Communicate_Data

April 8, 2021

0.1 Importing Libraries

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import pandas as pd
import seaborn as sb
import os
from google.colab import drive
```

[2]:
```
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[3]:
```
cd /content/drive/MyDrive/Professional/Udacity/Capstone/
```

```
/content/drive/MyDrive/Professional/Udacity/Capstone
```

[4]:
```
ls
```

```
 201902-fordgobike-tripdata.csv                   oak_png.PNG
 bay_area.png                                     sf_png.PNG
 Communicate_Data                                 sj_png.PNG
'Communicate Data Capstone Slide Deck.gslides'
```

0.2 Importing and Cleaning Data

[5]:
```
# Importing CSV file
df = pd.read_csv('201902-fordgobike-tripdata.csv')
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183412 entries, 0 to 183411
Data columns (total 16 columns):
 #   Column                    Non-Null Count   Dtype
```

```
---  ------                   --------------   -----
 0   duration_sec             183412 non-null  int64
 1   start_time               183412 non-null  object
 2   end_time                 183412 non-null  object
 3   start_station_id         183215 non-null  float64
 4   start_station_name       183215 non-null  object
 5   start_station_latitude   183412 non-null  float64
 6   start_station_longitude  183412 non-null  float64
 7   end_station_id           183215 non-null  float64
 8   end_station_name         183215 non-null  object
 9   end_station_latitude     183412 non-null  float64
 10  end_station_longitude    183412 non-null  float64
 11  bike_id                  183412 non-null  int64
 12  user_type                183412 non-null  object
 13  member_birth_year        175147 non-null  float64
 14  member_gender            175147 non-null  object
 15  bike_share_for_all_trip  183412 non-null  object
dtypes: float64(7), int64(2), object(7)
memory usage: 22.4+ MB
```

[7]:
```
# Create a copy to clean
df_clean = df.copy()
```

[8]:
```
# Drop null columns
df_clean.dropna(inplace=True)
```

[9]:
```
# Changing to correct data types
df_clean = df_clean.astype({"start_station_id": int, "end_station_id": int,␣
↪"bike_id": int})
df_clean = df_clean.astype({"member_birth_year": int})
df_clean.start_time = pd.to_datetime(df_clean.start_time, format='%Y-%m-%d %H:
↪%M:%S')
df_clean.end_time = pd.to_datetime(df_clean.end_time, format='%Y-%m-%d %H:%M:
↪%S')
```

[10]:
```
# No duplicates
sum(df_clean.duplicated())
```

[10]:
```
0
```

0.3 Exploratory Data Analysis

0.3.1 Starting Stations

Which stations are the busiest stations?

[11]:
```
df_clean.head()
```

[11]:
```
   duration_sec              start_time  ... member_gender
bike_share_for_all_trip
0         52185 2019-02-28 17:32:10.145  ...          Male
```

```
No
2         61854 2019-02-28 12:13:13.218  ...          Male
No
3         36490 2019-02-28 17:54:26.010  ...         Other
No
4          1585 2019-02-28 23:54:18.549  ...          Male
Yes
5          1793 2019-02-28 23:49:58.632  ...          Male
No

[5 rows x 16 columns]
```

