SF_bike_transit

May 15, 2019

1 San Francisco Bike Share data from 2013 to 2015

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

1.1 Let's explore the data!

The San Francisco bike sharing data came with four CSV files: station, status, weather, and trip

In [2]:
```
station = pd.read_csv('station.csv')
station
```

Out[2]:
```
    id                            name        lat        long  \
0    2       San Jose Diridon Caltrain Station  37.329732 -121.901782
1    3                San Jose Civic Center  37.330698 -121.888979
2    4               Santa Clara at Almaden  37.333988 -121.894902
3    5                    Adobe on Almaden  37.331415 -121.893200
4    6                    San Pedro Square  37.336721 -121.894074
5    7                Paseo de San Antonio  37.333798 -121.886943
6    8                 San Salvador at 1st  37.330165 -121.885831
7    9                           Japantown  37.348742 -121.894715
8   10                  San Jose City Hall  37.337391 -121.886995
9   11                         MLK Library  37.335885 -121.885660
10  12               SJSU 4th at San Carlos  37.332808 -121.883891
11  13                      St James Park  37.339301 -121.889937
12  14            Arena Green / SAP Center  37.332692 -121.900084
13  16         SJSU - San Salvador at 9th  37.333955 -121.877349
14  21                  Franklin at Maple  37.481758 -122.226904
15  22           Redwood City Caltrain Station  37.486078 -122.232089
16  23             San Mateo County Center  37.487616 -122.229951
17  24          Redwood City Public Library  37.484219 -122.227424
18  25             Stanford in Redwood City  37.485370 -122.203288
19  26          Redwood City Medical Center  37.487682 -122.223492
20  27              Mountain View City Hall  37.389218 -122.081896
21  28         Mountain View Caltrain Station  37.394358 -122.076713
22  29           San Antonio Caltrain Station  37.406940 -122.106758
23  30                 Evelyn Park and Ride  37.390277 -122.066553
```

24	31	San Antonio Shopping Center	37.400443	-122.108338
25	32	Castro Street and El Camino Real	37.385956	-122.083678
26	33	Rengstorff Avenue / California Street	37.400241	-122.099076
27	34	Palo Alto Caltrain Station	37.443988	-122.164759
28	35	University and Emerson	37.444521	-122.163093
29	36	California Ave Caltrain Station	37.429082	-122.142805
..	..	...	...	...
40	51	Embarcadero at Folsom	37.791464	-122.391034
41	39	Powell Street BART	37.783871	-122.408433
42	54	Embarcadero at Bryant	37.787152	-122.388013
43	55	Temporary Transbay Terminal (Howard at Beale)	37.789756	-122.394643
44	56	Beale at Market	37.792251	-122.397086
45	57	5th at Howard	37.781752	-122.405127
46	58	San Francisco City Hall	37.778650	-122.418235
47	59	Golden Gate at Polk	37.781332	-122.418603
48	60	Embarcadero at Sansome	37.804770	-122.403234
49	61	2nd at Townsend	37.780526	-122.390288
50	62	2nd at Folsom	37.785299	-122.396236
51	63	Howard at 2nd	37.786978	-122.398108
52	64	2nd at South Park	37.782259	-122.392738
53	65	Townsend at 7th	37.771058	-122.402717
54	66	South Van Ness at Market	37.774814	-122.418954
55	67	Market at 10th	37.776619	-122.417385
56	68	Yerba Buena Center of the Arts (3rd @ Howard)	37.784878	-122.401014
57	69	San Francisco Caltrain 2 (330 Townsend)	37.776600	-122.395470
58	70	San Francisco Caltrain (Townsend at 4th)	37.776617	-122.395260
59	71	Powell at Post (Union Square)	37.788446	-122.408499
60	72	Civic Center BART (7th at Market)	37.781039	-122.411748
61	73	Grant Avenue at Columbus Avenue	37.798522	-122.407245
62	74	Steuart at Market	37.794139	-122.394434
63	75	Mechanics Plaza (Market at Battery)	37.791300	-122.399051
64	76	Market at 4th	37.786305	-122.404966
65	77	Market at Sansome	37.789625	-122.400811
66	80	Santa Clara County Civic Center	37.352601	-121.905733
67	82	Broadway St at Battery St	37.798541	-122.400862
68	83	Mezes Park	37.491269	-122.236234
69	84	Ryland Park	37.342725	-121.895617

	dock_count	city	installation_date
0	27	San Jose	8/6/2013
1	15	San Jose	8/5/2013
2	11	San Jose	8/6/2013
3	19	San Jose	8/5/2013
4	15	San Jose	8/7/2013
5	15	San Jose	8/7/2013
6	15	San Jose	8/5/2013
7	15	San Jose	8/5/2013
8	15	San Jose	8/6/2013

