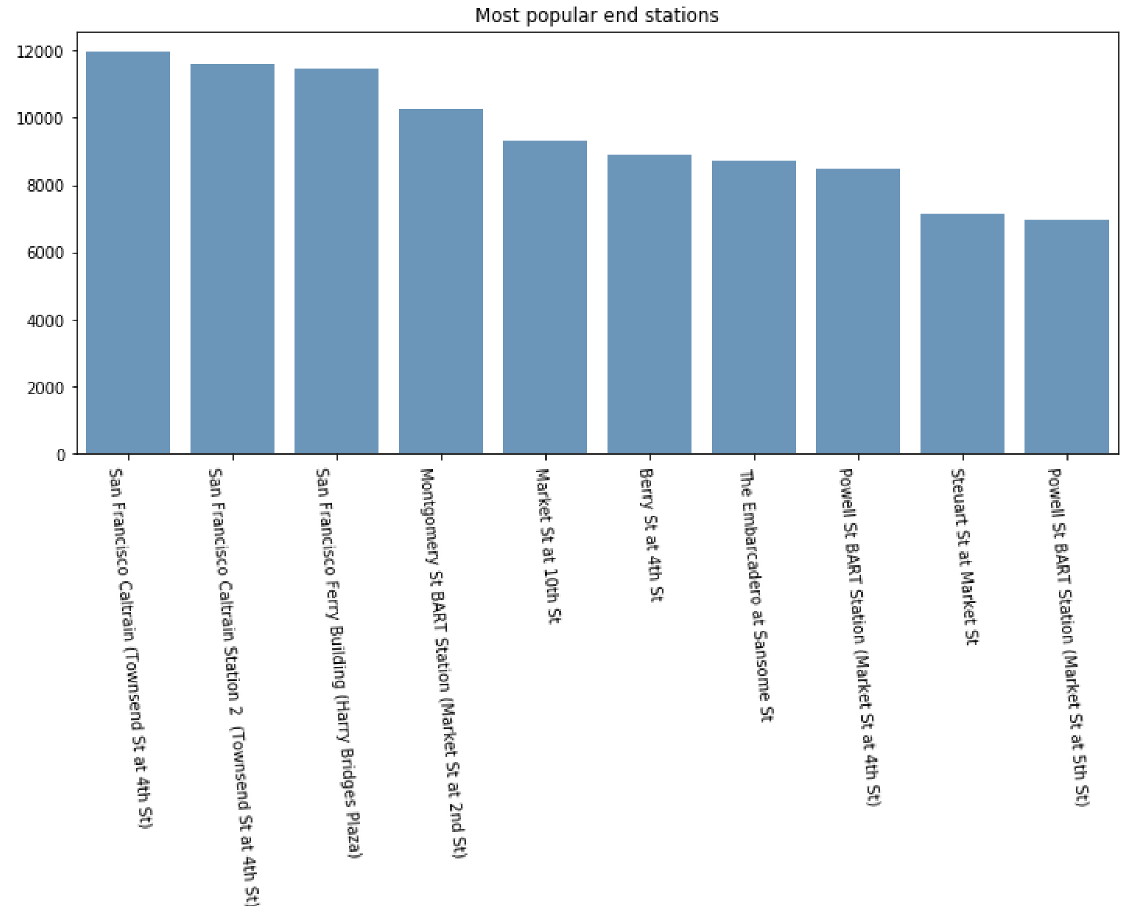
[88]:
```
top_start_stations = final['start_station_name'].value_counts()[:10]
top_end_stations = final['end_station_name'].value_counts()[:10]
```

[92]:
```
plt.figure(figsize=(12, 5))
sb.barplot(top_start_stations.index, top_start_stations.values, alpha=.8,␣
 ↪color='#377eb8')
plt.title("Most popular start stations")
plt.xticks(rotation=-85)
plt.show();
```



[93]:
```
plt.figure(figsize=(12, 5))
sb.barplot(top_end_stations.index, top_end_stations.values, alpha=.8,␣
 ↪color='#377eb8')
plt.title("Most popular end stations")
```

```
plt.xticks(rotation=-85)
plt.show();
```



The plots above show that Market st at 10th st has the highest number of outgoing trips while San Fransisco Caltrain has the highest number of incoming trips.

1.2.4 Observation on variables of Interest and transformations done

User type, Month, Weekday, Year and Hour did not need any transformations. Distance was feature engineered from the latitude and longitude of the stations. Duration and distance had unusually long time/distance, with a max value more than 2 times more than the 99th percentile. I considered these as outliers probably from an error on the part of a user forgetting to log off the app after his/her ride. None of the other variables had any outliers.

1.2.5 Unusual distributions and cleaning tasks

As earlier stated, distance and duration had unusual distributions and I considered the unusually large datapoints outliers. For this, I queried the dataset to eliminate distances and duration greater than the value of the 99th percentile, so that a distribution with better spread can be gotten. Without this, the number of bins were not able to accurately display all the datapoints appropriately since most trips were between 5-10 minutes and 600-1800 meters and critical information about the dataset was being lost. There were also entries with distance of zero, but i chose not to remove them from the dataset.

Bivariate Exploration

In this section, the relationships between pairs of variables introduced in the previous section will be investigated and explored.

What is the relationship between the times/distance people use the bikes and the stations they make the trips from and to?

[150]:
```
##relationship between duration and station
startstation_time= final.groupby('start_station_name').mean().
↪sort_values(by=['duration_min'], ascending=False)[:20]
endstation_time= final.groupby('end_station_name').mean().
↪sort_values(by=['duration_min'], ascending=False)[:20]
```