[12]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 174952 entries, 0 to 183411
Data columns (total 16 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   duration_sec             174952 non-null  int64
 1   start_time               174952 non-null  datetime64[ns]
 2   end_time                 174952 non-null  datetime64[ns]
 3   start_station_id         174952 non-null  int64
 4   start_station_name       174952 non-null  object
 5   start_station_latitude   174952 non-null  float64
 6   start_station_longitude  174952 non-null  float64
 7   end_station_id           174952 non-null  int64
 8   end_station_name         174952 non-null  object
 9   end_station_latitude     174952 non-null  float64
 10  end_station_longitude    174952 non-null  float64
 11  bike_id                  174952 non-null  int64
 12  user_type                174952 non-null  object
 13  member_birth_year        174952 non-null  int64
 14  member_gender            174952 non-null  object
 15  bike_share_for_all_trip  174952 non-null  object
dtypes: datetime64[ns](2), float64(4), int64(5), object(5)
memory usage: 22.7+ MB
```

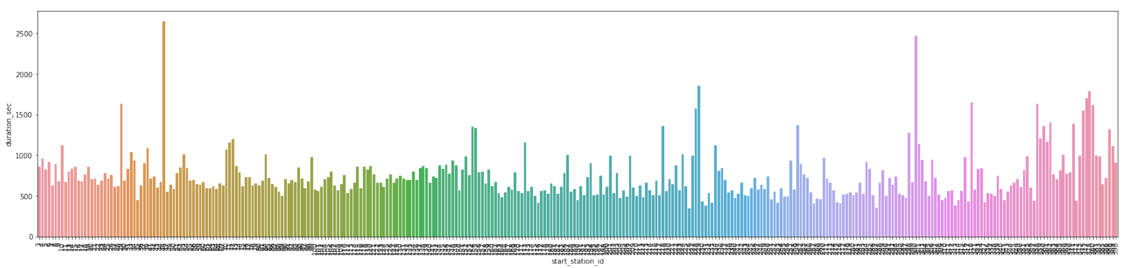
[13]:
```
# Grouping by start_station_id and creating a new dataframe
df_test = df_clean.groupby("start_station_id").mean().
 ↪sort_values(by="start_station_id").reset_index()
```

[14]:
```
df_test
```

[14]:
```
     start_station_id  duration_sec  ...      bike_id  member_birth_year
0                   3    855.046183  ...  4656.118321        1985.307252
1                   4    958.767568  ...  4837.493694        1983.491892
2                   5    827.316231  ...  4619.324627        1984.952892
3                   6    915.508354  ...  4887.746835        1983.709367
```

```
4                      7     632.424280  ...  4329.561952         1982.998748
..                   ...            ...  ...          ...                 ...
324                  385     646.489855  ...  4024.098551         1984.173913
325                  386     720.313084  ...  4733.598131         1984.719626
326                  388    1319.529412  ...  4633.058824         1987.588235
327                  389    1117.153846  ...  4803.076923         1978.846154
328                  398     912.937500  ...  5164.625000         1983.687500

[329 rows x 9 columns]
```

[15]:
```python
plt.figure(figsize = [28,6])
sb.barplot(data=df_test, x='start_station_id', y='duration_sec');
plt.xticks(rotation=90);
```



This question is too high level. Not much to do with this data. Will use deeper questions to find more specific results.

0.3.2 Station Difference Frequency

Which stations have the highest start trip and lowest end trip and vice versa? This would be interesting to know which stations may have a surplus of bikes over time while other stations may have a deficit of bikes.

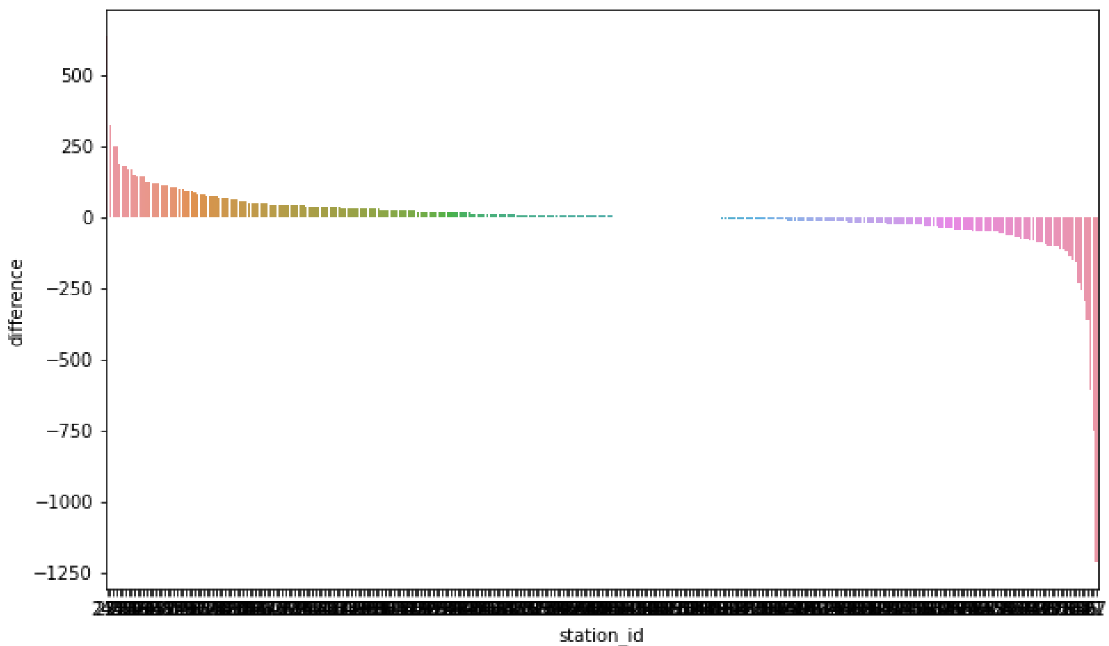
[16]:
```python
# Creating a new dataframe that subtracts the count of each end_station_id from␣
↪count of start_station_id
df_station_start_freq = df_clean.start_station_id.value_counts().reset_index()
df_station_start_freq.columns=['start_station_id', 'start_count']

