Part_I_exploration_template

October 24, 2022

1 Part I - Fordgo Bike Trip Dataset

1.1 by Matthew Chan

2 Introduction

The following dataset is about the ford gobike dataset, it contains the trips of its app users for the month of February.

3 Preliminary Wrangling

In [1]:
```
# 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 sns

%matplotlib inline
```

In [2]:
```
# loading the dataset
fordbike = pd.read_csv('201902-fordgobike-tripdata.csv')
```

In [3]:
```
# defining a function to explore and summarize datasets


def summary(df: pd.DataFrame) -> pd.DataFrame:
    """
    Returns the data type, # of null rows and unique rows of a given dataframe

    Args:
        A dataframe of n_rows and n_columns
    Returns:
        A dataframe of 4 columns [data_type, non-null-rows, unique_rows, missing_rows]
    """
    concat = pd.concat(
        [df.dtypes.to_frame(), df.count().to_frame(), df.nunique(), df.isnull().sum()],
    )
    concat.columns = ['data_type', 'non-null-rows', 'unique_rows', 'missing_rows']
    return concat
```

```
In [4]: # creating a new copy so we can revert to original data if needed after all the cleaning
        bike_df = fordbike.copy()

        # summarizing the dataset
        summary(bike_df)
```

Out[4]:

	data_type	non-null-rows	unique_rows	missing_rows
duration_sec	int64	183412	4752	0
start_time	object	183412	183401	0
end_time	object	183412	183397	0
start_station_id	float64	183215	329	197
start_station_name	object	183215	329	197
start_station_latitude	float64	183412	334	0
start_station_longitude	float64	183412	335	0
end_station_id	float64	183215	329	197
end_station_name	object	183215	329	197
end_station_latitude	float64	183412	335	0
end_station_longitude	float64	183412	335	0
bike_id	int64	183412	4646	0
user_type	object	183412	2	0
member_birth_year	float64	175147	75	8265
member_gender	object	175147	3	8265
bike_share_for_all_trip	object	183412	2	0

3.1 Cleaning and transforming the Dataset

We are going to perform the following data cleaning/preparations on the dataset: 1. Assigning the correct/appropriate datatypes 2. Adding an 'age' column to denote users age 3. Editing the datetime format of certain columns for readability and easier analysis

3.1.1 Casting into appropriate datatypes

```
In [5]: # casting the following variables into their correct/appropriate datatypes
        bike_df = (
            bike_df
            .astype({'start_time': 'datetime64[ns]',
                     'end_time': 'datetime64[ns]',
                     'start_station_id': 'str',
                     'end_station_id': 'str',
                     'bike_id': 'str',
                     'member_gender': 'category',
                     'user_type': 'category'})
        )
```

3.1.2 Creating new columns based on the start_time

```
In [6]: # adding age of riders 'age' column into dataset
        # adding new columns - 'date, hour, day and month' for datetime formats
```

```
bike_df = (
    bike_df
    .assign(age=lambda a: 2022-a.member_birth_year,
            start_date=lambda sd: sd.start_time.dt.strftime('%Y-%m-%d'),
            start_hour=lambda x: x.start_time.dt.strftime('%H'),
            start_day=lambda x: x.start_time.dt.strftime('%A'),
            start_month=lambda x: x.start_time.dt.strftime('%B'))
)

summary(bike_df)
```

Out[6]:

```
                              data_type  non-null-rows  unique_rows  \
duration_sec                      int64         183412         4752
start_time               datetime64[ns]         183412       183401
end_time                 datetime64[ns]         183412       183397
start_station_id                 object         183412          330
start_station_name               object         183215          329
start_station_latitude          float64         183412          334
start_station_longitude         float64         183412          335
end_station_id                   object         183412          330
end_station_name                 object         183215          329
end_station_latitude            float64         183412          335
end_station_longitude           float64         183412          335
bike_id                          object         183412         4646
user_type                      category         183412            2
member_birth_year               float64         175147           75
member_gender                  category         175147            3
bike_share_for_all_trip          object         183412            2
age                             float64         175147           75
start_date                       object         183412           28
start_hour                       object         183412           24
start_day                        object         183412            7
start_month                      object         183412            1

                         missing_rows
duration_sec                        0
start_time                          0
end_time                            0
start_station_id                    0
start_station_name                197
start_station_latitude              0
start_station_longitude             0
end_station_id                      0
end_station_name                  197
end_station_latitude                0
end_station_longitude               0
bike_id                             0
user_type                           0
```

```
member_birth_year              8265
member_gender                  8265
bike_share_for_all_trip           0
age                            8265
start_date                        0
start_hour                        0
start_day                         0
start_month                       0
```

In [7]:
```
# seems like there are missing rows in our age dataset, we will remove these columns
bike_df[bike_df['age'].isnull()].sample(5)
```

Out[7]:
```
        duration_sec               start_time                end_time  \
67099            684 2019-02-20 08:11:59.918 2019-02-20 08:23:24.379
141146          6010 2019-02-07 16:44:20.218 2019-02-07 18:24:30.523
35854            123 2019-02-23 17:40:47.149 2019-02-23 17:42:50.315
173009           179 2019-02-03 13:55:55.643 2019-02-03 13:58:54.752
127325           167 2019-02-10 16:15:53.516 2019-02-10 16:18:40.527

       start_station_id                                start_station_name  \
67099              67.0  San Francisco Caltrain Station 2  (Townsend St...
141146             13.0                     Commercial St at Montgomery St
35854             233.0          4th Ave at E 12th St (Temporary Location)
173009            173.0                             Shattuck Ave at 55th St
127325            345.0                               Hubbell St at 16th St

        start_station_latitude  start_station_longitude end_station_id  \
67099                37.776639              -122.395526           15.0
141146               37.794231              -122.402923          368.0
35854                37.795913              -122.255547          200.0
173009               37.840364              -122.264488          169.0
127325               37.766483              -122.398279          114.0

                                         end_station_name  \
67099   San Francisco Ferry Building (Harry Bridges Pl...
141146                             Myrtle St at Polk St
35854                              2nd Ave at E 18th St
173009                                     Bushrod Park
127325                         Rhode Island St at 17th St

        end_station_latitude     ...      bike_id   user_type  \
67099              37.795392     ...           48  Subscriber
141146             37.785434     ...         2351    Customer
35854              37.800214     ...         4682  Subscriber
173009             37.846516     ...          662    Customer
127325             37.764478     ...         5522  Subscriber

       member_birth_year  member_gender bike_share_for_all_trip age  \
```

```
67099                    NaN            NaN                      No NaN
141146                   NaN            NaN                      No NaN
35854                    NaN            NaN                      No NaN
173009                   NaN            NaN                      No NaN
127325                   NaN            NaN                      No NaN

        start_date start_hour  start_day start_month
67099   2019-02-20         08  Wednesday    February
141146  2019-02-07         16   Thursday    February
35854   2019-02-23         17   Saturday    February
173009  2019-02-03         13     Sunday    February
127325  2019-02-10         16     Sunday    February

[5 rows x 21 columns]
```

In [8]:
```python
# removing null/na numbers of members without age
bike_df = bike_df.dropna(subset=['age'])
# casting age into appropriate datatype (int)
bike_df = bike_df.astype({'age': 'int32'})

summary(bike_df)
```

Out[8]:
```
                              data_type  non-null-rows  unique_rows  \
duration_sec                      int64         175147         4432
start_time               datetime64[ns]         175147       175136
end_time                 datetime64[ns]         175147       175134
start_station_id                 object         175147          330
start_station_name               object         174952          329
start_station_latitude          float64         175147          334
start_station_longitude         float64         175147          335
end_station_id                   object         175147          330
end_station_name                 object         174952          329
end_station_latitude            float64         175147          335
end_station_longitude           float64         175147          335
bike_id                          object         175147         4635
user_type                      category         175147            2
member_birth_year               float64         175147           75
member_gender                  category         175147            3
bike_share_for_all_trip          object         175147            2
age                               int32         175147           75
start_date                       object         175147           28
start_hour                       object         175147           24
start_day                        object         175147            7
start_month                      object         175147            1

                         missing_rows
duration_sec                        0
start_time                          0
```

```
end_time                     0
start_station_id             0
start_station_name         195
start_station_latitude       0
start_station_longitude      0
end_station_id               0
end_station_name           195
end_station_latitude         0
end_station_longitude        0
bike_id                      0
user_type                    0
member_birth_year            0
member_gender                0
bike_share_for_all_trip      0
age                          0
start_date                   0
start_hour                   0
start_day                    0
start_month                  0
```

3.1.3 Structure of the dataset

Each dataset represents a unique, single trip by a user in the month of February. It contains the start, end, duration and other spatial data of the trip. There are a total of 16 variables, with around 183k records. These records can be broadly categorized into 3 main groups:

1. Timeseries data - e.g, duration_sec, start/end_time, birth_year
2. Spatial data - e.g, start/end_station_longitude/latitude
3. Member information - gender, age
4. Derived features - start_date/hour/day

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

We are interesting in understanding the usage patterns of riders, which involves their ride characteristics (e.g, trip durations) alongside the profile of a user (e.g, age, gender, user_type)