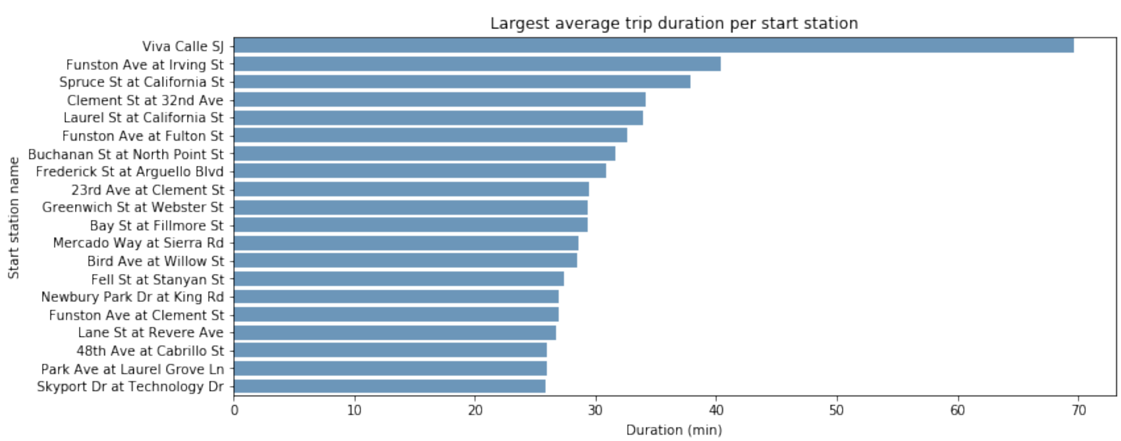
[154]:
```
startstation_time.head()
```

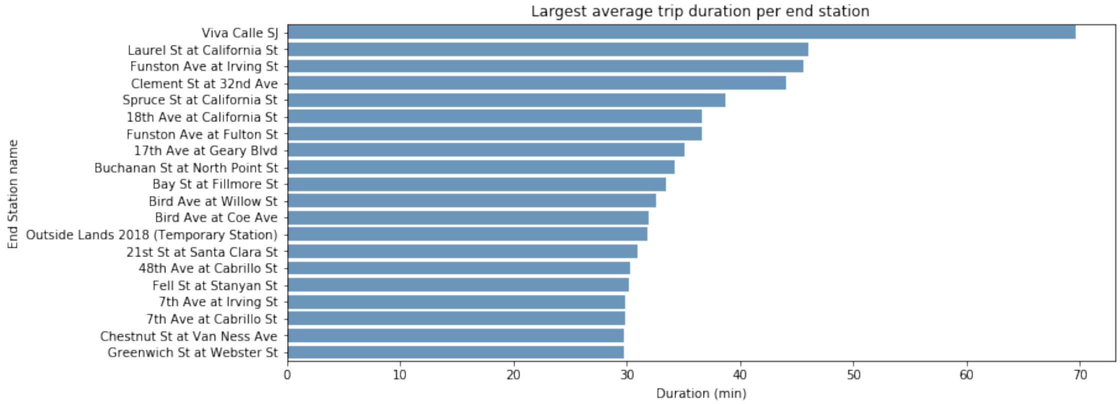
[154]:
```
                                 bike_id     distance  duration_min  \
start_station_name
Viva Calle SJ                1855.000000     0.000000     69.650000
Funston Ave at Irving St    80628.000000  1788.614789     40.369608
Spruce St at California St 302352.200000  1096.846720     37.846667
Clement St at 32nd Ave       7235.142857  2433.649386     34.126190
Laurel St at California St 190598.000000  1053.340403     33.966667

                            duration_sec  end_station_id  \
start_station_name
Viva Calle SJ                4179.000000      374.000000
Funston Ave at Irving St     2422.176471      345.235294
Spruce St at California St   2270.800000      424.000000
Clement St at 32nd Ave       2047.571429      416.428571
Laurel St at California St   2038.000000      387.400000

                            end_station_latitude  end_station_longitude  \
start_station_name
Viva Calle SJ                          37.263310            -121.833332
Funston Ave at Irving St               37.769364            -122.454971
Spruce St at California St             37.784809            -122.441780
Clement St at 32nd Ave                 37.781308            -122.471642
Laurel St at California St             37.785006            -122.443447

                            start_station_id  start_station_latitude  \
start_station_name
Viva Calle SJ                          374.0               37.263310
```

```
Funston Ave at Irving St                450.0               37.763934
Spruce St at California St              517.0               37.786578
Clement St at 32nd Ave                  516.0               37.781722
Laurel St at California St              514.0               37.786692

                            start_station_longitude  time_of_day    year
start_station_name
Viva Calle SJ                           -121.833332    11.000000  2018.0
Funston Ave at Irving St                -122.470651    13.294118  2020.0
Spruce St at California St              -122.453423    15.400000  2020.0
Clement St at 32nd Ave                  -122.492844    13.000000  2020.0
Laurel St at California St              -122.450081    14.600000  2020.0
```

[151]:

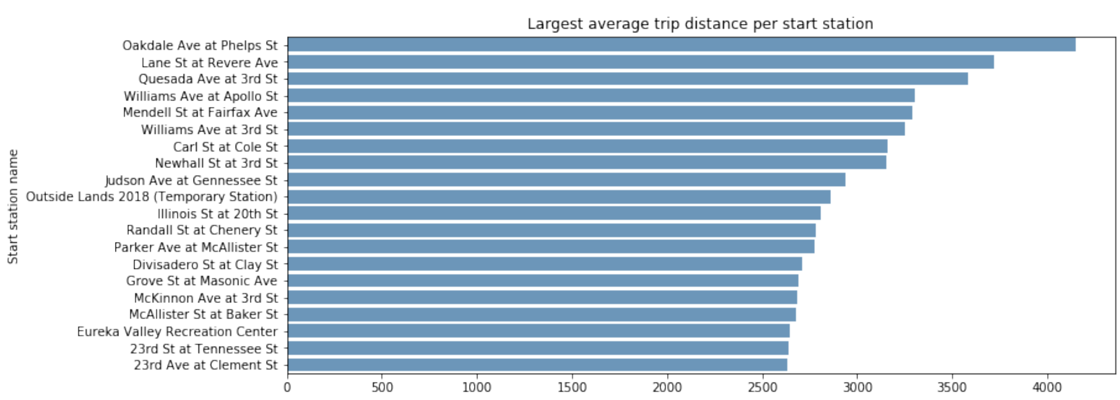
```
plt.figure(figsize=(12, 5))
sb.barplot(startstation_time.duration_min, startstation_time.index, alpha=.8,␣
 ↪color='#377eb8')
plt.title("Largest average trip duration per start station")
plt.xlabel("Duration (min)")
plt.ylabel("Start station name")
plt.show();

plt.figure(figsize=(12, 5))
sb.barplot(endstation_time.duration_min, endstation_time.index, alpha=.8,␣
 ↪color='#377eb8')
plt.title("Largest average trip duration per end station")
plt.xlabel("Duration (min)")
plt.ylabel("End Station name")
plt.show();
```

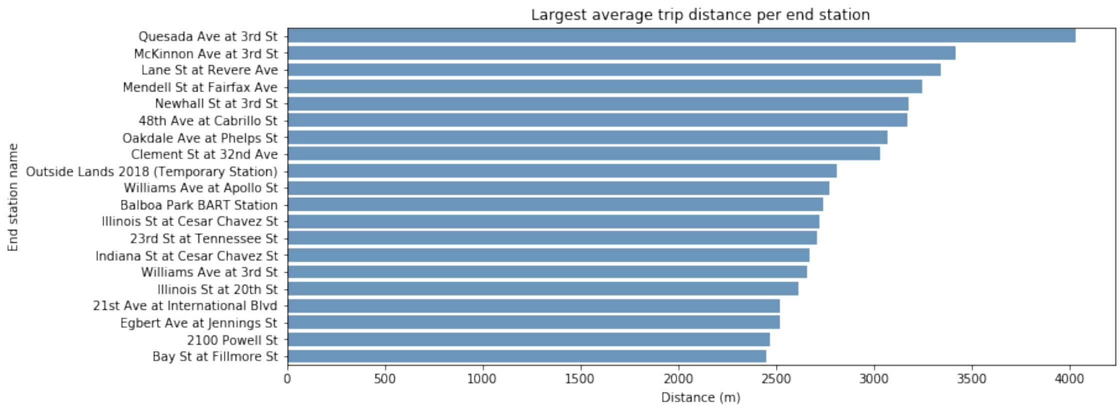




[152]:
```
##relationship between distance and station
startstation_distance= final.groupby('start_station_name').mean().
 ↪sort_values(by=['distance'], ascending=False)[:20]
endstation_distance= final.groupby('end_station_name').mean().
 ↪sort_values(by=['distance'], ascending=False)[:20]
```