9	19	San Jose	8/6/2013
10	19	San Jose	8/7/2013
11	15	San Jose	8/6/2013
12	19	San Jose	8/5/2013
13	15	San Jose	8/7/2013
14	15	Redwood City	8/12/2013
15	25	Redwood City	8/15/2013
16	15	Redwood City	8/15/2013
17	15	Redwood City	8/12/2013
18	15	Redwood City	8/12/2013
19	15	Redwood City	8/12/2013
20	15	Mountain View	8/16/2013
21	23	Mountain View	8/15/2013
22	23	Mountain View	8/15/2013
23	15	Mountain View	8/16/2013
24	15	Mountain View	12/31/2013
25	11	Mountain View	12/31/2013
26	15	Mountain View	8/16/2013
27	23	Palo Alto	8/14/2013
28	11	Palo Alto	8/15/2013
29	15	Palo Alto	8/14/2013
..	...	...	...
40	19	San Francisco	8/20/2013
41	19	San Francisco	8/25/2013
42	15	San Francisco	8/20/2013
43	23	San Francisco	8/20/2013
44	19	San Francisco	8/20/2013
45	15	San Francisco	8/21/2013
46	19	San Francisco	8/21/2013
47	23	San Francisco	8/21/2013
48	15	San Francisco	8/21/2013
49	27	San Francisco	8/22/2013
50	19	San Francisco	8/22/2013
51	19	San Francisco	8/22/2013
52	15	San Francisco	8/22/2013
53	15	San Francisco	8/22/2013
54	19	San Francisco	8/23/2013
55	27	San Francisco	8/23/2013
56	19	San Francisco	8/23/2013
57	23	San Francisco	8/23/2013
58	19	San Francisco	8/23/2013
59	19	San Francisco	8/23/2013
60	23	San Francisco	8/23/2013
61	15	San Francisco	8/21/2013
62	23	San Francisco	8/25/2013
63	19	San Francisco	8/25/2013
64	19	San Francisco	8/25/2013
65	27	San Francisco	8/25/2013

```
66           15        San Jose        12/31/2013
67           15   San Francisco         1/22/2014
68           15    Redwood City         2/20/2014
69           15        San Jose          4/9/2014

[70 rows x 7 columns]
```

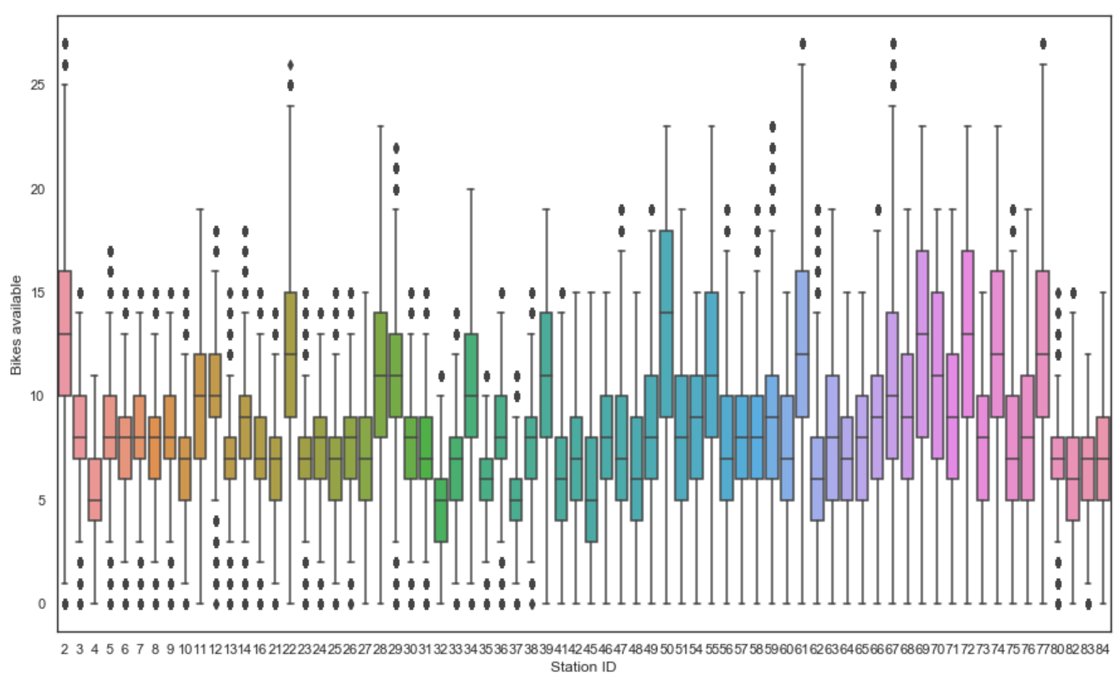
```
In [3]: status = pd.read_csv('status.csv')
```

```
In [4]: status.head()
```

```
Out[4]:    station_id  bikes_available  docks_available                 time
        0           2                2               25  2013/08/29 12:06:01
        1           2                2               25  2013/08/29 12:07:01
        2           2                2               25  2013/08/29 12:08:01
        3           2                2               25  2013/08/29 12:09:01
        4           2                2               25  2013/08/29 12:10:01
```