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

The start and end time variables will be useful in understanding the usage patterns. Also, start_day/month allows us to understand which days are most popular with users. The member information like user type, gender and age will help us find out who are the main target customer groups, use the different groups to summarize bike usage data to see if there is any special pattern associated with a specific group of riders.

```
In [9]: # overview of dataset
        bike_df.sample(5)
```

```
Out[9]:         duration_sec              start_time                end_time  \
        18613            618 2019-02-26 18:10:51.600 2019-02-26 18:21:10.171
        135259           472 2019-02-08 14:16:20.930 2019-02-08 14:24:13.784
        47066            535 2019-02-22 09:04:38.510 2019-02-22 09:13:33.526
        42025           1716 2019-02-22 17:35:46.618 2019-02-22 18:04:23.168
        124256           479 2019-02-11 08:42:07.088 2019-02-11 08:50:06.996

               start_station_id             start_station_name  \
        18613              81.0             Berry St at 4th St
        135259             27.0         Beale St at Harrison St
        47066             130.0        22nd St Caltrain Station
        42025               8.0  The Embarcadero at Vallejo St
        124256             31.0      Raymond Kimbell Playground

                start_station_latitude  start_station_longitude end_station_id  \
        18613                37.775880              -122.393170          126.0
        135259               37.788059              -122.391865           81.0
        47066                37.757288              -122.392051           30.0
        42025                37.799953              -122.398525           77.0
        124256               37.783813              -122.434559           19.0

                                          end_station_name  end_station_latitude  \
        18613                                  Esprit Park             37.761634
        135259                          Berry St at 4th St             37.775880
        47066   San Francisco Caltrain (Townsend St at 4th St)             37.776598
        42025                          11th St at Natoma St             37.773507
        124256                          Post St at Kearny St             37.788975

                   ...    bike_id   user_type member_birth_year  member_gender  \
        18613      ...        567    Customer            1991.0           Male
        135259     ...       5529  Subscriber            1982.0           Male
        47066      ...       4332  Subscriber            1983.0         Female
        42025      ...       5242  Subscriber            1952.0         Female
        124256     ...       4848  Subscriber            1994.0           Male

               bike_share_for_all_trip age  start_date start_hour start_day  \
        18613                       No  31  2019-02-26         18   Tuesday
        135259                      No  40  2019-02-08         14    Friday
        47066                       No  39  2019-02-22         09    Friday
        42025                       No  70  2019-02-22         17    Friday
        124256                      No  28  2019-02-11         08    Monday

               start_month
        18613     February
        135259    February
```

```
47066     February
42025     February
124256    February

[5 rows x 21 columns]
```

4 Univariate Exploration

```
In [97]: # define a default chart size for all visualizations
         plt.rcParams["figure.figsize"] = (9,7)
         # seaborn plot size
         plt.figure(figsize=[9, 7])
```

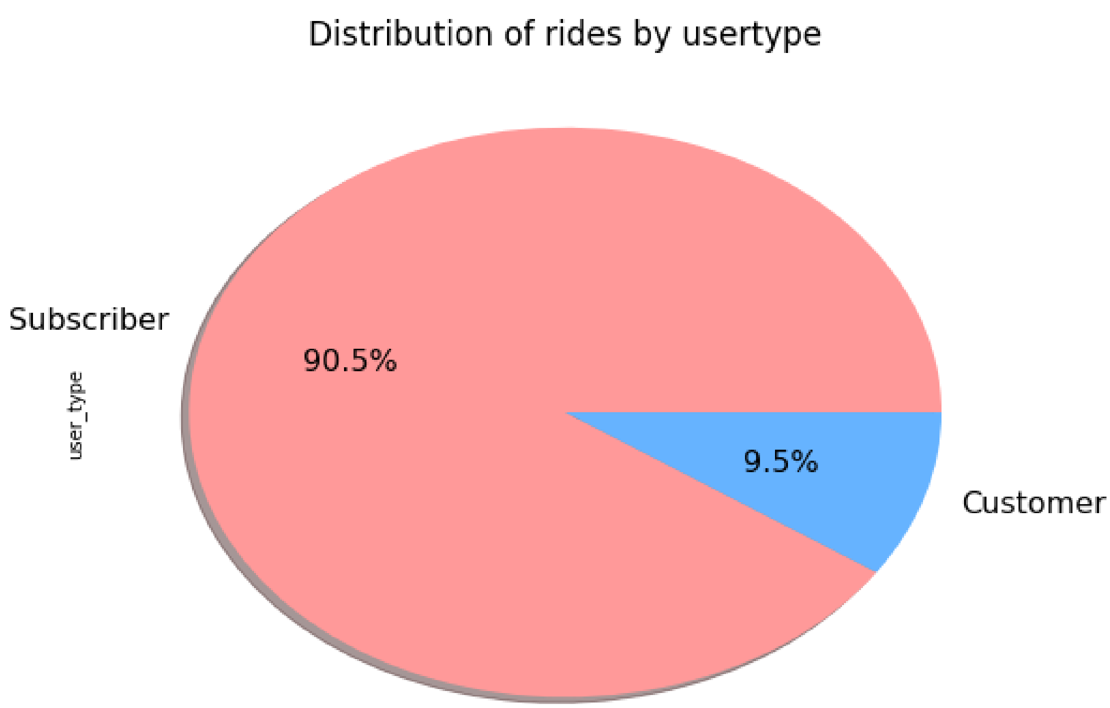
```
Out[97]: <matplotlib.figure.Figure at 0x7f90fc839e10>
```

```
<matplotlib.figure.Figure at 0x7f90fc839e10>
```

4.1 Visualization 1: What is the distribution of rides by user_type?

```
In [11]: # segmenting out our dataset for the pie plot
         bike_df.user_type.value_counts().plot(kind='pie', autopct='%1.1f%%', shadow=True, color
         # naming the line chart
         plt.title("Distribution of rides by usertype", fontsize=17)
```

```
Out[11]: Text(0.5,1,'Distribution of rides by usertype')
```

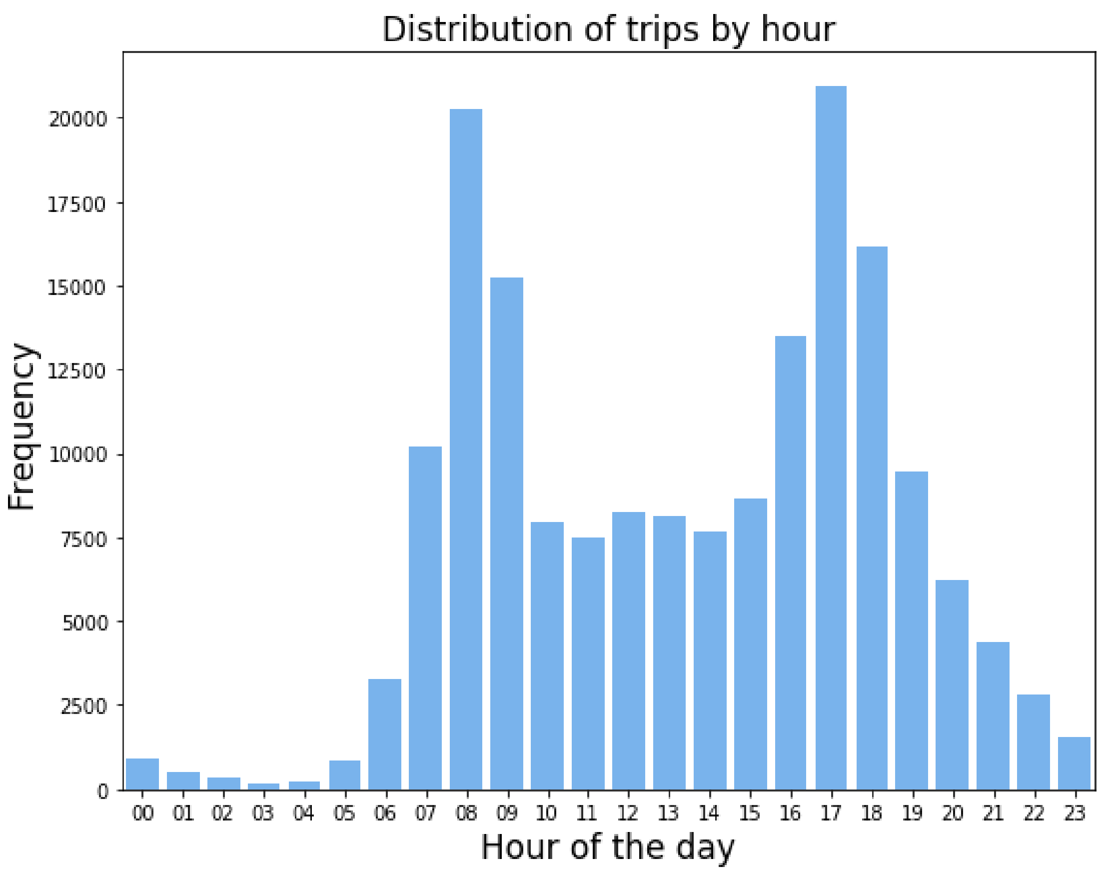


As observed, a significant majority of rides were completed by subscribers (90.5%) as compared to customers at 9.5%.