[153]:
```
plt.figure(figsize=(12, 5))
sb.barplot(startstation_distance.distance, startstation_distance.index, alpha=.
 ↪8, color='#377eb8')
plt.title("Largest average trip distance per start station")
plt.xlabel("Distance (m)")
plt.ylabel("Start station name")
plt.show();

plt.figure(figsize=(12, 5))
sb.barplot(endstation_distance.distance, endstation_distance.index, alpha=.8,␣
 ↪color='#377eb8')
plt.title("Largest average trip distance per end station")
plt.xlabel("Distance (m)")
plt.ylabel("End station name")
plt.show();
```





[198]:
```python
print(endstation_distance.index)
```

```
Index(['Quesada Ave at 3rd St', 'McKinnon Ave at 3rd St',
       'Lane St at Revere Ave', 'Mendell St at Fairfax Ave',
       'Newhall St at 3rd St', '48th Ave at Cabrillo St',
       'Oakdale Ave at Phelps St', 'Clement St at 32nd Ave',
       'Outside Lands 2018 (Temporary Station)', 'Williams Ave at Apollo St',
       'Balboa Park BART Station', 'Illinois St at Cesar Chavez St',
       '23rd St at Tennessee St', 'Indiana St at Cesar Chavez St',
       'Williams Ave at 3rd St', 'Illinois St at 20th St',
       '21st Ave at International Blvd', 'Egbert Ave at Jennings St',
       '2100 Powell St', 'Bay St at Fillmore St'],
      dtype='object', name='end_station_name')
```

From the plots above, one can see that there is a very clear difference between duration trends and distance usage trends. When it comes to duration, the start and end stations tend to be very different. Stations that have highest duration for outgoing trips do not appear in the list of stations with highest duration for incoming trips. For instance, on the average, Funston ave at Irving st has more people driving long durations from it and Laurel St at California St has more people riding longer times to it. Vive Calle SJ might be an outlier as it has the longest duration to and fro but 0 distance. On the other hand, the distance plots for the start and end stations seem to be in sync. Some of the stations that have highest distances for outgoing trips can be found in the list of stations with highest distance for incoming trips. Places like Quesada Ave at 3rd St, Oakdale Ave at Phelps St, Williams Ave at Apollo St, etc, have more people driving longer distances to and from them.

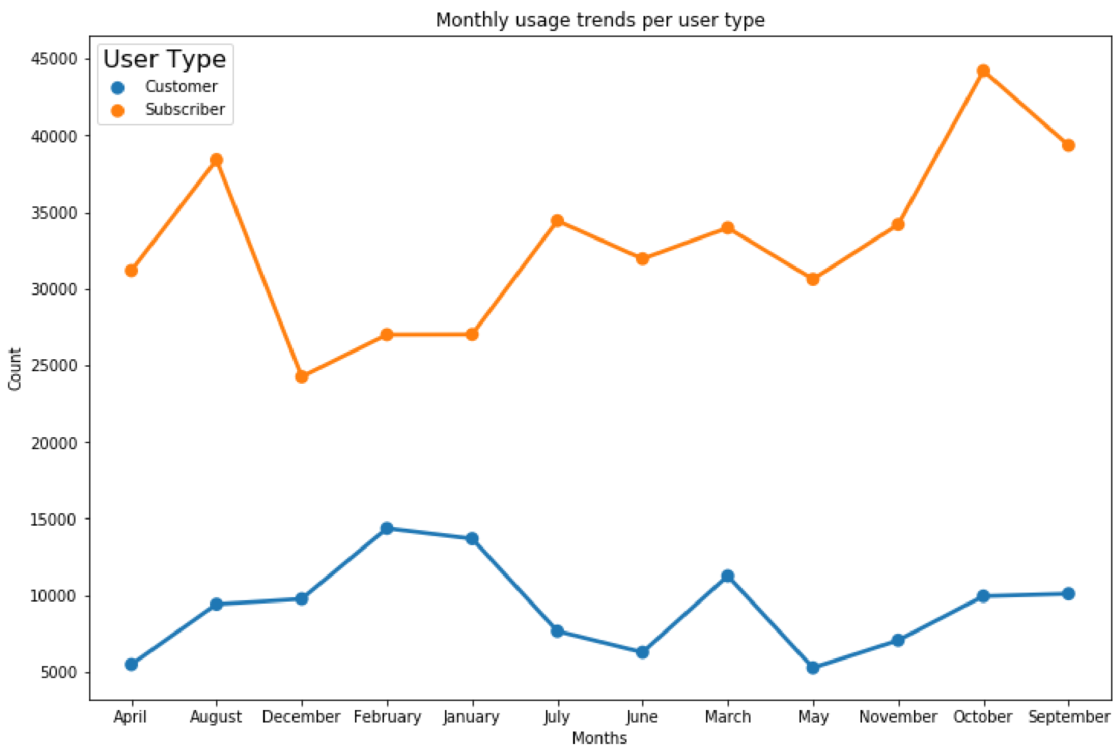
What are the user trends per hour, day, month and year?

[113]:
```python
user_month = final.groupby(["ride_month", "user_type"]).size().reset_index()
user_month.head()
```

[113]:

	ride_month	user_type	0
0	April	Customer	5485
1	April	Subscriber	31175
2	August	Customer	9414
3	August	Subscriber	38395
4	December	Customer	9768

[114]:
```
plt.figure(figsize=(12,8))
ax = sb.pointplot(x='ride_month', y=0, hue='user_type', data=user_month)
plt.title('Monthly usage trends per user type')
plt.xlabel('Months')
plt.ylabel('Count')
leg = ax.legend()
leg.set_title('User Type',prop={'size':16});
```