1.2 Let's see what bike availability looks like for each station.

```
In [88]: plt.figure(figsize=(15,9))
         sns.set(style="white", palette="Set2")
         sns.boxplot(data = status, x = 'station_id', y = 'bikes_available')
         plt.xlabel("Station ID")
         plt.ylabel("Bikes available")
         plt.savefig('bike_availability_by_station.jpeg')
```



It seems that stations 2-38 are less likely to run out of bikes as compared to stations 39-77. Why could that be? Looking at the station names from the station.csv file it is obvious that station 39-77 are more popular because they are in the city of San Francisco. Some of the less used stations are as far out as San Jose.

1.3 Can we look at those stations 2-38 more closely, perhaps with a different plot to glean more information?

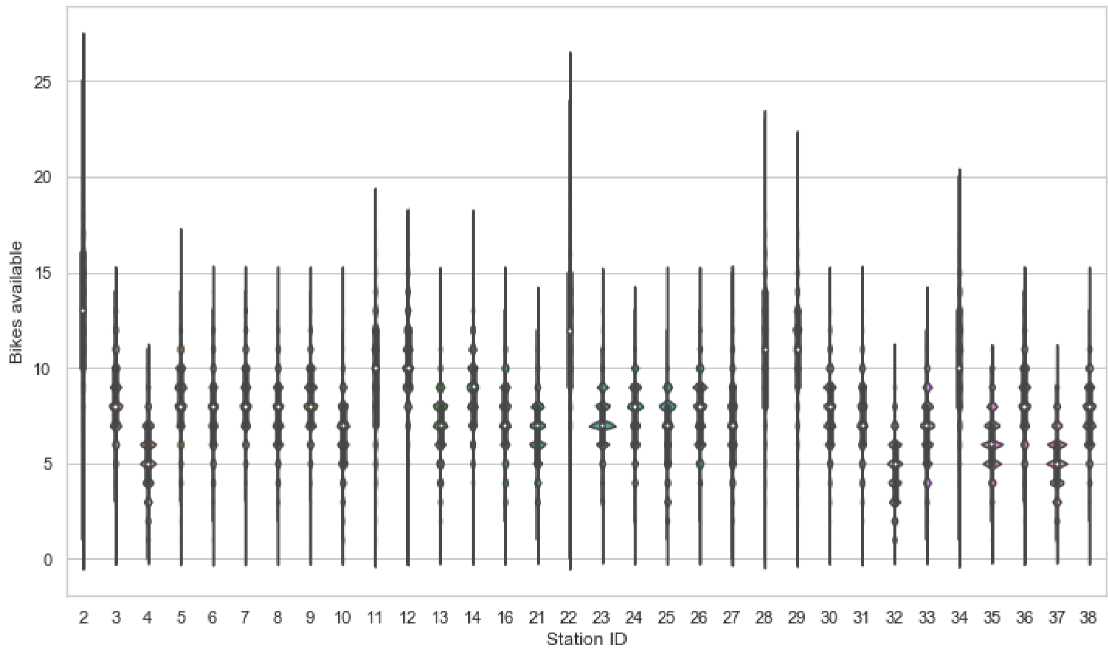
```
In [6]: status_2_38 = status[ (status.station_id>=2) &(status.station_id<=38)]
        status_2_38.head()
```

Out[6]:

	station_id	bikes_available	docks_available	time
0	2	2	25	2013/08/29 12:06:01
1	2	2	25	2013/08/29 12:07:01
2	2	2	25	2013/08/29 12:08:01
3	2	2	25	2013/08/29 12:09:01
4	2	2	25	2013/08/29 12:10:01

```
In [7]: plt.figure(figsize=(12,7))
        sns.set(style="whitegrid", palette="Set2")
        sns.violinplot(data = status_2_38, x = 'station_id', y = 'bikes_available')
        plt.xlabel("Station ID")
        plt.ylabel("Bikes available")
        plt.savefig('bike_availability_by_station_2_38.pdf')
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

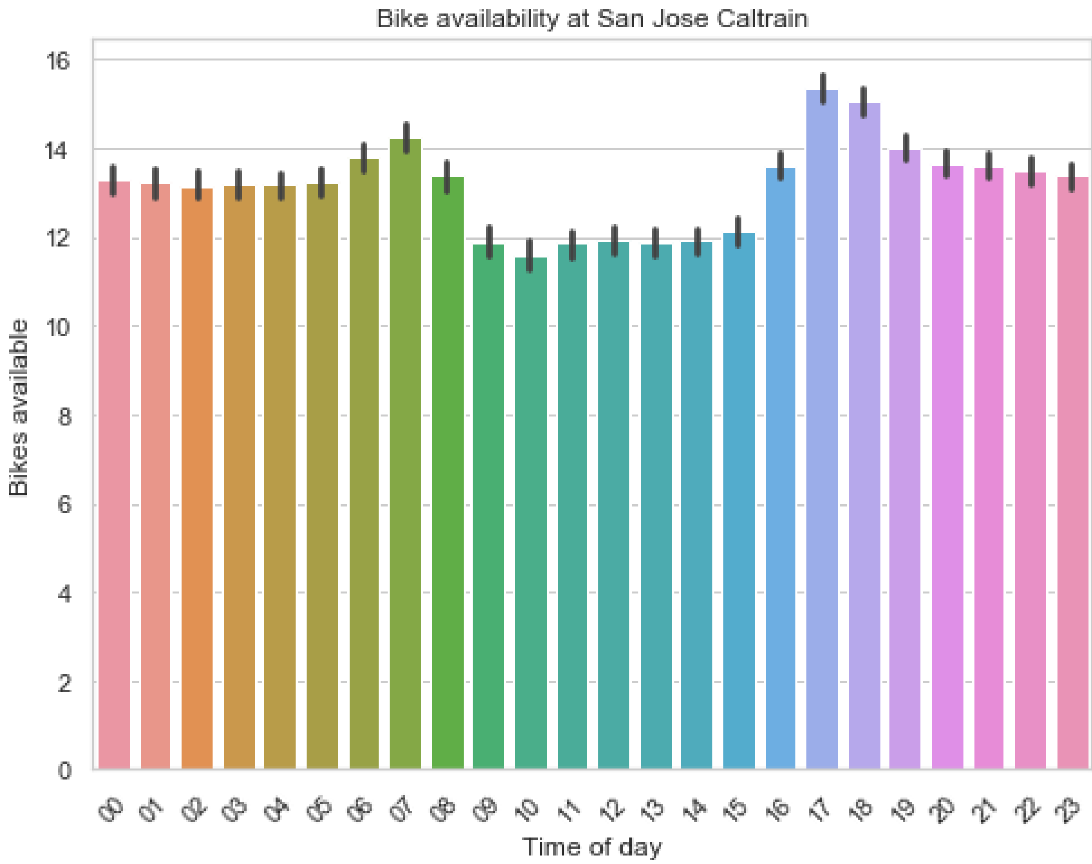


That violin plot does not give much information, there is no mean distribution that the bike availability clusters around, it fluctuates a lot.

1.4 Let's try looking at one station in particular, San Jose Diridon Caltrain Station (id = 2), and see how its bike availability changes throughout the day

```
In [8]: station_groups = status.groupby('station_id')

In [9]: station_2 = station_groups.get_group(2)

In [10]: station_2.index = pd.to_datetime(station_2['time'])
         station_2.head()

Out[10]:                      station_id  bikes_available  docks_available  \
         time
         2013-08-29 12:06:01           2                2               25
         2013-08-29 12:07:01           2                2               25
         2013-08-29 12:08:01           2                2               25
         2013-08-29 12:09:01           2                2               25
         2013-08-29 12:10:01           2                2               25

                                             time
         time
         2013-08-29 12:06:01  2013/08/29 12:06:01
         2013-08-29 12:07:01  2013/08/29 12:07:01
         2013-08-29 12:08:01  2013/08/29 12:08:01
         2013-08-29 12:09:01  2013/08/29 12:09:01
         2013-08-29 12:10:01  2013/08/29 12:10:01

In [11]: hourly = station_2.resample('H').agg({'bikes_available': 'mean'})

In [12]: hourly= pd.DataFrame(hourly)
         hourly['time_of_day'] = hourly.index
         hourly['time_of_day'] =hourly['time_of_day'].dt.strftime('%H')
         hourly.head()

Out[12]:                      bikes_available time_of_day
         time
         2013-08-29 12:00:00         2.000000          12
         2013-08-29 13:00:00         2.698113          13
         2013-08-29 14:00:00         2.000000          14
         2013-08-29 15:00:00         2.000000          15
         2013-08-29 16:00:00         2.000000          16

In [13]: plt.figure(figsize=(8,6))
         sns.set_palette('bright')
         ax = sns.barplot(data = hourly, x = 'time_of_day', y = 'bikes_available')
```

```
plt.xticks(rotation=45)
plt.xlabel("Time of day")
plt.ylabel("Bikes available")
plt.title("Bike availability at San Jose Caltrain")
plt.savefig('bike_availability.pdf')
```



Not a very surprising result that there is greatest demand for bikes between 8am and 4pm.

1.5 Station 2 in San Jose is not one of the most used stations, let's compare with station 62, 2nd at Folsom, in San Francisco

In [14]:
```
station_62 = station_groups.get_group(62)
station_62.index = pd.to_datetime(station_62['time'])
station_62.head()
```

Out[14]:
```
                     station_id  bikes_available  docks_available  \
time
2013-08-29 12:06:01          62               10                9
2013-08-29 12:07:01          62               10                9
2013-08-29 12:08:01          62               10                9
2013-08-29 12:09:01          62               10                9
```