df_station_end_freq = df_clean.end_station_id.value_counts().reset_index()
df_station_end_freq.columns=['end_station_id', 'end_count']

df_station_freq = df_station_start_freq.join(df_station_end_freq.
↪set_index('end_station_id'), on='start_station_id')
df_station_freq = df_station_freq.rename(columns={'start_station_id':␣
↪'station_id'})
df_station_freq['difference'] = df_station_freq.start_count - df_station_freq.
↪end_count
```

[17]:
```
# Verify dataframe was created correctly
df_station_freq.head()
```

[17]:

	station_id	start_count	end_count	difference
0	58	3649	3709	-60
1	67	3408	4624	-1216
2	81	2952	2782	170
3	21	2711	3461	-750
4	3	2620	2854	-234

[18]:
```
# Plot all the data
plt.figure(figsize=[10,6])
sb.barplot(data=df_station_freq, x='station_id', y='difference',␣
↪order=df_station_freq.sort_values('difference', ascending=False).station_id);
```



This chart shows that there are certain stations where people take out more bikes than bikes are returned to and vice versa. Will isolate the extremes (top 5 and bottom 5)

[19]:
```
# We are only concerned with the top 5 and bottom 5 differences
df_station_freq_top5 = df_station_freq.sort_values('difference',␣
↪ascending=False)[0:5]
df_station_freq_bot5 = df_station_freq.sort_values('difference',␣
↪ascending=False)[-5:]
df_station_freq_bot5.difference = df_station_freq_bot5.difference * -1
df_station_freq_bot5
```

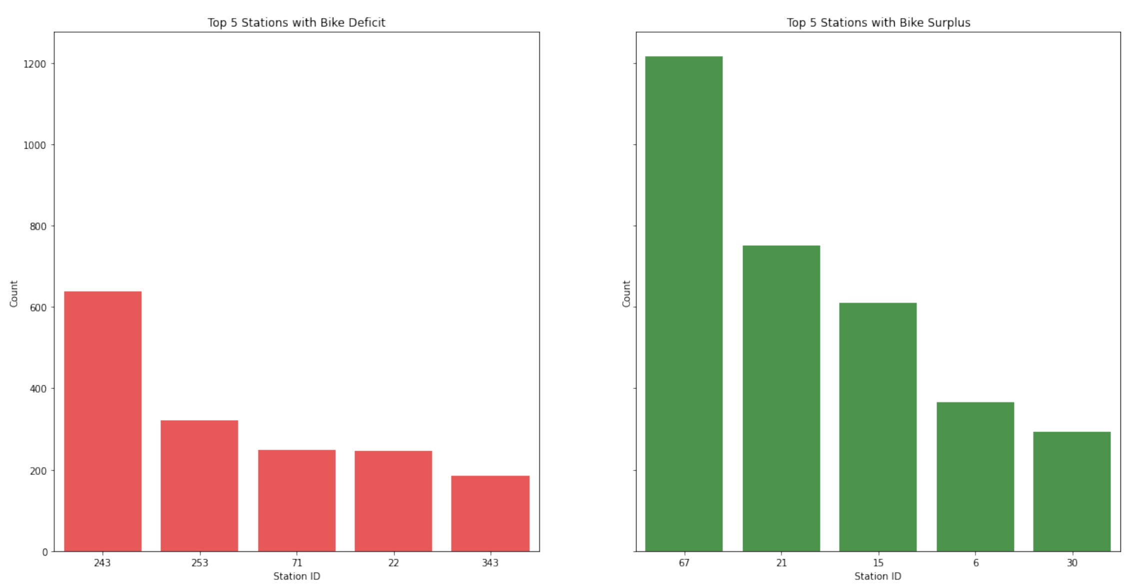
[19]:

	station_id	start_count	end_count	difference
5	30	2577	2870	293

10	6	1975	2341	366
6	15	2541	3151	610
3	21	2711	3461	750
1	67	3408	4624	1216

[20]:

```
fig, axes = plt.subplots(1,2, sharey=True, figsize=(20,10))

# Plot top 5 stations with bike deficit (start > end)
sb.barplot(data=df_station_freq_top5, ax=axes[0], x='station_id', y='difference', color="red", alpha=.75, order=df_station_freq_top5.sort_values('difference',ascending=False).station_id);
axes[0].set_title('Top 5 Stations with Bike Deficit')
axes[0].set(xlabel='Station ID', ylabel='Count')

# Plot top 5 stations with bike surplus (end > start)
sb.barplot(data=df_station_freq_bot5, ax=axes[1], x='station_id', y='difference', color="green", alpha=.75, order=df_station_freq_bot5.sort_values('difference',ascending=False).station_id);
axes[1].set_title('Top 5 Stations with Bike Surplus')
axes[1].set(xlabel='Station ID', ylabel='Count')

plt.show()
```



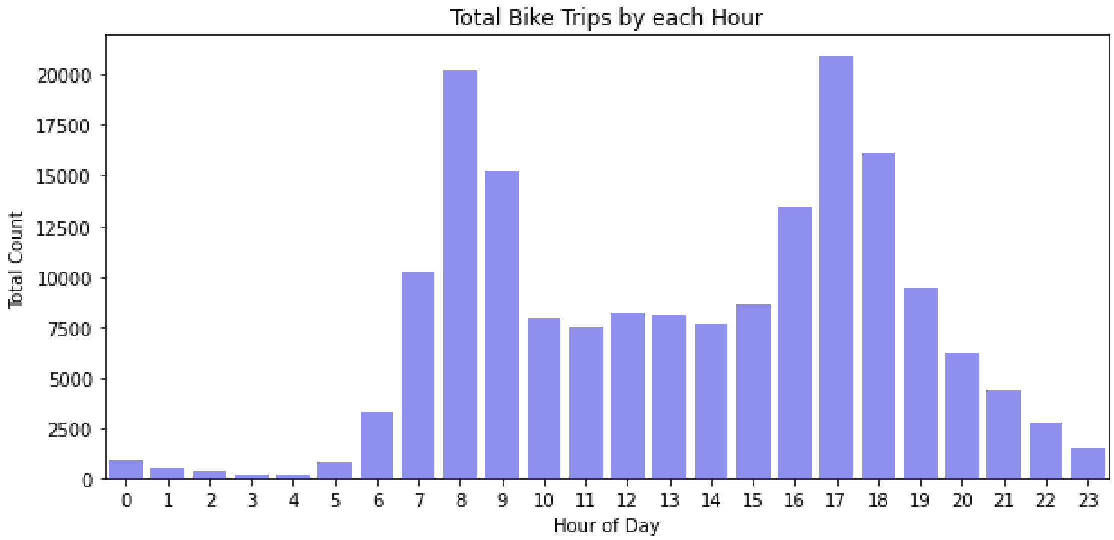
0.3.3 Frequency per date/time

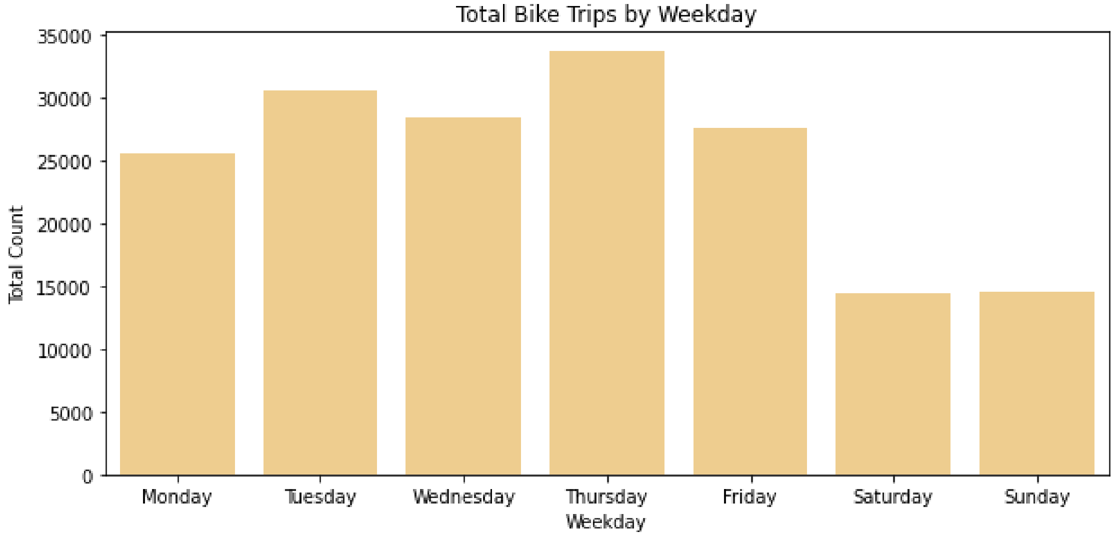
Is there a time during the day our bikes are being used the most? Is there a day of the week our bikes are being used the most?

[21]:
```