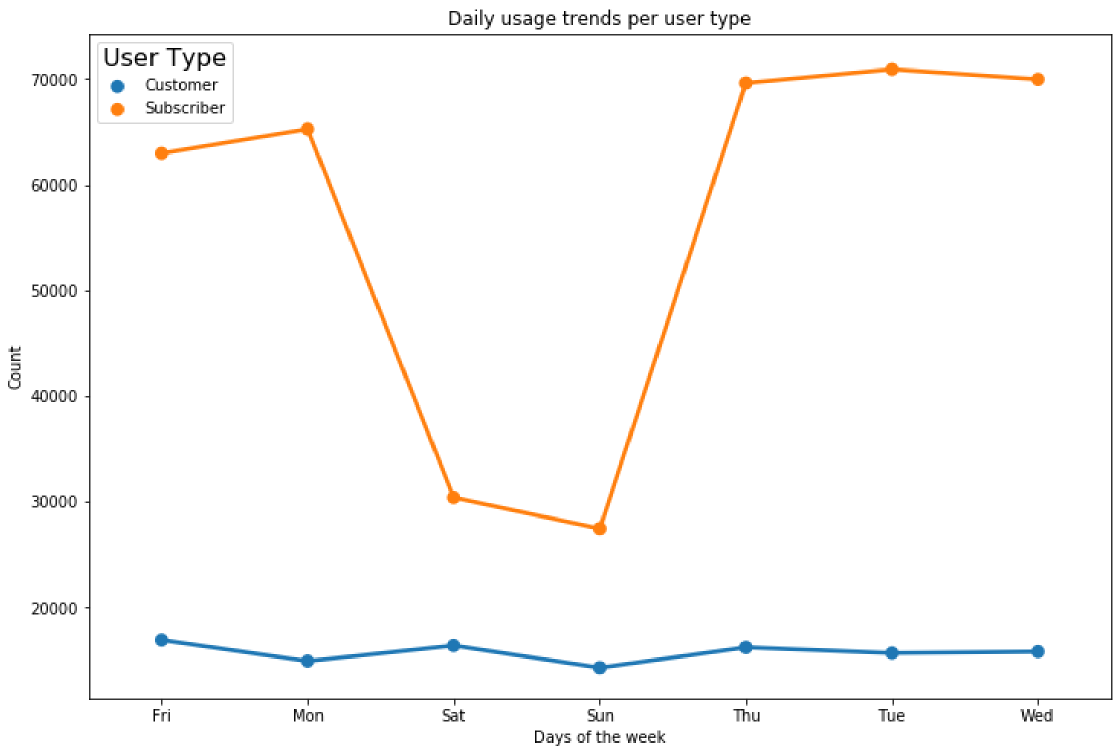


[115]:
```
user_day = final.groupby(["day_of_week", "user_type"]).size().reset_index()
user_day.head()
```

[115]:

	day_of_week	user_type	0
0	Fri	Customer	16928
1	Fri	Subscriber	62953
2	Mon	Customer	14932
3	Mon	Subscriber	65252
4	Sat	Customer	16401

[116]:
```python
plt.figure(figsize=(12,8))
ax = sb.pointplot(x='day_of_week', y=0, hue='user_type', data=user_day)
plt.title('Daily usage trends per user type')
plt.xlabel('Days of the week')
plt.ylabel('Count')
leg = ax.legend()
leg.set_title('User Type',prop={'size':16});
```

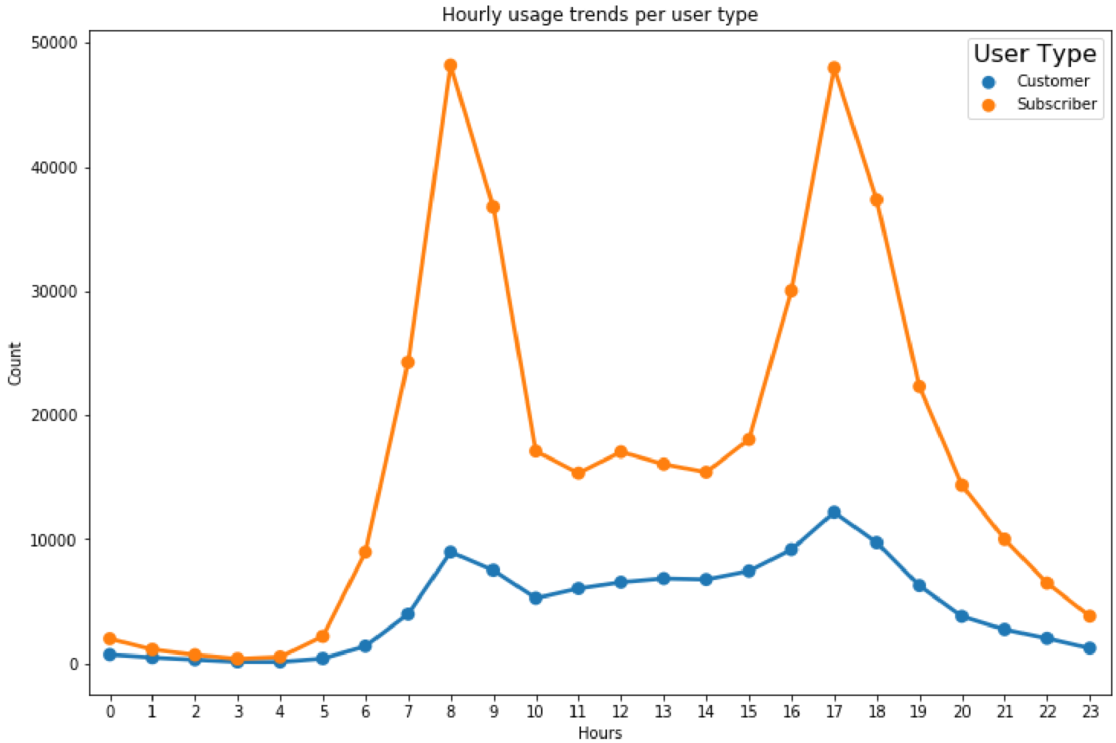


[117]:
```python
user_time = final.groupby(["time_of_day", "user_type"]).size().reset_index()
user_time.head()
```