```
2013-08-29 12:10:01          62               10                 9

                                           time
time
2013-08-29 12:06:01  2013/08/29 12:06:01
2013-08-29 12:07:01  2013/08/29 12:07:01
2013-08-29 12:08:01  2013/08/29 12:08:01
2013-08-29 12:09:01  2013/08/29 12:09:01
2013-08-29 12:10:01  2013/08/29 12:10:01
```

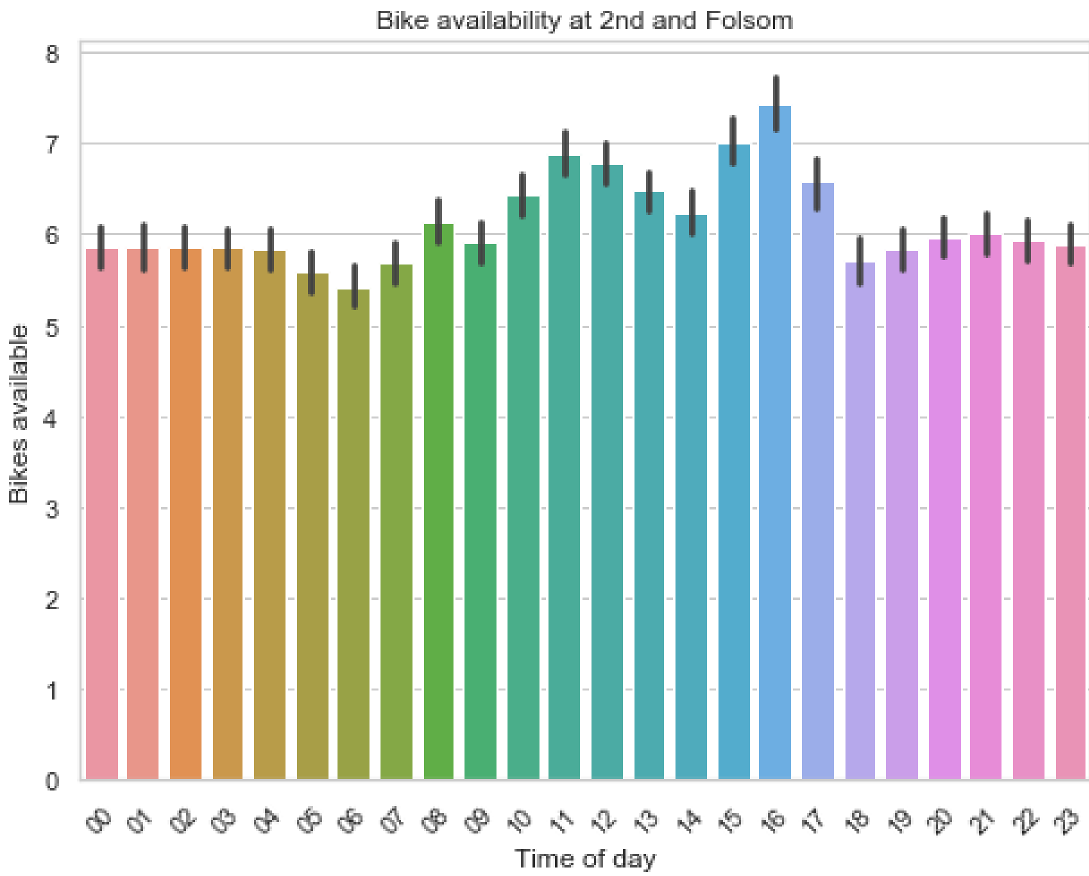
In [15]:
```
hourly_62 = station_62.resample('H').agg({'bikes_available': 'mean'})
```

In [16]:
```
hourly_62= pd.DataFrame(hourly_62)
hourly_62['time_of_day'] = hourly_62.index
hourly_62['time_of_day'] =hourly_62['time_of_day'].dt.strftime('%H')
hourly_62.head()
```

Out[16]:

time	bikes_available	time_of_day
2013-08-29 12:00:00	9.500000	12
2013-08-29 13:00:00	9.264151	13
2013-08-29 14:00:00	9.928571	14
2013-08-29 15:00:00	10.055556	15
2013-08-29 16:00:00	10.000000	16

In [17]:
```
plt.figure(figsize=(8,6))
sns.set_palette('bright')
ax = sns.barplot(data = hourly_62, x = 'time_of_day', y = 'bikes_available')
plt.xticks(rotation=45)
plt.xlabel("Time of day")
plt.ylabel("Bikes available")
plt.title("Bike availability at 2nd and Folsom")
plt.savefig('bike_availability_station_62.pdf')
```



Interesting, unlike station 2 in San Jose, station 62 in San Francisco actually has greater bike availability during business hours from people commuting in.

1.6 Now looking at bike trips per month over the three years of data provided. Has usership grown? Waned? Are there any identifyable drop-offs?

In [18]:
```
trip = pd.read_csv('trip.csv')
```

In [35]:
```
trip['start_date'] = pd.to_datetime(trip['start_date'])
```

In [36]:
```
trip.start_date.head()
```

Out[36]:
```
start_date
2013-08-29 14:13:00   2013-08-29
2013-08-29 14:42:00   2013-08-29
2013-08-29 10:16:00   2013-08-29
2013-08-29 11:29:00   2013-08-29
2013-08-29 12:02:00   2013-08-29
Name: start_date, dtype: datetime64[ns]
```

In [37]:
```
#let's count trips per month
trip.index = trip['start_date']
```

In [38]:
```python
#let's resample by months