# Create new columns for hour of day and weekday
df_clean["hour"]= df_clean.start_time.dt.hour
df_clean['weekday'] = df_clean.start_time.dt.weekday + 1
```

[22]:
```
# Counting occurence of a trip during specific time (hour and weekday)
df_hour = df_clean.hour.value_counts().reset_index()
df_hour.columns=['hour', 'hour_count']
df_weekday = df_clean.weekday.value_counts().reset_index()
df_weekday.columns=['weekday', 'weekday_count']
```

[23]:
```
fig, axes = plt.subplots(2, 1, figsize=(10, 10))

sb.barplot(data=df_hour, ax=axes[0], x='hour', y='hour_count', color='blue',␣
 ↪alpha=0.5, order=df_hour.sort_values('hour').hour);
axes[0].set_title('Total Bike Trips by each Hour')
axes[0].set(xlabel='Hour of Day', ylabel='Total Count')

sb.barplot(data=df_weekday, ax=axes[1], x='weekday', y='weekday_count',␣
 ↪color='orange', alpha=0.5, order=df_weekday.sort_values('weekday').weekday);
axes[1].set_title('Total Bike Trips by Weekday')
axes[1].set(xlabel='Weekday', ylabel='Total Count')
axes[1].
 ↪set_xticklabels(['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])