4.2 Visualization 2: What is the trip distribution over the hours of a day?

In [28]:
```
trip_hour_distribution = sns.countplot(data=bike_df, x='start_hour', color='#66b3ff')

# set title of plot
trip_hour_distribution.axes.set_title('Distribution of trips by hour', fontsize=17)
# set x_label of plot
trip_hour_distribution.axes.set_xlabel('Hour of the day', fontsize=17)
# set y_label of plot
trip_hour_distribution.axes.set_ylabel('Frequency', fontsize=17)
```

Out[28]:
```
Text(0,0.5,'Frequency')
```

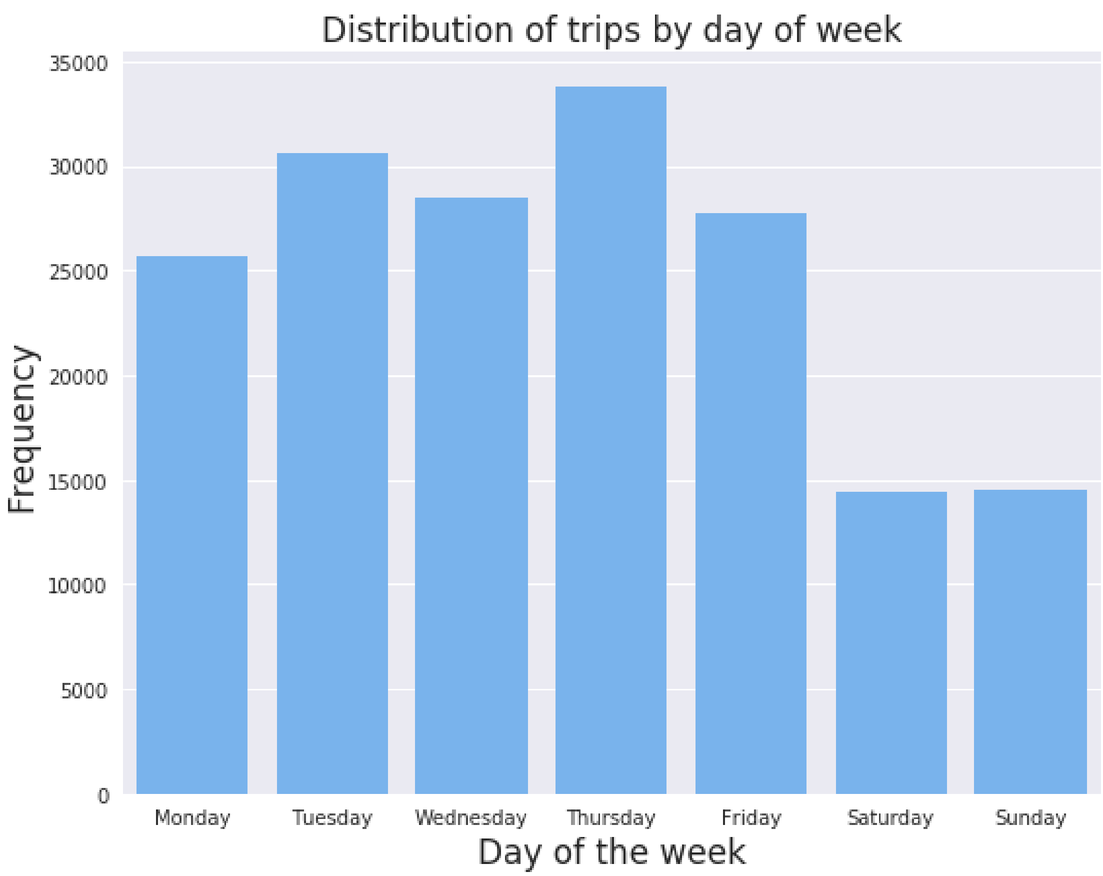


Trips peaked around 8am and 5pm, which seems to be during the rush hour periods.

4.3 Visualization 3: What is the trip distribution over days of the week?

In [171]:
```
# defining days of the week for our chart
days_of_week = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S
# declaring the day list as ordered data
days_of_week_cat = pd.api.types.CategoricalDtype(ordered=True, categories=days_of_week
bike_df = bike_df.astype({'start_day': days_of_week_cat})

# defining the countplot
trip_day_distribution = sns.countplot(data=bike_df, x='start_day', color='#66b3ff')

# set title of plot
trip_day_distribution.axes.set_title('Distribution of trips by day of week', fontsize=
# set x_label of plot
trip_day_distribution.axes.set_xlabel('Day of the week', fontsize=17)
# set y_label of plot
trip_day_distribution.axes.set_ylabel('Frequency', fontsize=17)
```

Out[171]:
```
Text(0,0.5,'Frequency')
```

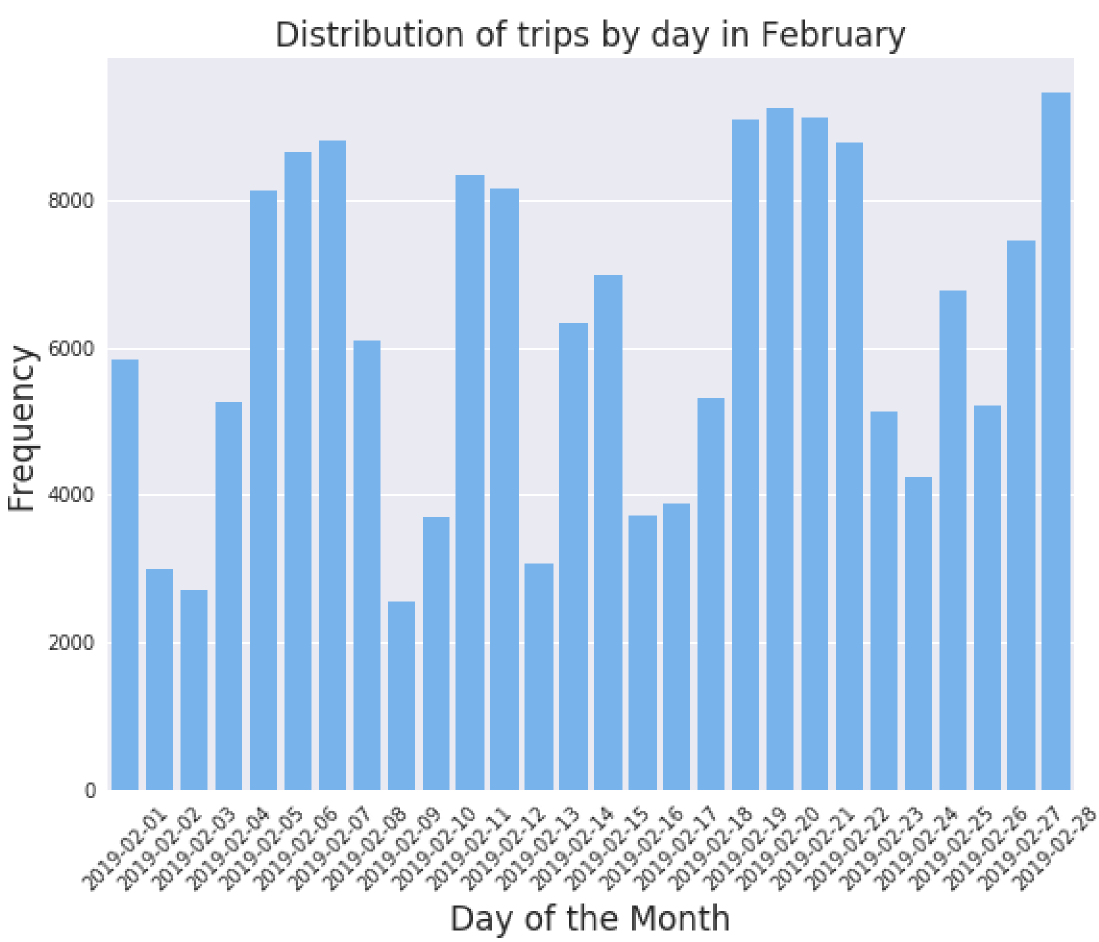


Trips typically happened more during the weekdays rather than the weekends.

4.4 Visualization 4: What is the trip distribution of days in the month of February?

In [91]:
```
# defining days of the month for our chart
days_of_month = bike_df.start_date.unique().tolist().reverse()
days_of_month_cat = pd.api.types.CategoricalDtype(ordered=True, categories=days_of_mont
bike_df = bike_df.astype({'start_date': days_of_month_cat})

# defining the countplot
trip_month_distribution = sns.countplot(data=bike_df, x='start_date', color='#66b3ff')
# rotation x-axis for clarity
plt.xticks(rotation=45)
# set title of plot
trip_month_distribution.axes.set_title('Distribution of trips by day in February', font
# set x_label of plot
trip_month_distribution.axes.set_xlabel('Day of the Month', fontsize=17)
# set y_label of plot
trip_month_distribution.axes.set_ylabel('Frequency', fontsize=17)
```

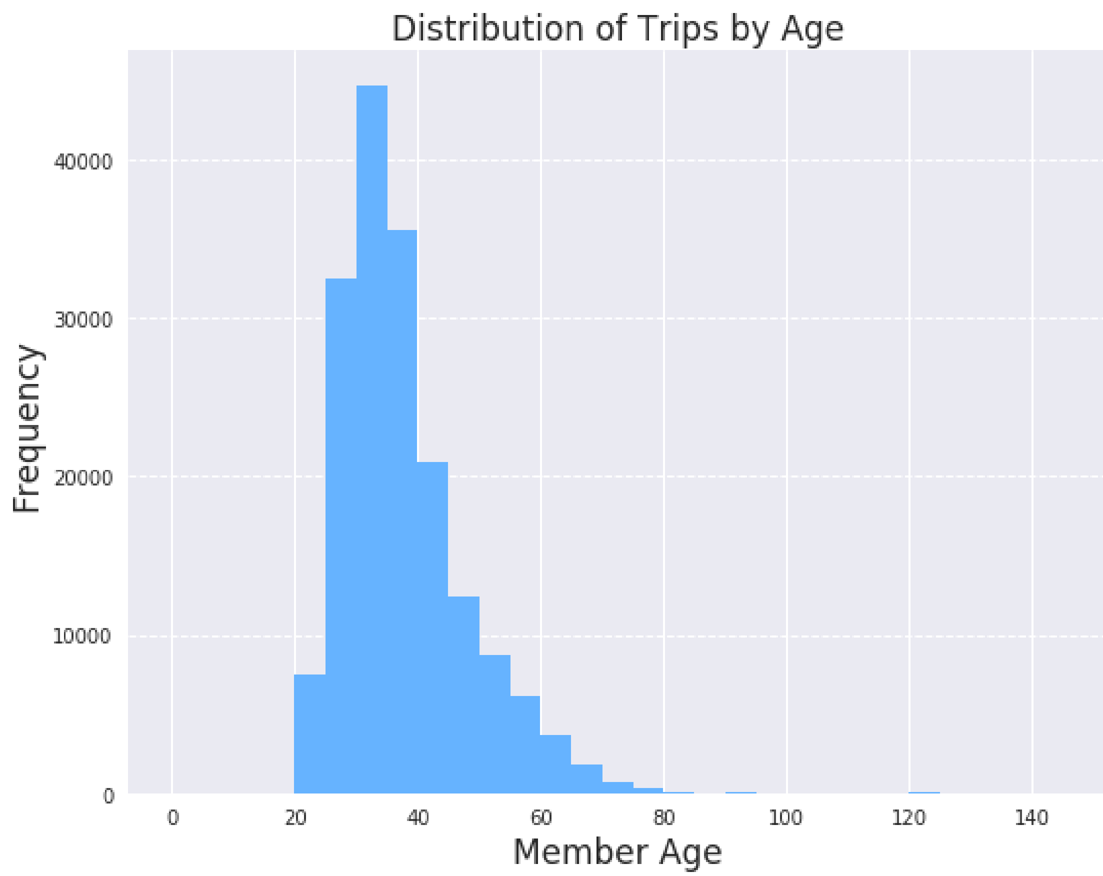
Out[91]:
```
Text(0,0.5,'Frequency')
```