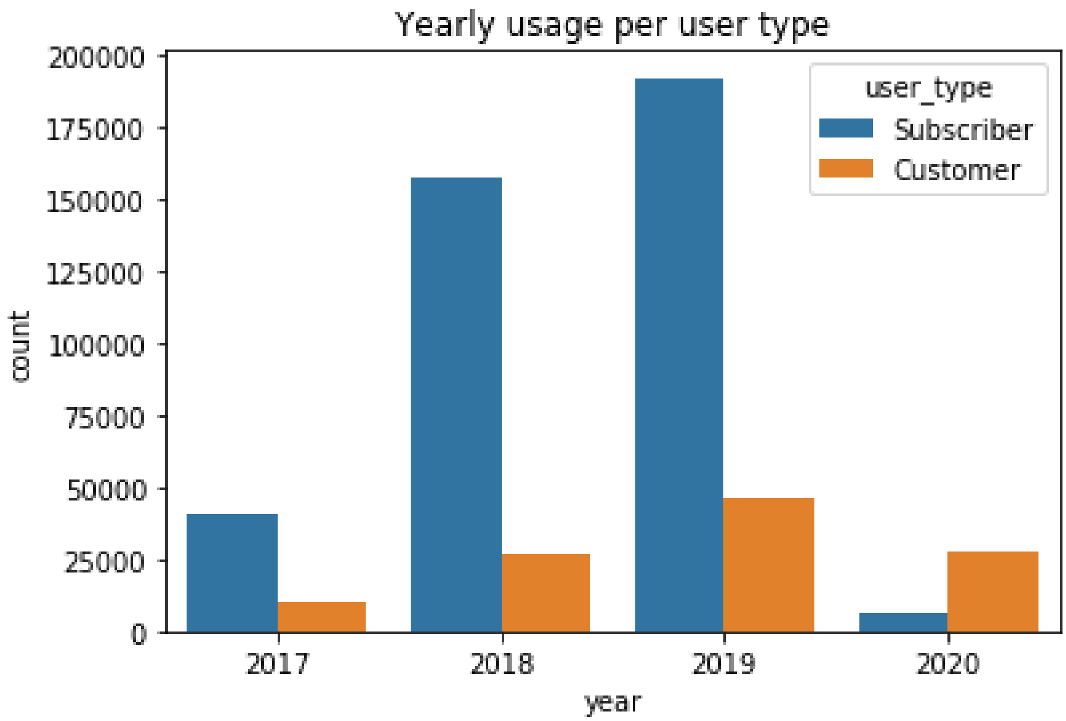
[117]:

	time_of_day	user_type	0
0	0	Customer	725
1	0	Subscriber	2012
2	1	Customer	488
3	1	Subscriber	1146
4	2	Customer	313

[119]:
```python
plt.figure(figsize=(12,8))
ax = sb.pointplot(x='time_of_day', y=0, hue='user_type', data=user_time)
plt.title('Hourly usage trends per user type')
plt.xlabel('Hours')
plt.ylabel('Count')
leg = ax.legend()
leg.set_title('User Type',prop={'size':16});
```



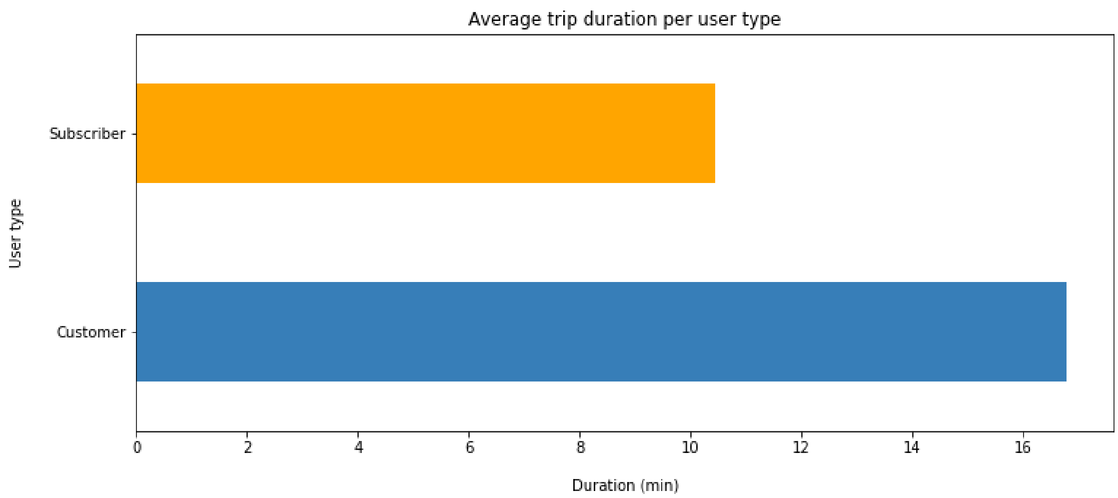
[121]:
```
ax = sb.countplot(x=final.year, hue=final.user_type, data=final)
plt.title("Yearly usage per user type")
plt.show();
```



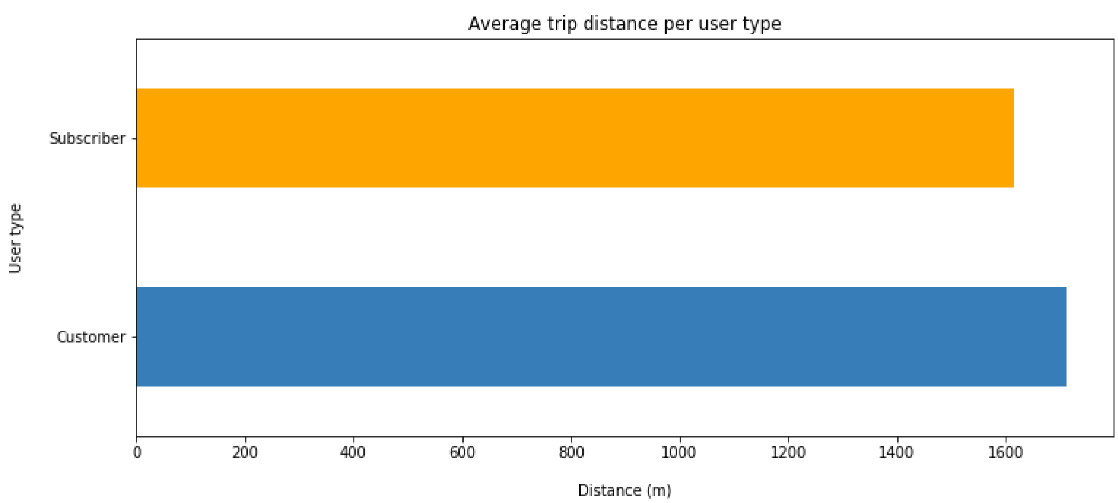
The monthly distribution for user types varies quite a lot. While October and December has the highest and lowest patronage respectively for Subscribers to the service, Customers seem to be using the service most in February and least in May. Weekday usage is also different. While Subscribers use the service typically during the week and much less on weekends, Customers use the service more on weekends. Hourly distribution follows fairly the same pattern of spiking at 7-9am and again at 4-6pm for both types of users, but Customers have a relatively high plateau of usage between these peaks as well. Yearly usage shows that Customer patronage has increased over the years, and even more surprising was that there was more representation for Customers in the data than Subscribers for 2020 data.

What are the trends in how long and how far different types of users use the bike share service?

[158]:
```
##user trends for duration
ax = final.groupby('user_type')['duration_min'].mean().plot(kind='barh',␣
↪color=['#377eb8', 'orange'], figsize=(12,5))
ax.set_title('Average trip duration per user type')
ax.set_ylabel('User type', labelpad=16)
ax.set_xlabel('Duration (min)', labelpad=16);
```



[159]:
```
##user trends for distance
ax = final.groupby('user_type')['distance'].mean().plot(kind='barh',␣
↪color=['#377eb8', 'orange'], figsize=(12,5))
ax.set_title('Average trip distance per user type')
ax.set_ylabel('User type', labelpad=16)
ax.set_xlabel('Distance (m)', labelpad=16);
```



On the average, Customers travel longer duration and distances with the bike sharing service than Subscribers.