plt.show()
```





0.3.4 Demographic

Which is the most popular demographic for our bike service?

[24]:
```
# Check member birth years
df_member_year = df_clean.member_birth_year.unique()
df_member_year.sort()
df_member_year
```

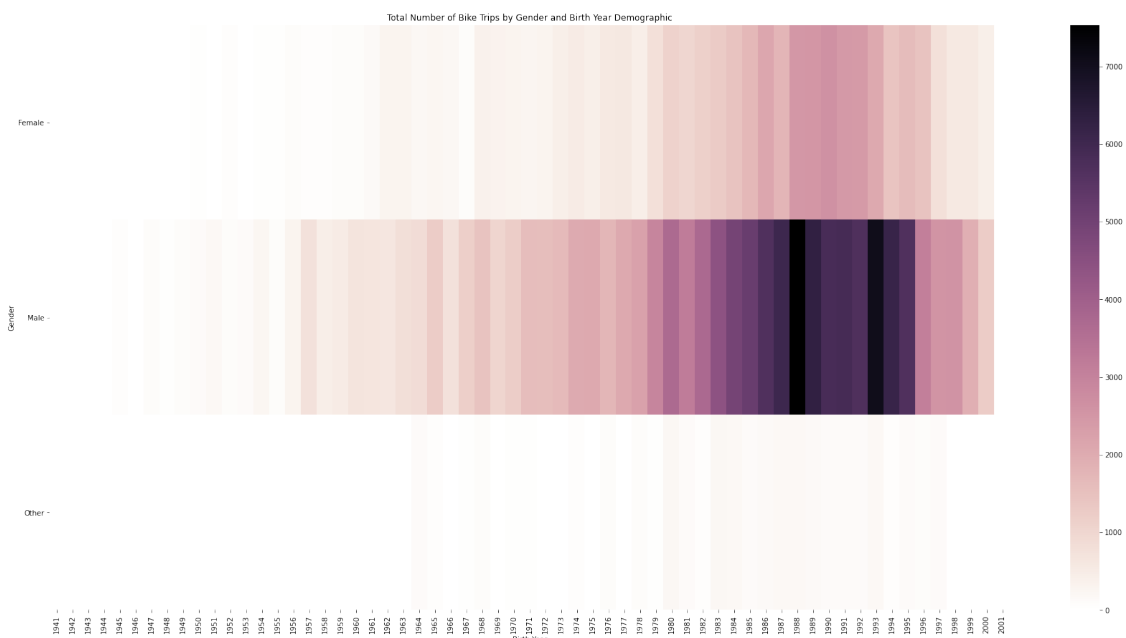
[24]:
```
array([1878, 1900, 1901, 1902, 1910, 1920, 1927, 1928, 1930, 1931, 1933,
       1934, 1938, 1939, 1941, 1942, 1943, 1944, 1945, 1946, 1947, 1948,
       1949, 1950, 1951, 1952, 1953, 1954, 1955, 1956, 1957, 1958, 1959,
       1960, 1961, 1962, 1963, 1964, 1965, 1966, 1967, 1968, 1969, 1970,
       1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980, 1981,
       1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1991, 1992,
```

```
       1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001])
```

[25]:
```
# Drop data where member birth year is less tahn 1940 (dropping everyone who is older than 79 as data is either user error or insignificant)
df_demo = df_clean[df.member_birth_year > 1940].reset_index(drop=True)