Dips in the trip frequency throughout the month seems to coincide with the weekends.

4.5 Visualization 5: What is the distribution of trips by member age?

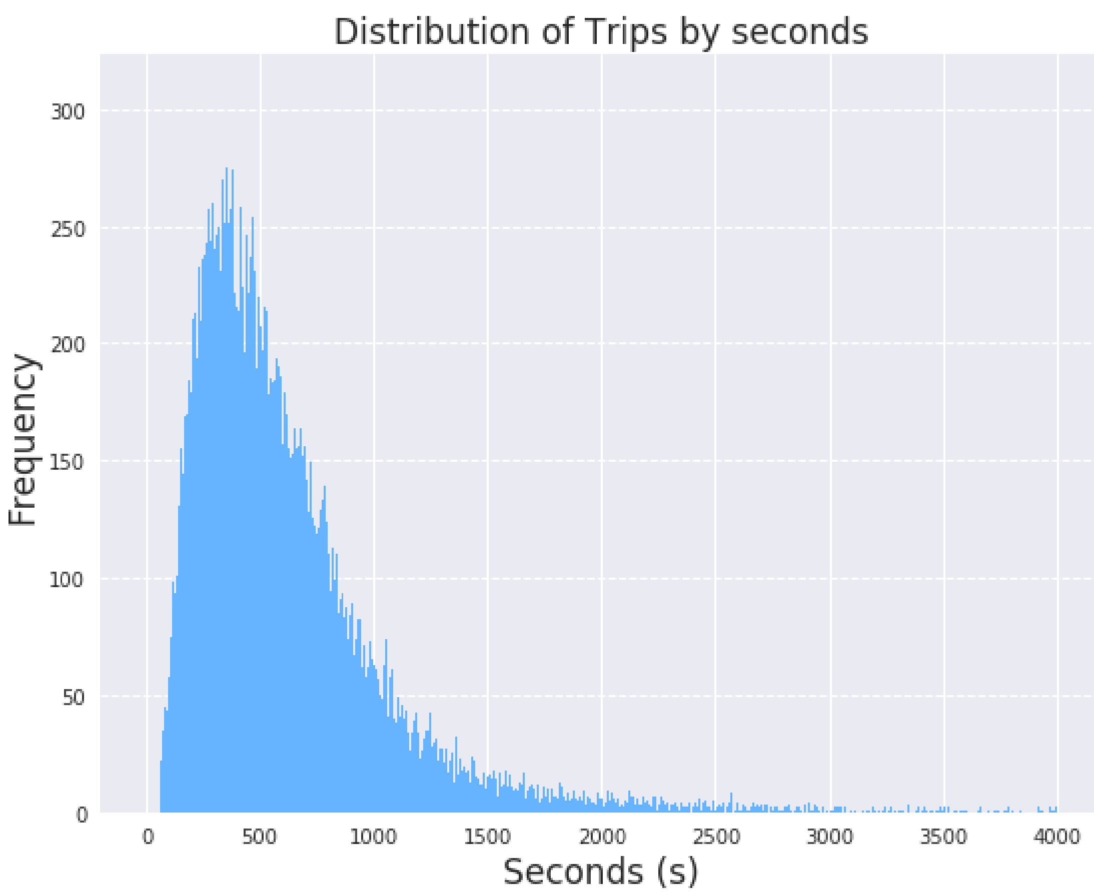
In [93]:
```
bins = np.arange(0, bike_df['age'].max()+5, 5)
plt.hist(data=bike_df, x='age', bins=bins, color='#66b3ff')

# set title of the histogram
plt.title('Distribution of Trips by Age', fontsize=17)
# set x_label of plot
plt.xlabel('Member Age', fontsize=17)
# set y_label of plot
plt.ylabel('Frequency', fontsize=17)
# add gridlines
plt.grid(axis='y', linestyle='--')
```



Fewer individuals in their 20s, but interestingly there seems to be datapoints for users at age > 100. Might be an error.

4.6 Visualization 6: What is the distribution of trip by duration (seconds)?

In [96]:
```
bins = np.arange(0, 4000, 1)
ticks = np.arange(0, 100, 5)
plt.hist(data=bike_df, x='duration_sec', bins=bins, color='#66b3ff')

# set title of the histogram
plt.title('Distribution of Trips by seconds', fontsize=17)
# set x_label of plot
plt.xlabel('Seconds (s)', fontsize=17)
# set y_label of plot
plt.ylabel('Frequency', fontsize=17)
# add gridlines
plt.grid(axis='y', linestyle='--')
```



From the histogram, it seems that the distribution of trips duration is right skewed. This tells us most trips are concentrated around the 500-700 seconds duration (8~11 minutes long). This might indicate that individuals typically use the bikes for specific use cases rather than leisure.

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

Trips typically peaked around 8am and 5pm, which seems to be the rush hour time period for working/schooling individuals. There were also significantly more subscribers (90+%) than customers in our dataset.

Most rides happened during the weekdays (Mon-Fri) and were short in duration (< 10 minutes) per trip. Also, a large proportion of users age were around late 30s to early 40s.

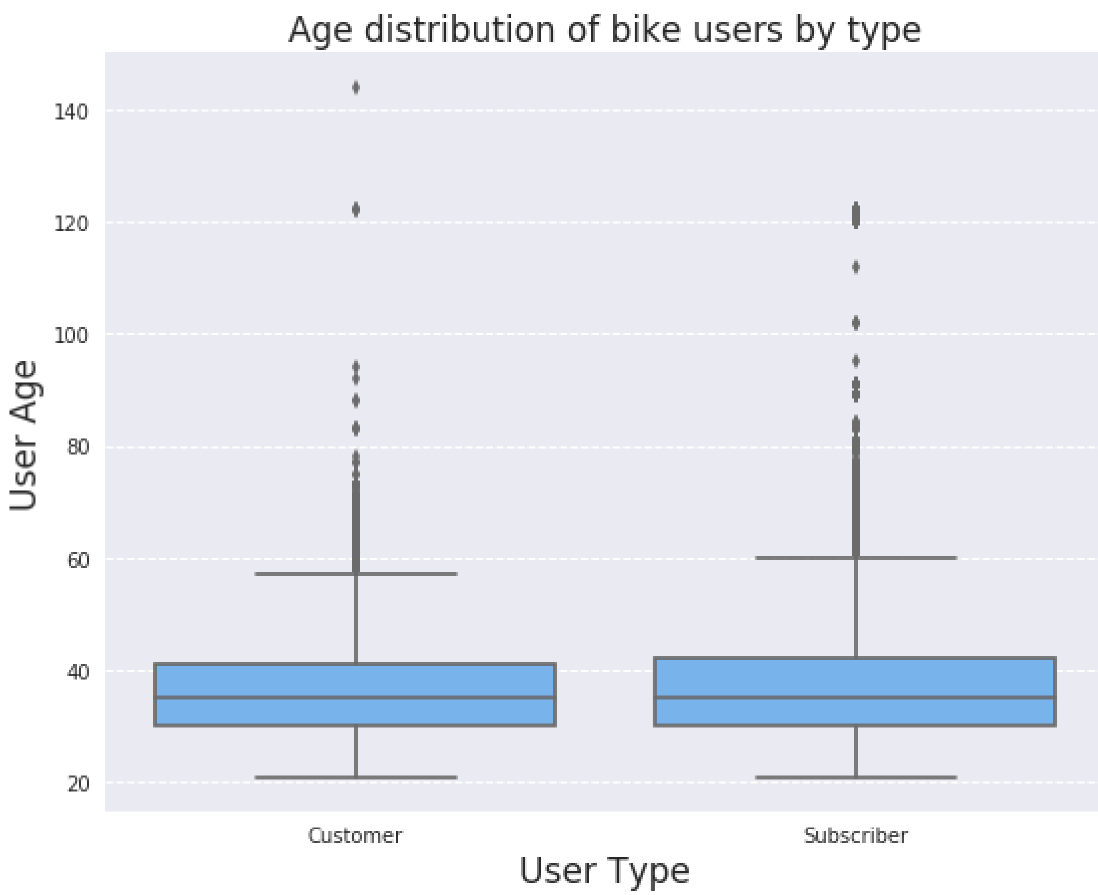
4.6.2 Of the features you investigated, were there any unusual distributions? Did you perform any operations on the data to tidy, adjust, or change the form of the data? If so, why did you do this?