monthly_trips = trip.resample('M').size()
monthly_trips= pd.DataFrame(monthly_trips)
```

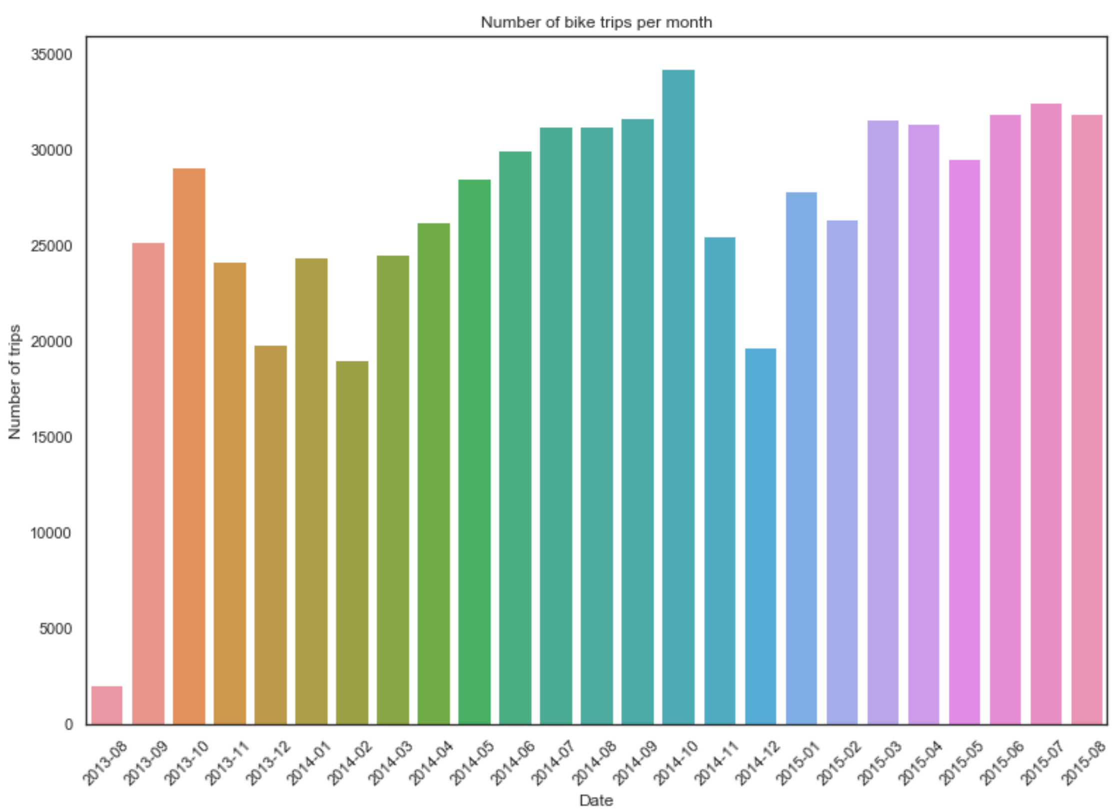
In [39]:
```python
monthly_trips.columns = ['trip_count']
monthly_trips['date']= monthly_trips.index
monthly_trips.head()
```

Out[39]:

start_date	trip_count	date
2013-08-31	2102	2013-08-31
2013-09-30	25243	2013-09-30
2013-10-31	29105	2013-10-31
2013-11-30	24219	2013-11-30
2013-12-31	19894	2013-12-31

In [40]:
```python
monthly_trips['date'] = monthly_trips['date'].dt.strftime('%Y-%m')
```

In [89]:
```python
plt.figure(figsize=(13,9))
sns.set_palette('bright')
ax = sns.barplot(data = monthly_trips, x = 'date', y = 'trip_count')
plt.xticks(rotation=45)
plt.xlabel("Date")
plt.ylabel("Number of trips")
plt.title("Number of bike trips per month")
plt.savefig('montly_trips.jpeg')
```



Looks like usership ramped up to 25,000 trips per month quickly. There was more fluctuation in 2013 and early 2014, but then trip numbers stabilized around 30,000 per month. There is a drop-off seen for November and December of 2014 probably due to the holidays. January and February are a little bit less utilized, perhaps due to weather (?), but trip numbers once again stabilize around 30,000 from March 2015 onward. Looking at data for years 2015-2019, not included in this analysis, would confirm the seasonal drop off. This information could be used to schedule bike/ station maintenance.

1.7 How does the weather impact trips?