1.2.6 How did the feature(s) of interest vary with other features in the dataset?

From the investigation, user type has a large influence on monthly, daily and hourly usage. Average duration and average distance also varies by user type. The relationship between stations and the duration and distance travelled to/from them was quite interesting to see, as this highlights which stations are important.

1.2.7 Interesting relationships between the other features (not the main feature(s) of interest)

I noticed an interesting relationship between stations and duration/distance travelled to and from them. I would like to see how this relationship varies by user type in the following sections. I will also like to do a more complex investigation into the relationship between user type, days and hours.

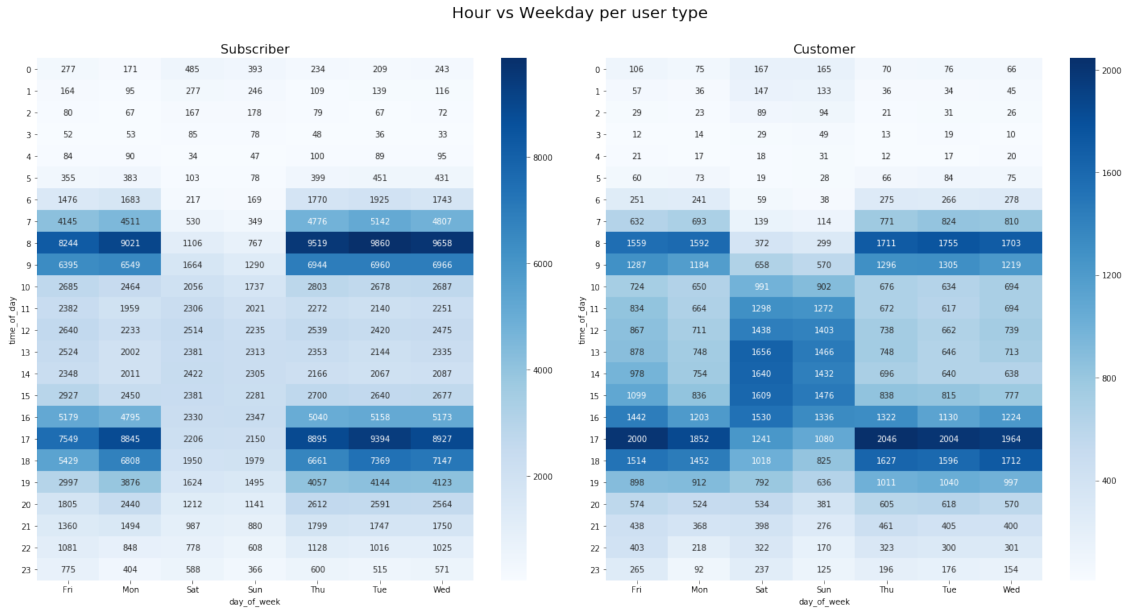
Multivariate Exploration

Here, plots of three or more variables are created to investigate the data even more complex relationships.

How do the different user type use the service per hours in a week?

[160]:
```
sub_df = final.query('user_type == "Subscriber"').
 ↪groupby(['time_of_day','day_of_week']).agg({'bike_id' : 'count'})
sub_df = sub_df.pivot_table(index='time_of_day', columns='day_of_week',␣
 ↪values='bike_id')
cus_df = final.query('user_type == "Customer"').
 ↪groupby(['time_of_day','day_of_week']).agg({'bike_id' : 'count'})
cus_df = cus_df.pivot_table(index='time_of_day', columns='day_of_week',␣
 ↪values='bike_id')
```

[162]:
```
plt.subplots(figsize=(20,10))

fig1 = plt.subplot(1,2,1)
ax1 = sb.heatmap(sub_df, annot=True, fmt='d', cmap='Blues')
plt.title('Subscriber',size=16)
plt.yticks(rotation=360)

fig2 = plt.subplot(1,2,2)
ax2 = sb.heatmap(cus_df, annot=True, fmt='d', cmap='Blues')
plt.title('Customer',size=16)
plt.yticks(rotation=360)
plt.suptitle("Hour vs Weekday per user type", size=20, y=1.05)
plt.tight_layout();
```



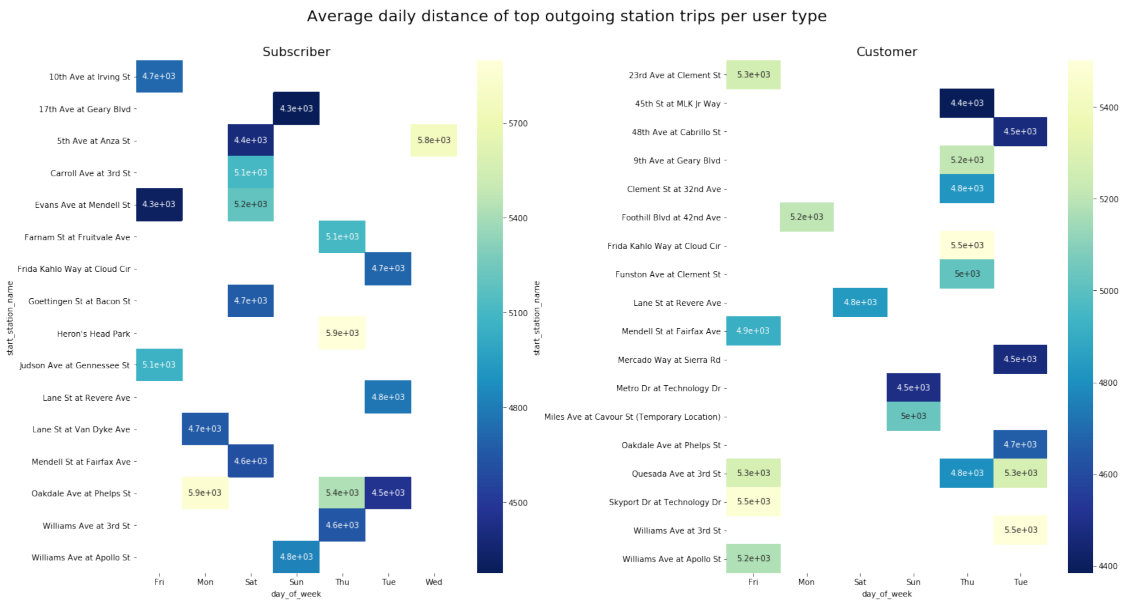
One can see from the above plots that Subscribers use the service mostly during a certain time of the day and days of the week while Customers don't particularly have specific times. We can say that usage is more routine-like for Subscribers while Customer usage is more random-like.

What stations do the different user types travel long distances and durations from each week?