# Create dataframe and pivot for bivariate data
df_demo = df_demo.groupby(['member_birth_year', 'member_gender']).size()
df_demo = df_demo.reset_index(name='count')
df_demo = df_demo.pivot(index='member_gender', columns='member_birth_year', values='count')
df_demo.fillna(0, inplace=True)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: UserWarning:
Boolean Series key will be reindexed to match DataFrame index.
```

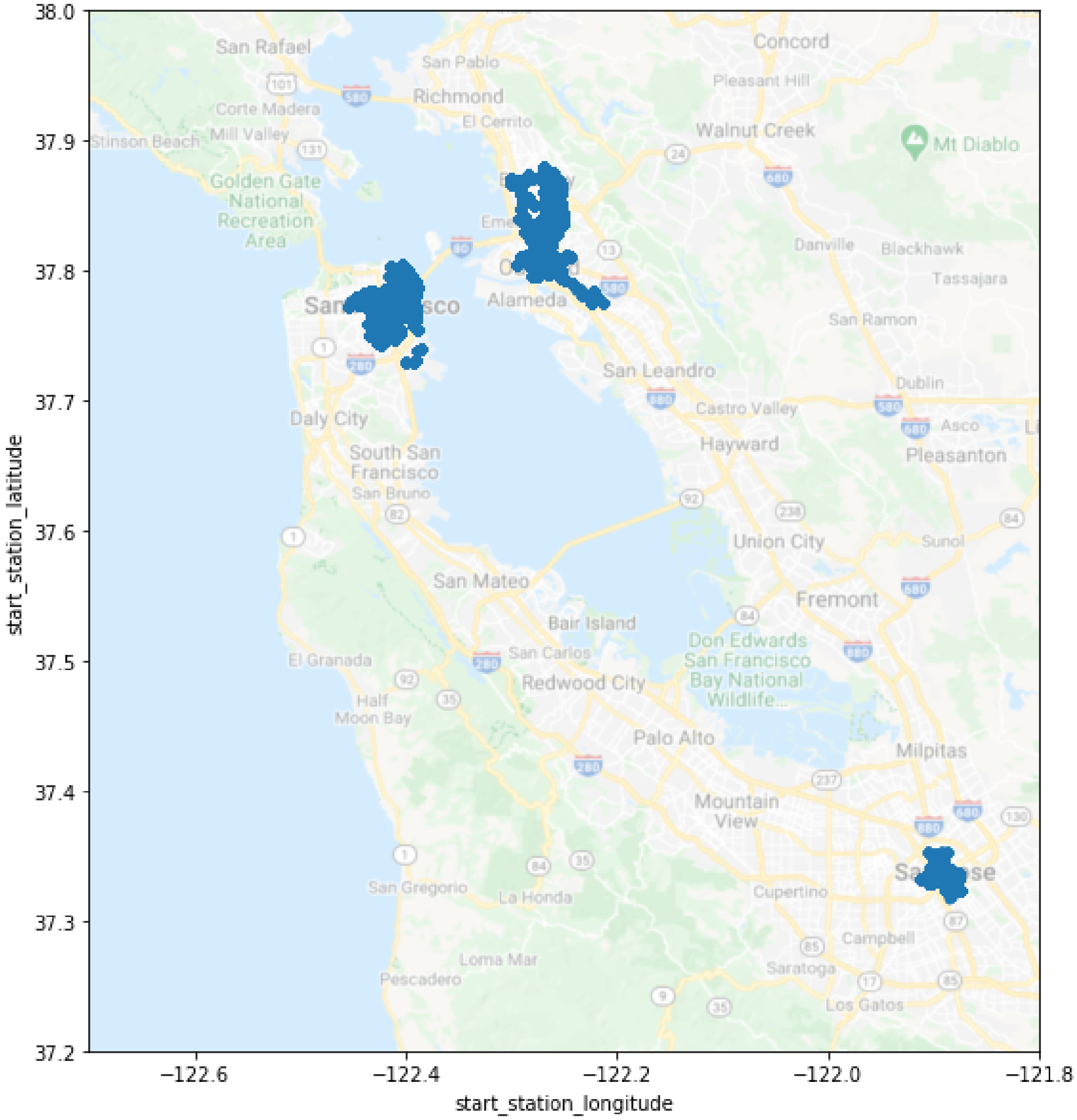
[26]:
```
plt.figure(figsize = (30,15))

cmap = sb.cubehelix_palette(dark=0, light=1, as_cmap=True)
sb.heatmap(df_demo, cmap=cmap)
plt.title('Total Number of Bike Trips by Gender and Birth Year Demographic')
plt.xlabel('Birth Year')
plt.ylabel('Gender')
plt.yticks(rotation = 0)

plt.show()
```



0.3.5 Geolocation

Which geographical areas have the highest usage of our bike service?

[27]:
```python
# Find geographical locations and plotting overlay on google maps
bay_img = mpimg.imread('bay_area.png')

ax = df_clean.plot(kind="scatter", x='start_station_longitude',
 ↪y='start_station_latitude', figsize=(8.9,10))
ax.imshow(bay_img, extent=[-122.7, -121.8, 37.2, 38.0], alpha=0.5,
 ↪aspect='auto')

plt.show()
```



Interesting to see that we have 3 groups of data corresponding to 3 cities: San Francisco, Oakland and San Jose

[28]:
```
# Creating separate df for each of the 3 clustered locations (cities: San␣
↪Francisco, Oaklan, San Jose)
df_sf = df_clean[df.start_station_longitude < -122.32].reset_index(drop=True)

df_oak = df_clean[df.start_station_longitude >= -122.32]
df_oak = df_oak[df.start_station_longitude < -122].reset_index(drop=True)

df_sj = df_clean[df.start_station_longitude >= -122].reset_index(drop=True)