```
In [42]: weather = pd.read_csv('weather.csv')
```

```
In [43]: weather['date'] = pd.to_datetime(weather['date'])
         trip['start_date'] = pd.to_datetime(trip['start_date'])
```

```
In [44]: #for making the dates into the same format for merging
         trip['start_date'] = trip['start_date'].dt.strftime('%Y-%m-%d')
         weather['date'] = weather['date'].dt.strftime('%Y-%m-%d')
```

Let's merge trips and weather

```
In [45]: trip_weather = trip.merge(weather, how = 'left', left_on ='start_date', right_on ='da
```

```
/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1: FutureWarning: 'start_date' is
Defaulting to column, but this will raise an ambiguity error in a future version
  """Entry point for launching an IPython kernel.
```

```
In [46]: trip_weather.index = pd.to_datetime(trip_weather['start_date'])
```

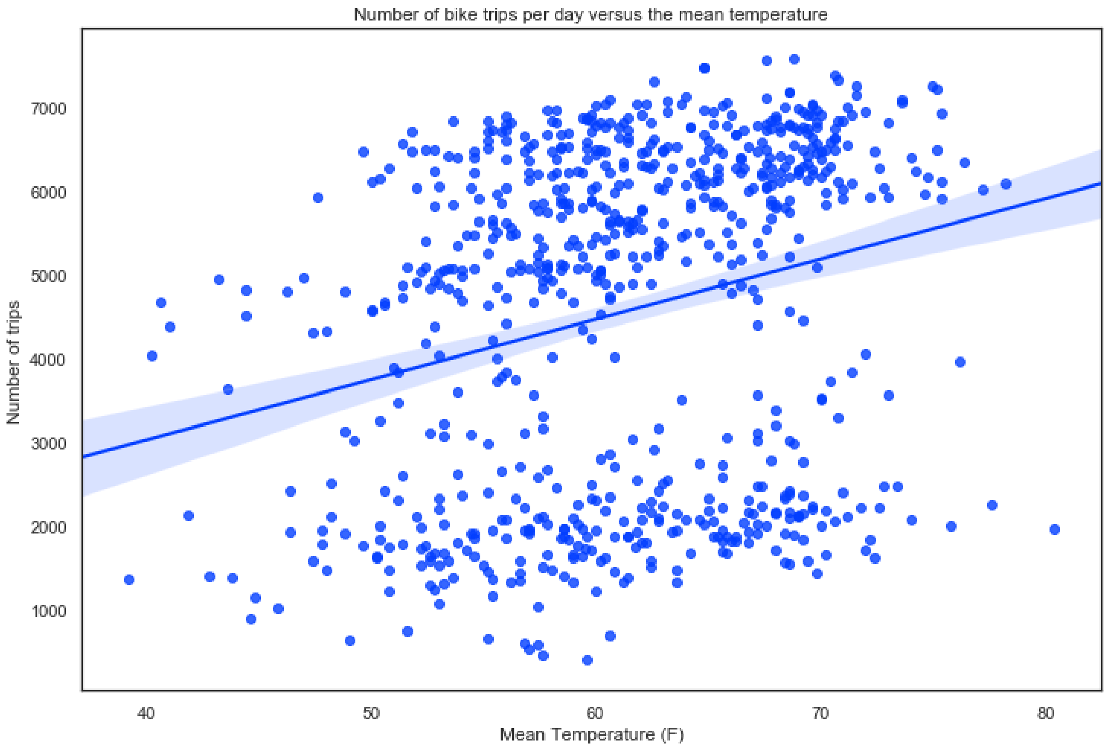
```
In [76]: daily_trip_weather = trip_weather.resample('D').agg({'start_date':'count', 'mean_tempe
```

```
In [77]: daily_trip_weather.columns = ['trip_number', 'mean_temp']
         daily_trip_weather['date']= daily_trip_weather.index
         daily_trip_weather.head()
```

```
Out[77]:             trip_number  mean_temp       date
         start_date
         2013-08-29         3740       70.4 2013-08-29
         2013-08-30         3570       73.0 2013-08-30
         2013-08-31         3200       68.0 2013-08-31
         2013-09-01         3530       70.0 2013-09-01
         2013-09-02         3305       70.8 2013-09-02
```

```
In [90]: plt.figure(figsize=(12,8))
         sns.regplot(data = daily_trip_weather, x = 'mean_temp', y = 'trip_number')
         plt.xlabel("Mean Temperature (F)")
         plt.ylabel("Number of trips")
         plt.title("Number of bike trips per day versus the mean temperature")
         plt.savefig('temp_trips.jpeg')
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Wow, there's a lot of noise here, but there seems to be a trend for more bike trips with warmer weather. Most likely, since the weather in the bay area is so conistently comfortable, between 50-75 Farenheit, the temperature effect will not be as noticable as it would be if the temperature ranged from 30-100 F.