[181]:
```
##distance of trip from station per day per user type
stat_day_sub_dist = final.query('user_type == "Subscriber"').
 ↪groupby(['start_station_name', 'day_of_week']).mean().
 ↪sort_values(by=['distance'], ascending=False)[:20]
stat_day_sub_dist = stat_day_sub_dist.pivot_table(index='start_station_name',␣
 ↪columns='day_of_week', values='distance')
stat_day_cus_dist = final.query('user_type == "Customer"').
 ↪groupby(['start_station_name', 'day_of_week']).mean().
 ↪sort_values(by=['distance'], ascending=False)[:20]
stat_day_cus_dist = stat_day_cus_dist.pivot_table(index='start_station_name',␣
 ↪columns='day_of_week', values='distance')
```

[184]:
```
plt.subplots(figsize=(20,10))

fig1 = plt.subplot(1,2,1)
ax1 = sb.heatmap(stat_day_sub_dist, annot=True, cmap='YlGnBu_r')
plt.title('Subscriber',size=16)
plt.yticks(rotation=360)
```

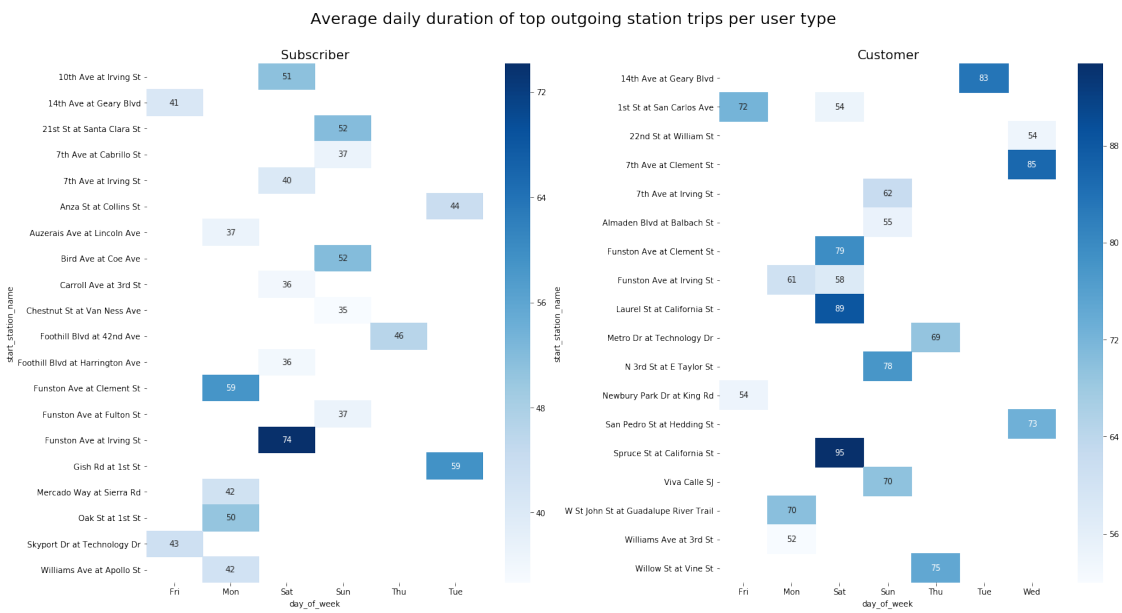
```
fig2 = plt.subplot(1,2,2)
ax2 = sb.heatmap(stat_day_cus_dist, annot=True, cmap='YlGnBu_r')
plt.title('Customer',size=16)
plt.yticks(rotation=360)
plt.suptitle("Average daily distance of top outgoing station trips per user␣
↪type", size=20, y=1.05)
plt.tight_layout();
```



[186]:
```
##duration of trip from station per day per user type
stat_day_sub_dur = final.query('user_type == "Subscriber"').
↪groupby(['start_station_name', 'day_of_week']).mean().
↪sort_values(by=['duration_min'], ascending=False)[:20]
stat_day_sub_dur = stat_day_sub_dur.pivot_table(index='start_station_name',␣
↪columns='day_of_week', values='duration_min')
stat_day_cus_dur = final.query('user_type == "Customer"').
↪groupby(['start_station_name', 'day_of_week']).mean().
↪sort_values(by=['duration_min'], ascending=False)[:20]
stat_day_cus_dur = stat_day_cus_dur.pivot_table(index='start_station_name',␣
↪columns='day_of_week', values='duration_min')
```

[192]:
```
plt.subplots(figsize=(20,10))

fig1 = plt.subplot(1,2,1)
ax1 = sb.heatmap(stat_day_sub_dur, annot=True, cmap='Blues')
plt.title('Subscriber',size=16)
plt.yticks(rotation=360)
```

```
fig2 = plt.subplot(1,2,2)
ax2 = sb.heatmap(stat_day_cus_dur, annot=True, cmap='Blues')
plt.title('Customer',size=16)
plt.yticks(rotation=360)
plt.suptitle("Average daily duration of top outgoing station trips per user␣
 ↪type", size=20, y=1.05)
plt.tight_layout();
```



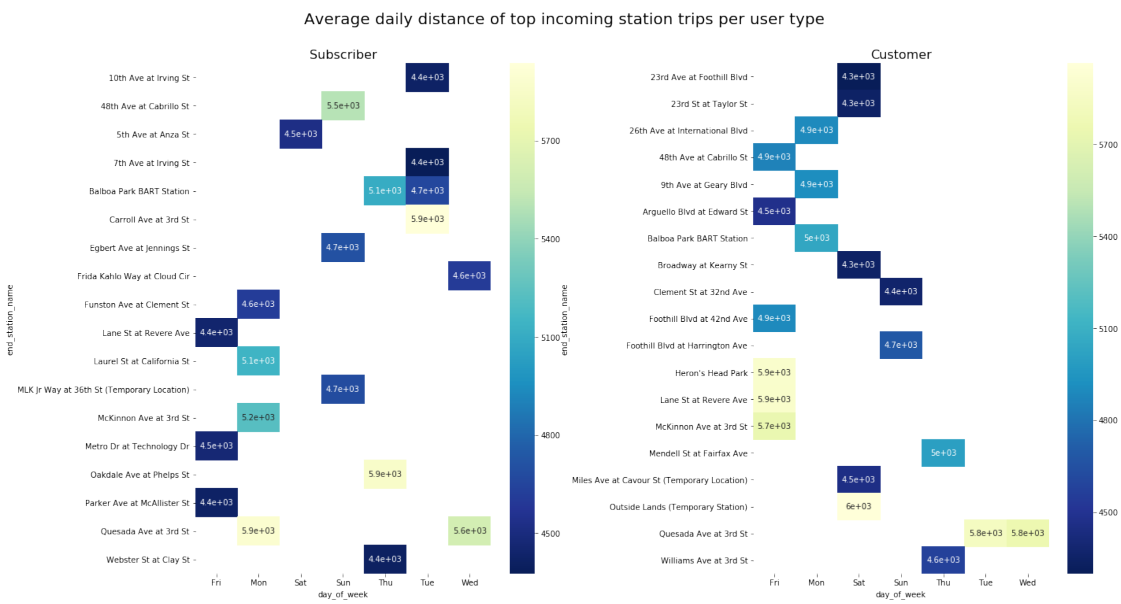
For subscribers, the distance map is very streamlined, showing that they practice routine rides. They seem to be biking long distances a lot from Heron's Head Park on Thursdays, Oakdale Ave at Phelps str on Mondays and 5th Ave at Anza St on Wednesdays. On the other hand, Customers are driving a lot of long distance from many different locations on different days. However, Thursdays and Fridays seem to be a very popular spot for a lot of locations. The duration heat map shows that the highest average outgoing trip comes from Funstonn Ave at Irving St on Saturdays for Subscribers, and from Spuce St at California St also on Saturdays.