The trip duration seems to have some extreme outliers that skewed the chart, this is something that I will attempt to clean in the bivariate exploration stage when the issue becomes more apparent.

5 Bivariate Exploration

5.1 Visualization 7: What is the age distribution of bike users membership type?

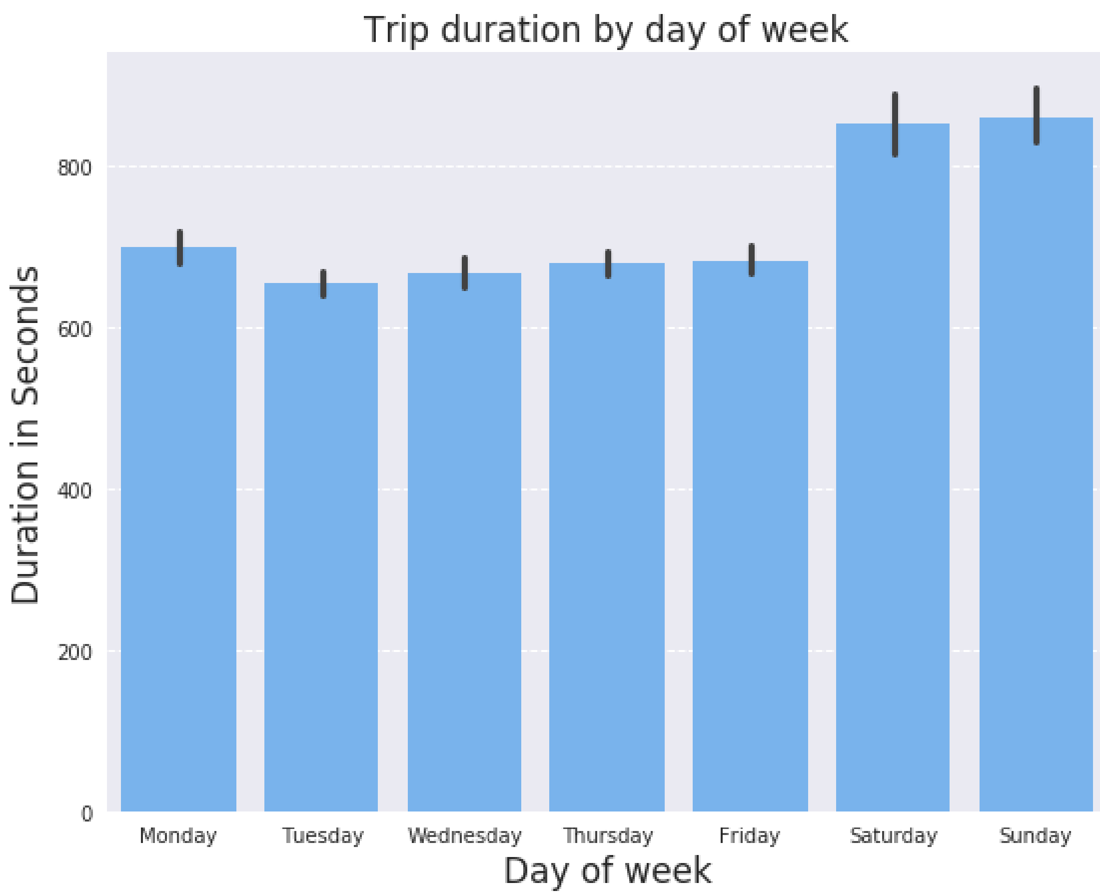
In [95]:
```
sns.boxplot(data=bike_df, x='user_type', y='age', color='#66b3ff')

# set title of the histogram
plt.title('Age distribution of bike users by type', fontsize=17)
# set x_label of plot
plt.xlabel('User Type', fontsize=17)
# set y_label of plot
plt.ylabel('User Age', fontsize=17)
# add gridlines
plt.grid(axis='y', linestyle='--')
```



The median user age and age distribution between Customer and Subscribers are quite similar.

5.2 Visualization 8: Average trip duration by day of the week

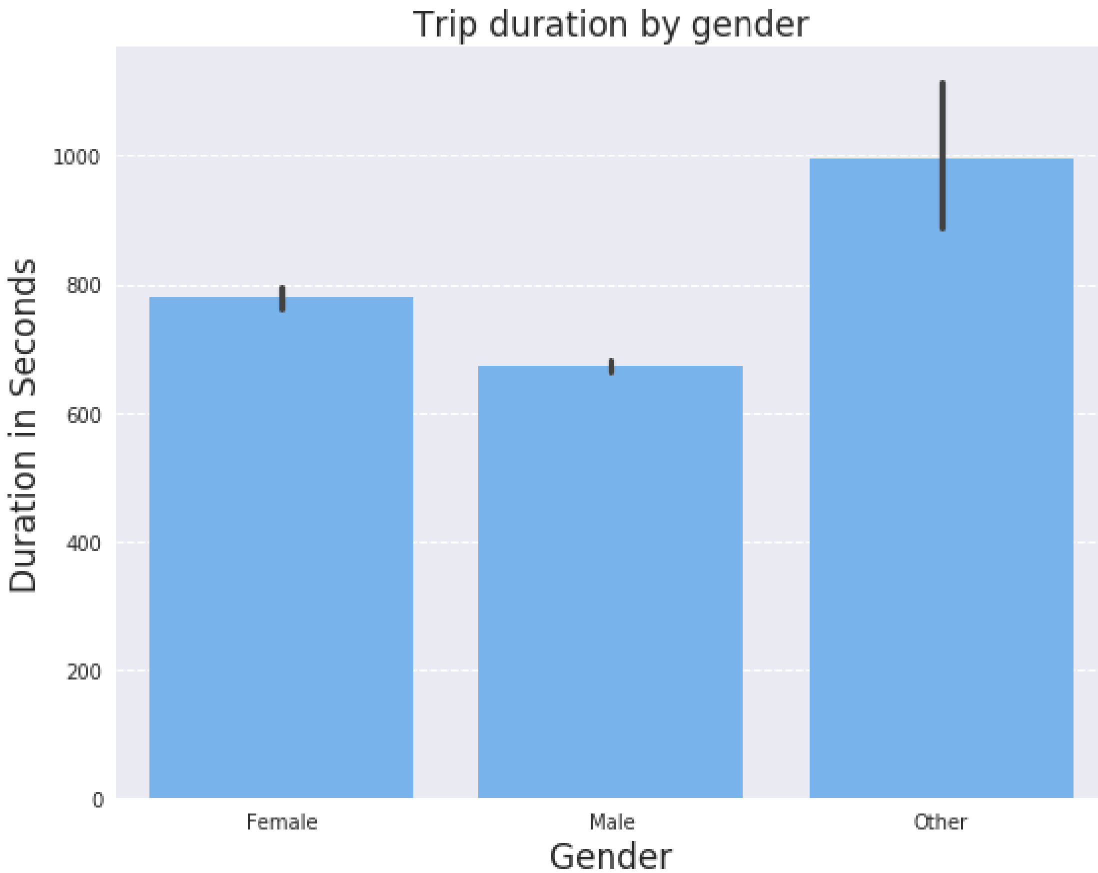
In [100]:
```
sns.barplot(data=bike_df, x='start_day', y='duration_sec', color='#66b3ff')

# set title of the barplot
plt.title('Trip duration by day of week', fontsize=17)
# set x_label of plot
plt.xlabel('Day of week', fontsize=17)
# set y_label of plot
plt.ylabel('Duration in Seconds', fontsize=17)
# add gridlines
plt.grid(axis='y', linestyle='--')
```



Even though more trips happened during weekdays, the duration of each trip seems to be longer during the weekends. This is very interesting insights.

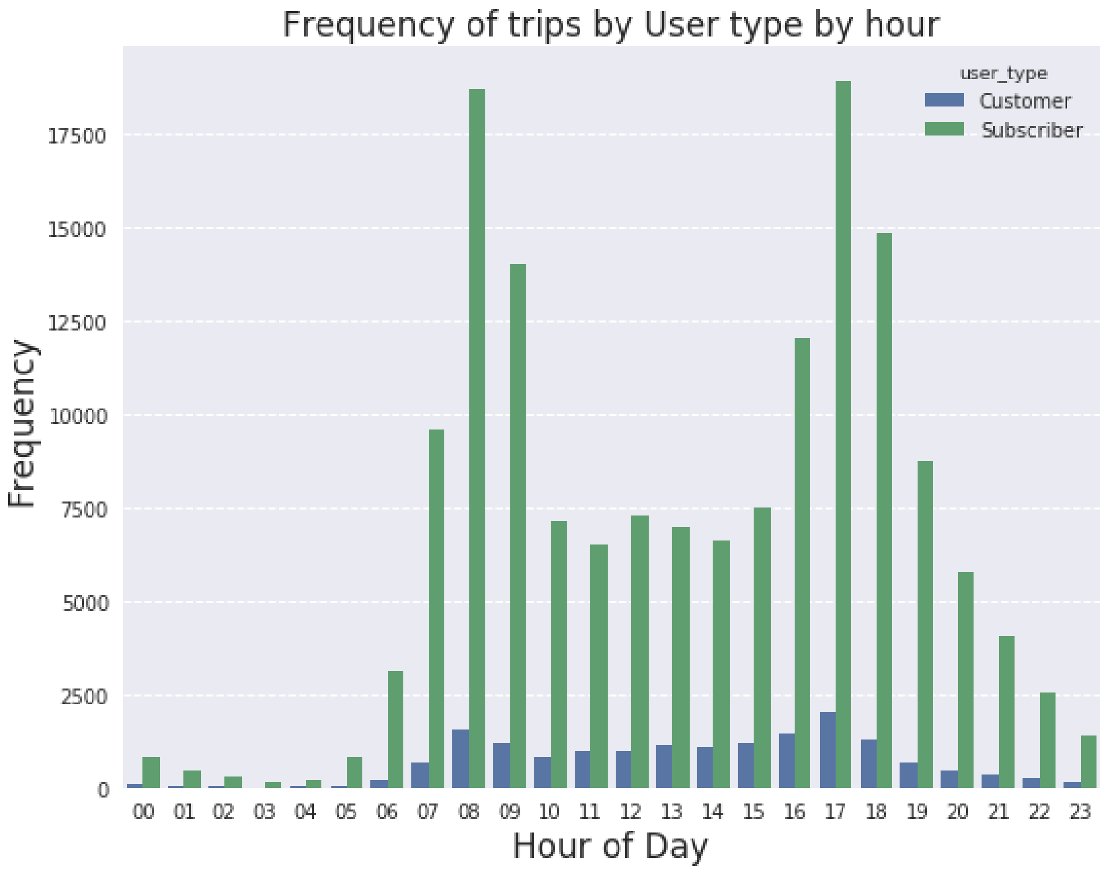
5.3 Visualization 9: Average trip duration by Gender