# Verifying all data points are allocated to a dataframe
df_sf.shape[0] + df_oak.shape[0] + df_sj.shape[0] == df_clean.shape[0]
```

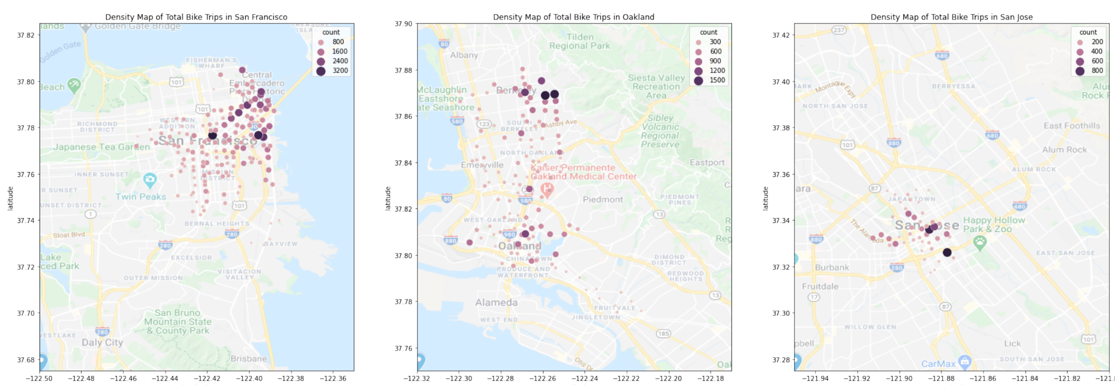
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: UserWarning:
Boolean Series key will be reindexed to match DataFrame index.

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4: UserWarning:
Boolean Series key will be reindexed to match DataFrame index.
  after removing the cwd from sys.path.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: UserWarning:
Boolean Series key will be reindexed to match DataFrame index.
  """
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: UserWarning:
Boolean Series key will be reindexed to match DataFrame index.
  import sys
```

[28]:
```
True
```

[29]:
```
df_sf_plt = df_sf.groupby(['start_station_latitude',␣
↪'start_station_longitude']).size()
df_sf_plt = df_sf_plt.reset_index()
df_sf_plt.columns = ['latitude', 'longitude', 'count']

df_oak_plt = df_oak.groupby(['start_station_latitude',␣
↪'start_station_longitude']).size()
df_oak_plt = df_oak_plt.reset_index()
df_oak_plt.columns = ['latitude', 'longitude', 'count']

df_sj_plt = df_sj.groupby(['start_station_latitude',␣
↪'start_station_longitude']).size()
df_sj_plt = df_sj_plt.reset_index()
df_sj_plt.columns = ['latitude', 'longitude', 'count']
```

[30]:
```
# Find geographical locations and plotting overlay on google maps
sf_img = mpimg.imread('sf_png.PNG')
oak_img = mpimg.imread('oak_png.PNG')
sj_img = mpimg.imread('sj_png.PNG')
```

```
fig, axes = plt.subplots(1, 3, figsize=(30, 10))

sb.scatterplot(ax=axes[0], data = df_sf_plt, x='longitude', y='latitude', hue='count', size='count', sizes=(20,200));
axes[0].imshow(sf_img, extent=[-122.5, -122.35, 37.675, 37.825], alpha=0.5, aspect='auto')
axes[0].set_title('Density Map of Total Bike Trips in San Francisco')

sb.scatterplot(ax=axes[1], data = df_oak_plt, x='longitude', y='latitude', hue='count', size='count', sizes=(20,200));
axes[1].imshow(oak_img, extent=[-122.32, -122.17, 37.75, 37.9], alpha=0.5, aspect='auto')
axes[1].set_title('Density Map of Total Bike Trips in Oakland')

sb.scatterplot(ax=axes[2], data = df_sj_plt, x='longitude', y='latitude', hue='count', size='count', sizes=(20,200));
axes[2].imshow(sj_img, extent=[-121.95, -121.8, 37.275, 37.425], alpha=0.5, aspect='auto')
axes[2].set_title('Density Map of Total Bike Trips in San Jose')

plt.show()
```



[30]:

```
```