What stations do the different user types travel long distances and durations to each week?

[183]:
```
##distance of trip to station per day per user type
endstat_day_sub_dist = final.query('user_type == "Subscriber"').
 ↪groupby(['end_station_name', 'day_of_week']).mean().
 ↪sort_values(by=['distance'], ascending=False)[:20]
endstat_day_sub_dist = endstat_day_sub_dist.
 ↪pivot_table(index='end_station_name', columns='day_of_week',␣
 ↪values='distance')
```

```
endstat_day_cus_dist = final.query('user_type == "Customer"').
 ↪groupby(['end_station_name', 'day_of_week']).mean().
 ↪sort_values(by=['distance'], ascending=False)[:20]
endstat_day_cus_dist = endstat_day_cus_dist.
 ↪pivot_table(index='end_station_name', columns='day_of_week',␣
 ↪values='distance')
```

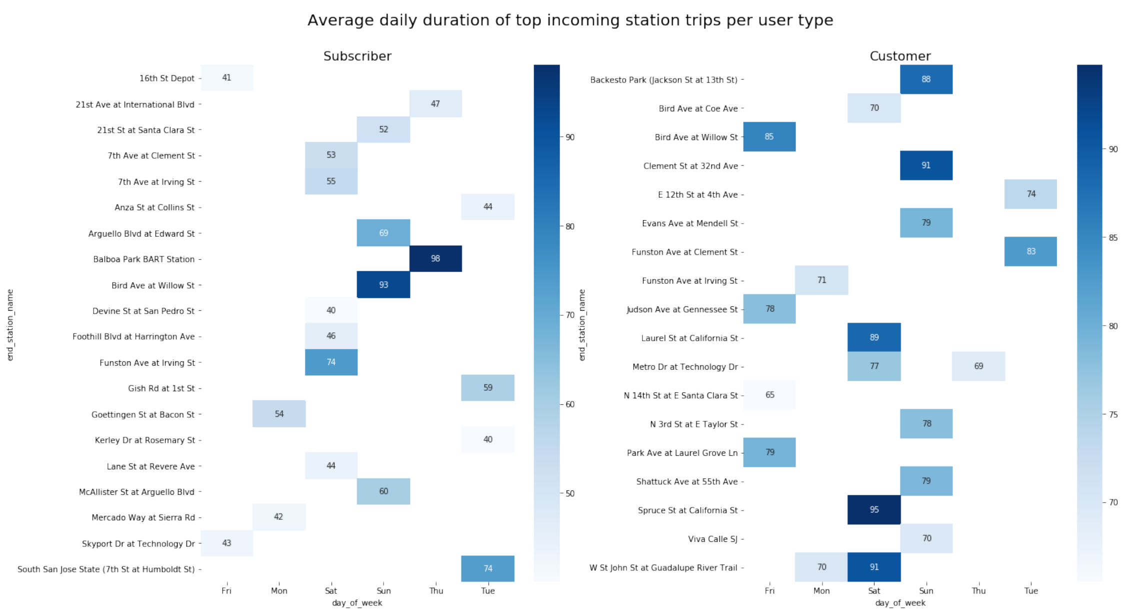
[193]:
```
plt.subplots(figsize=(20,10))

fig1 = plt.subplot(1,2,1)
ax1 = sb.heatmap(endstat_day_sub_dist, annot=True, cmap='YlGnBu_r')
plt.title('Subscriber',size=16)
plt.yticks(rotation=360)


fig2 = plt.subplot(1,2,2)
ax2 = sb.heatmap(endstat_day_cus_dist, annot=True, cmap='YlGnBu_r')
plt.title('Customer',size=16)
plt.yticks(rotation=360)
plt.suptitle("Average daily distance of top incoming station trips per user␣
 ↪type", size=20, y=1.05)
plt.tight_layout();
```



[188]:
```
##duration of trip to station per day per user type
endstat_day_sub_dur = final.query('user_type == "Subscriber"').
 ↪groupby(['end_station_name', 'day_of_week']).mean().
 ↪sort_values(by=['duration_min'], ascending=False)[:20]
```

```
endstat_day_sub_dur = endstat_day_sub_dur.pivot_table(index='end_station_name',␣
↪columns='day_of_week', values='duration_min')
endstat_day_cus_dur = final.query('user_type == "Customer"').
↪groupby(['end_station_name', 'day_of_week']).mean().
↪sort_values(by=['duration_min'], ascending=False)[:20]
endstat_day_cus_dur = endstat_day_cus_dur.pivot_table(index='end_station_name',␣
↪columns='day_of_week', values='duration_min')
```

[194]:
```
plt.subplots(figsize=(20,10))

fig1 = plt.subplot(1,2,1)
ax1 = sb.heatmap(endstat_day_sub_dur, annot=True, cmap='Blues')
plt.title('Subscriber',size=16)
plt.yticks(rotation=360)


fig2 = plt.subplot(1,2,2)
ax2 = sb.heatmap(endstat_day_cus_dur, annot=True, cmap='Blues')
plt.title('Customer',size=16)
plt.yticks(rotation=360)
plt.suptitle("Average daily duration of top incoming station trips per user␣
↪type", size=20, y=1.05)
plt.tight_layout();
```



We see that Subscribers are travelling long distances and durations on the average to few particular areas e.g. Quesada Ave at 3rd str on Mondays, Oakdale Ave at Phelps St on Thursdays and Biloboa Park also on Thursdays, while Customers are biking long distances and durations to multiple areas e.g. Herod's Head Park, Lane St at Revere Ave on Fridays and Outside Lands on Saturdays.

1.2.8 Relationships observed in this part of the investigation.

There was a strong pattern to the days of the week and hour of the day Subscribers use the service. Also, stations and distances/durations travelled to and from them already had a strong correlation from the previous section, but when days of the week and user types were introduced into investigation, it allowed us see better the way user behaviour influences trip usage.

1.2.9 Were there any interesting or surprising interactions between features?

A very interesting interaction was how user type affect the bike sharing service. Across the investigations, Subscribers tend to be more routine-like in their usage while Customers tend to be more random.