1.8 Perhaps percipitation is a better indicator of how many bike trips will be made per day

```
In [65]: trip_weather.fillna(value={'events': 'Beautiful'}, inplace=True)
```

```
In [117]: weather_groups = trip_weather.groupby('events').agg({'start_date': 'count'})
```

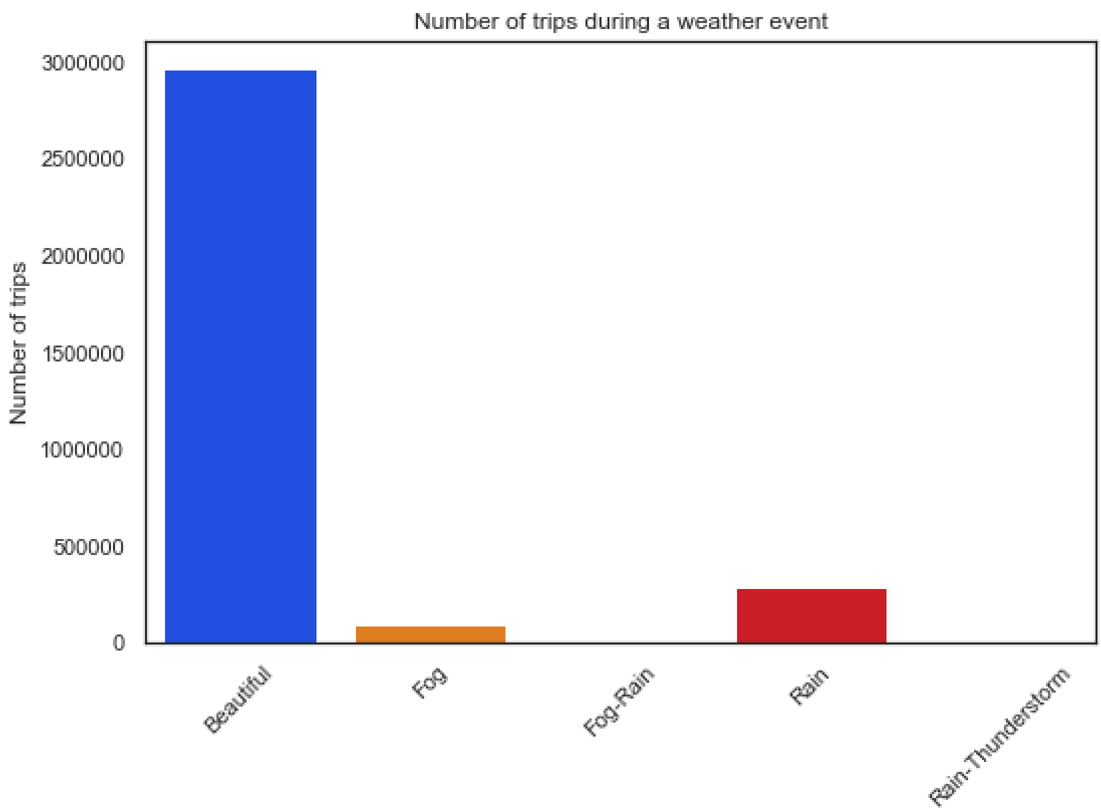
```
In [118]: weather_groups.columns = ['trip_number']
```

```
In [119]: #Add rain and Rain
          weather_groups.loc['Rain']= weather_groups.loc['Rain'] + weather_groups.loc['rain']
```

```
In [120]: weather_groups.drop('rain', inplace = True)
          weather_groups['event'] = weather_groups.index
          weather_groups
```

```
Out[120]:                     trip_number                event
          events
          Beautiful               2958504            Beautiful
          Fog                       95474                  Fog
          Fog-Rain                  11672             Fog-Rain
          Rain                     282395                 Rain
          Rain-Thunderstorm          1750    Rain-Thunderstorm
```

```
In [121]: plt.figure(figsize=(8,6))
          sns.barplot(data = weather_groups, x = 'event', y = 'trip_number')
          plt.xticks(rotation=45)
          plt.tight_layout()
          plt.xlabel("")
          plt.ylabel("Number of trips")
          plt.title('Number of trips during a weather event')
          plt.savefig('weather_events.jpeg')
```



Looks like weather is not a big factor for this bike share program. The number of rides carried out on beautiful days far eclipses the othe categories. Of course this analysis is not counting how many days were beautiful, rather how many rides were carried out on beautiful days, so it is biased in that sense.