In [104]:
```
sns.barplot(data=bike_df, x='member_gender', y='duration_sec', color='#66b3ff')

# set title of the barplot
plt.title('Trip duration by gender', fontsize=17)
# set x_label of plot
plt.xlabel('Gender', fontsize=17)
# set y_label of plot
plt.ylabel('Duration in Seconds', fontsize=17)
# add gridlines
plt.grid(axis='y', linestyle='--')
```



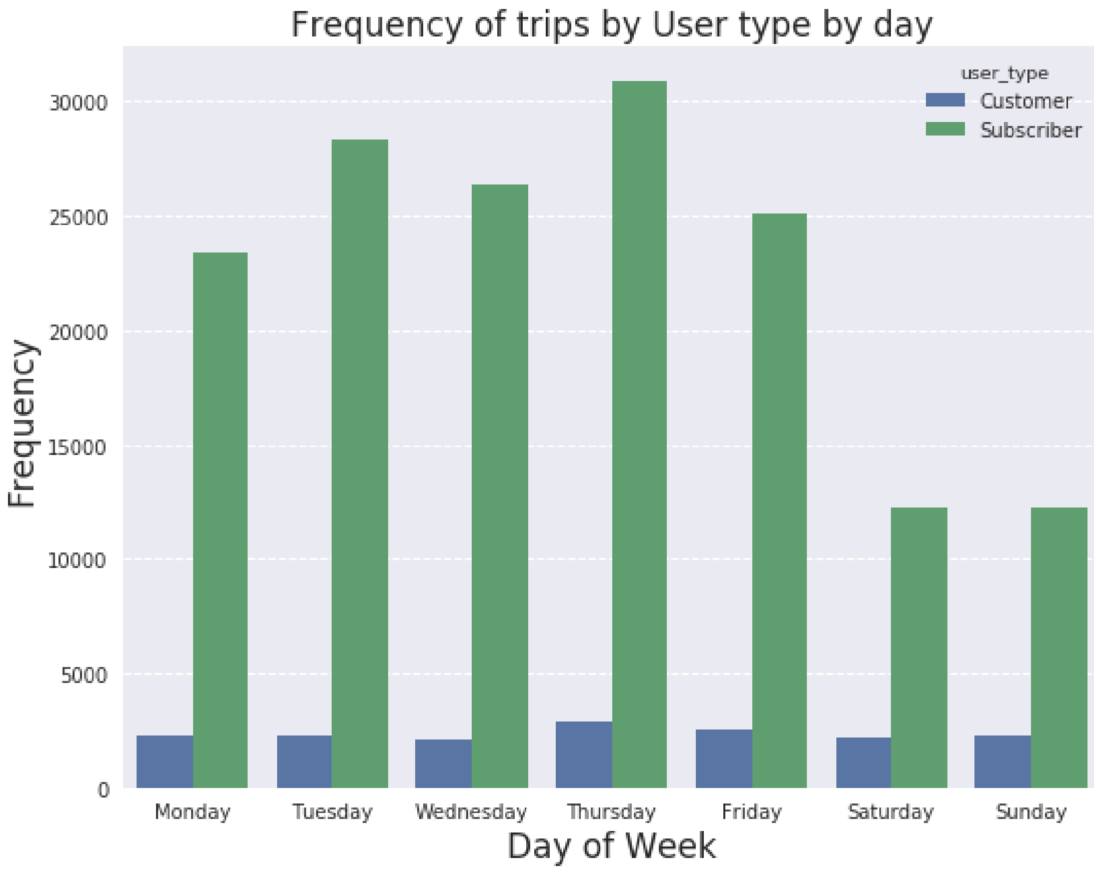
5.4 Visualization 10: Frequency of trips between user types by hour

```
In [110]: sns.countplot(data=bike_df, x='start_hour', hue='user_type')

          # set title of the barplot
          plt.title('Frequency of trips by User type by hour', fontsize=17)
          # set x_label of plot
          plt.xlabel('Hour of Day', fontsize=17)
          # set y_label of plot
          plt.ylabel('Frequency', fontsize=17)
          # add gridlines
          plt.grid(axis='y', linestyle='--')
```



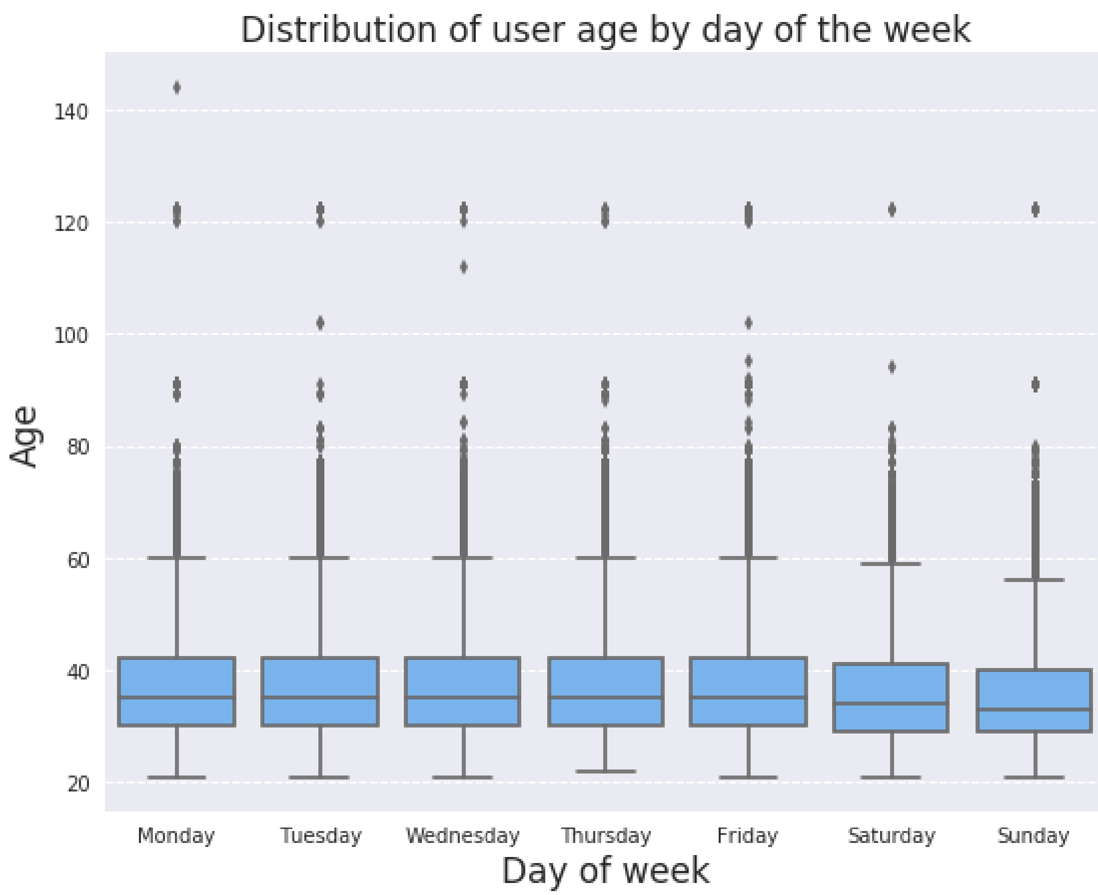
5.5 Visualization 11: Frequency of trips between user types by day

```
In [111]: sns.countplot(data=bike_df, x='start_day', hue='user_type')

          # set title of the barplot
          plt.title('Frequency of trips by User type by day', fontsize=17)
          # set x_label of plot
          plt.xlabel('Day of Week', fontsize=17)
          # set y_label of plot
          plt.ylabel('Frequency', fontsize=17)
          # add gridlines
          plt.grid(axis='y', linestyle='--')
```



5.6 Visualization 12: Distribution of users' age by Day of the week

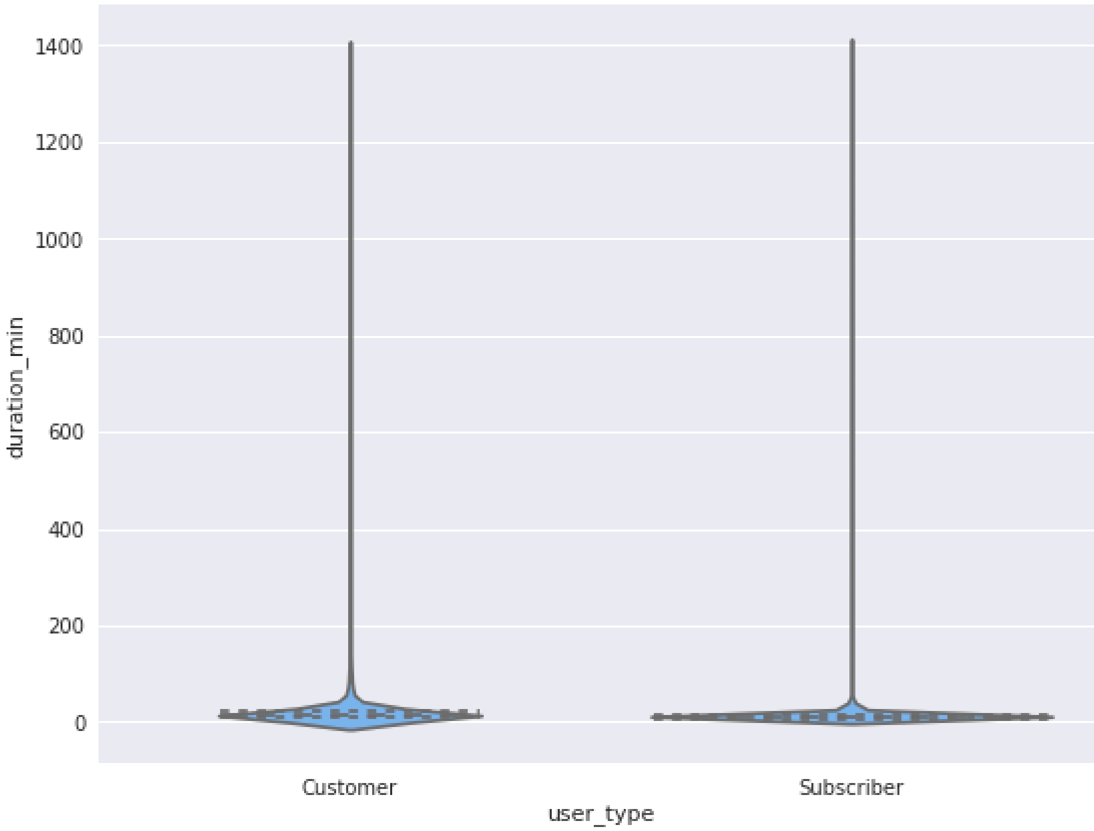
In [113]:
```
sns.boxplot(data=bike_df, x='start_day', y='age', color='#66b3ff')

# set title of the barplot
plt.title('Distribution of user age by day of the week', fontsize=17)
# set x_label of plot
plt.xlabel('Day of week', fontsize=17)
# set y_label of plot
plt.ylabel('Age', fontsize=17)
# add gridlines
plt.grid(axis='y', linestyle='--')
```



5.7 Visualization 13: Distribution of trip durations by user type

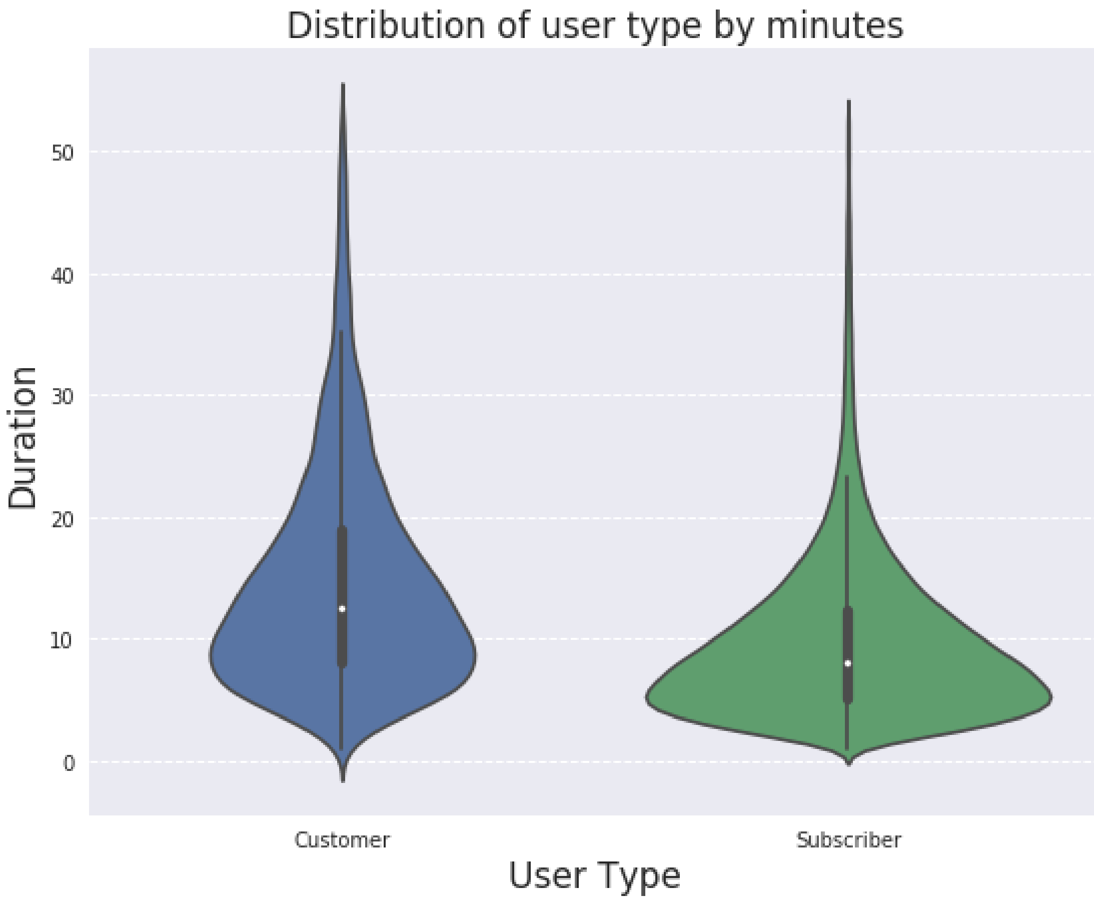
In [130]:
```
# creating a minute column
bike_df['duration_min'] = bike_df['duration_sec']/60

# trying to create a violin plot of distribution by minute
sns.violinplot(data=bike_df, x='user_type', y='duration_min', color='#66b3ff', inner='
```

Out[130]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f90fb894b00>
```



The duration (in minutes) seems to be extremely skewed by outliers, we will attempt to remove it in the next step.

```
In [132]: # we partition the distribution up till the 99th quantile, allowing us to filter out a
          q = bike_df['duration_min'].quantile(0.99)

          # filtering out for extreme outliers
          duration_outliers_removed = bike_df[bike_df['duration_min'] < q]

          # creating our violin plot
          sns.violinplot(data=duration_outliers_removed, x='user_type', y='duration_min')

          # set title of the barplot
          plt.title('Distribution of user type by minutes', fontsize=17)
          # set x_label of plot
          plt.xlabel('User Type', fontsize=17)
          # set y_label of plot
          plt.ylabel('Duration', fontsize=17)
          # add gridlines
          plt.grid(axis='y', linestyle='--')
```



After plotting our distribution, we can identify the following:

1. Customers had a higher median ride duration as compared to subscribers (as denoted by the white dot in our violinplot).
2. As the "width" of the violin plot represents the kernel density estimation of our dataset, we can conclude that Subscribers have a higher probability of taking shorter trips - as denoted by the thicker sections around the 5min duration range while Customers have a higher probability of taking trips closer to that of 10 minutes.

5.7.1 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?

Subscription use is far higher than customer usage. Customers and subscribers have quite different riding habits and patterns. Most trips on work days (Mon-Fri) and especially during rush hours (when going to work in the morning and getting off work in the afternoon) were made by subscribers because they use the bike sharing system for commuting, whereas customers typically ride for fun in the afternoon or early evening on weekends.

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

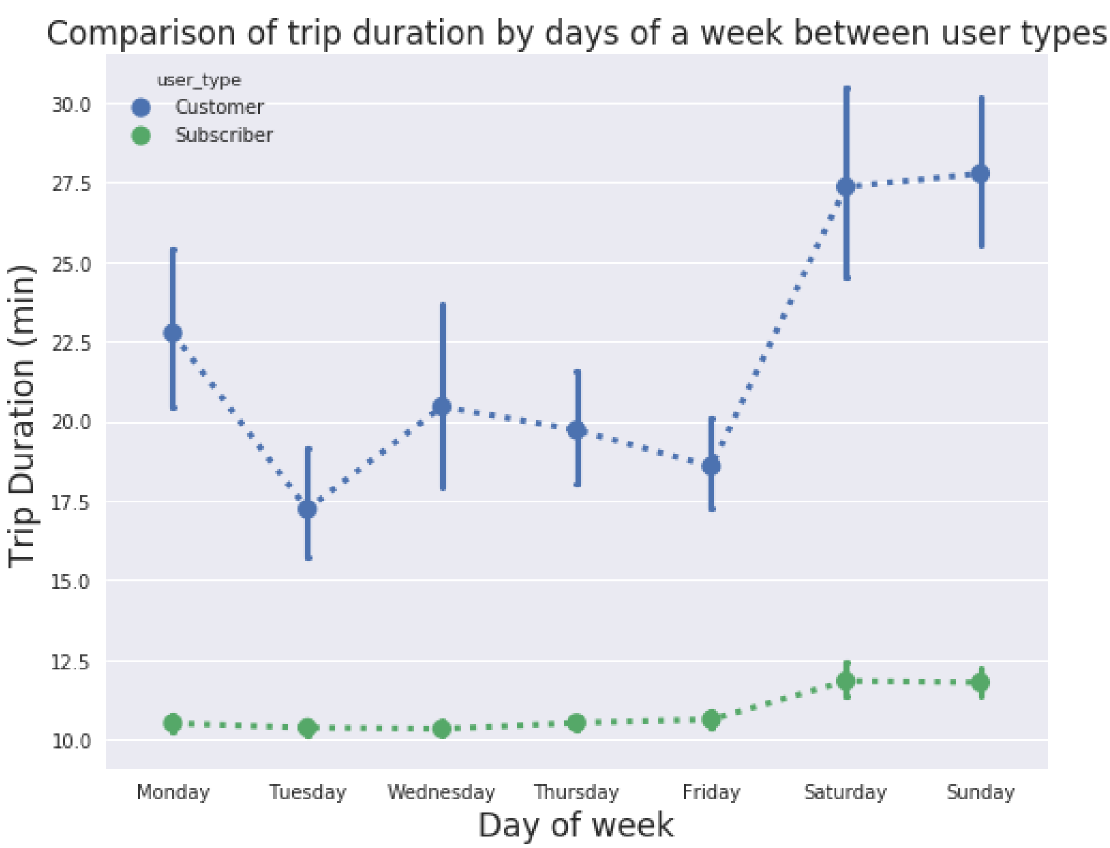
It's interesting to note that subscribers tend to ride much more quickly and for shorter distances than typical customers. Additionally, subscribers used their bikes the most on weekdays rather than weekends - which signifies that they might be using it for work/school commute rather than for leisure.

5.8 Multivariate Exploration

5.9 Visualization 14: Average trip duration in days of the week between user types

In [143]:
```
# creating our pointplot
sns.pointplot(data=bike_df, x='start_day', y='duration_min', hue='user_type', capsize=

# set title of the barplot
plt.title('Comparison of trip duration by days of a week between user types', fontsize
# set x_label of plot
plt.xlabel('Day of week', fontsize=17)
# set y_label of plot
plt.ylabel('Trip Duration (min)', fontsize=17)
```

Out[143]:
```
Text(0,0.5,'Trip Duration (min)')
```



As observed from the point plot, in general: 1. Customers took longer trips as compared to Subscribers 2. There is an increase (though more significant in Customers) on increase in trip duration during the weekends 3. The error bars give us an insight into the measure of central tendency between both user types, whereby customers typically have a much wider spread in trip duration - which is unlike the Subscribers who had a much more concentrated data spread, indicating that users are more likely to have a trip duration close to the median.

This might be due to the terms of bike duration per trip (e.g, Subscribers have free trips for the first xx minutes, thereafter incurring additional charges after the daily free trip duration.)

5.10 Visualization 15: Hourly usage between user types across days of the week

In [154]:
```
# defining a function to transform our dataset
def heatmap_transform(df: pd.DataFrame, target:str) -> pd.DataFrame:
    """
    Returns a pivot table of frequency count per day, by the hour

    Args:
        df - A dataframe of n_rows and n_columns
        target - user type we are interested in filtering for
    Returns:
        A pivot table
    """

    transformed_df = (
        df
        # filter out for given target argument
        .query(f'user_type == "{target}"')
        .groupby(['start_day', 'start_hour'])
        .size()
        .reset_index(name='count')
        .pivot(index='start_day', columns='start_hour', values='count')
        .fillna(0)
    )

    return transformed_df
```

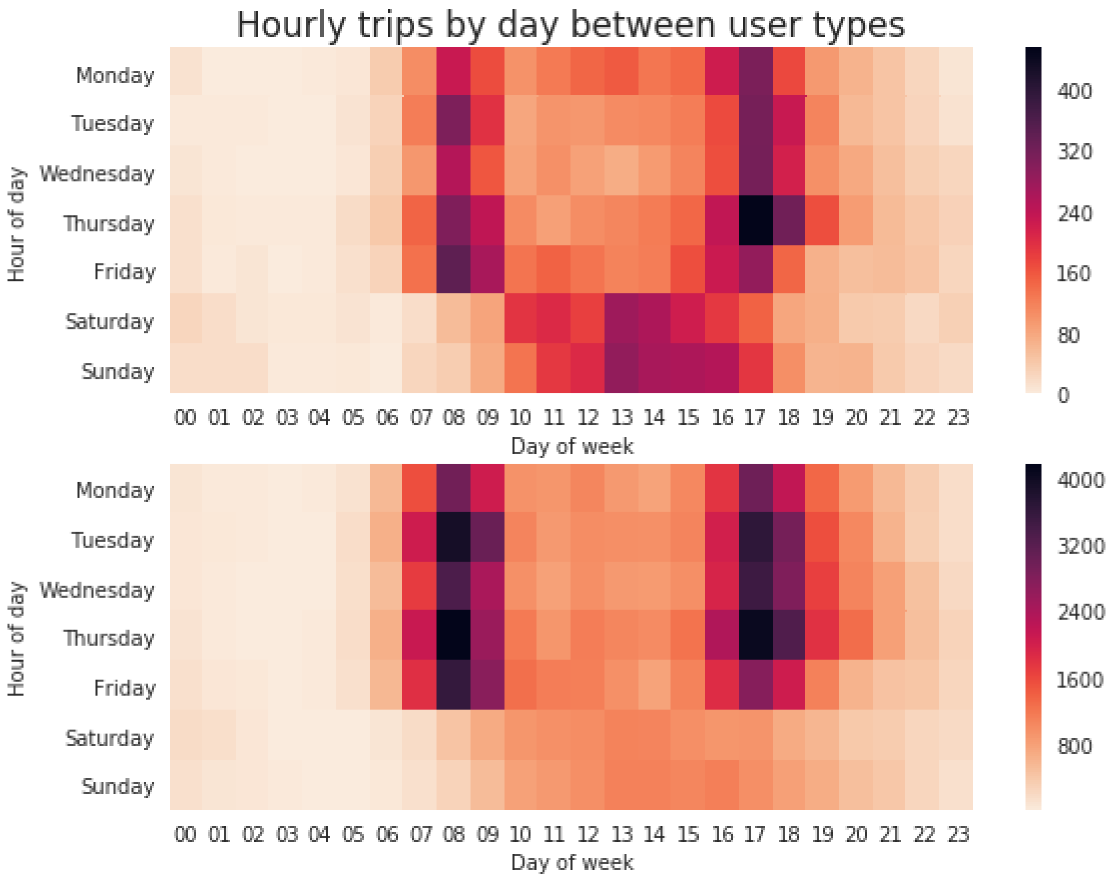
In [156]:
```
cust_count = heatmap_transform(bike_df, 'Customer')
subs_count = heatmap_transform(bike_df, 'Subscriber')

# sample of transformed pivot table
subs_count
```

Out[156]:
```
start_hour   00   01   02   03   04   05   06    07    08    09 ...    14    15  \
start_day                                                       ...
Monday       86   43   39   20   37  124  556  1545  2966  2062 ...   784  1047
Tuesday      77   51   31   17   30  169  656  2061  3929  3043 ...   968  1072
```

```
Wednesday     75    43   29   14   25   152   530   1707   3332   2416 ...    859    982
Thursday     109    41   26   19   40   165   661   2121   4167   2569 ...   1008   1241
Friday       131    77   55   28   40   138   578   1822   3583   2726 ...    786   1089
Saturday     187   145   66   22   19    25    88    188    442    699 ...   1076    981
Sunday       137    81   72   33   19    26    50    137    289    519 ...   1104   1067

start_hour    16     17     18     19     20    21    22    23
start_day
Monday      1782   2997   2193   1331    861   561   346   172
Tuesday     2018   3656   2919   1543   1045   622   325   164
Wednesday   1960   3500   2836   1682   1069   815   473   214
Thursday    2357   4065   3300   1800   1282   819   489   277
Friday      1862   2766   2071   1109    621   466   430   256
Saturday     917    930    711    592    395   363   252   201
Sunday      1125    980    825    691    492   415   252   133

[7 rows x 24 columns]
```

In [170]:
```python
# defining subplot 1
plt.subplot(2,1,1)
sns.heatmap(cust_count, cmap='rocket_r')
# set x_label of plot 1
plt.xlabel('Day of week', fontsize=10)
# set y_label of plot 1
plt.ylabel('Hour of day', fontsize=10)

# set title of the barplot
plt.title('Hourly trips by day between user types', fontsize='17')

# defining subplot 2
plt.subplot(2,1,2)
sns.heatmap(subs_count, cmap='rocket_r')
# set x_label of plot 2
plt.xlabel('Day of week', fontsize=10)
# set y_label of plot 2
plt.ylabel('Hour of day', fontsize=10)
```

Out[170]:
```
Text(60,0.5,'Hour of day')
```



5.10.1 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?

The relationship between the various variables plotted is seen collectively and information is displayed simultaneously, strengthening some of the patterns identified in the preceding bivariate investigation as well as in the univariate research. Subscribers' efficient/short periods of consumption are consistent with their high concentration during Monday through Friday rush hours, showing that the use is mostly for commuting to work. Customers clearly utilize the bike sharing system considerably differently than subscribers, frequently on weekends and in the afternoons, likely for leisure or city tours, as seen by the more flexible and lax pattern of their usage.

5.10.2 Were there any interesting or surprising interactions between features?

When all the interactions between the features are considered together, they all complement one another and make sense, so there aren't any major surprises. Because there are disproportionately more female riders and records than male ones, there may not be a significant difference in usage habits between men and women throughout the investigation. If there were more female data, it would be interesting to observe the differences in usage between men and women if we were able to obtain a more balanced dataset between both genders

5.11 Conclusions

We performed three levels of visualization and analysis - Univariate, Bivariate and Multivariate on the bike sharing dataset. During the exercise, we also removed extreme outliers to help us better visualize the dataset to generate insights.

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```
In [ ]:
```