Lyft_Baywheels_capstone_2019

August 30, 2019

```
In [2]: import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
```

```
In [319]: import certifi
          import ssl
          import geopy.geocoders
          ctx = ssl.create_default_context(cafile=certifi.where())
          geopy.geocoders.options.default_ssl_context = ctx
          from geopy.geocoders import GoogleV3
```

```
In [463]: def get_file_contents(filename):
              """ Given a filename,
                  return the contents of that file
              """
              try:
                  with open(filename, 'r') as f:
                      # It's assumed our file contains a single line,
                      # with our API key
                      return f.read().strip()
              except FileNotFoundError:
                  print("'%s' file not found" % filename)

          secret_api_key = get_file_contents('secret.py')
```

1 Dear user, please enter a San Francisco address below:

By entering an address and running the cells below, you will get a prediction of the average weekly rides that would be taken from your proposed station. You will also get a normalized number of rides predicted, for comparison to other stations. Basically, above 1.0 is more than average and below 1.0 is less than average. From that you get a recommendation of whether your proposed address is a good location for a new bike station. You will also see a map of the current stations and their usage and your proposed new location.

```
In [464]: address = "1800 Montgomery St, San Francisco, CA 94111"
          #example: address = "1800 Montgomery St, San Francisco, CA 94111"
```

In [502]:
```
geolocator = GoogleV3(api_key=secret_api_key)
location = geolocator.geocode(address, timeout=10)
print(location.address)
print((location.latitude, location.longitude))
proposed_station = [location.latitude, location.longitude]
print('Calculating...')
coordinate_predictions = coordinates_to_predictions(proposed_station)
```

```
1800 Montgomery St, San Francisco, CA 94111, USA
(37.80599309999999, -122.4051806)
Calculating...
The predicted number of trips per week, starting at this location, is: 612
The normalized weekly trip count is:  3.58556842726421
The trip count is more than average, this may be a good location.
```

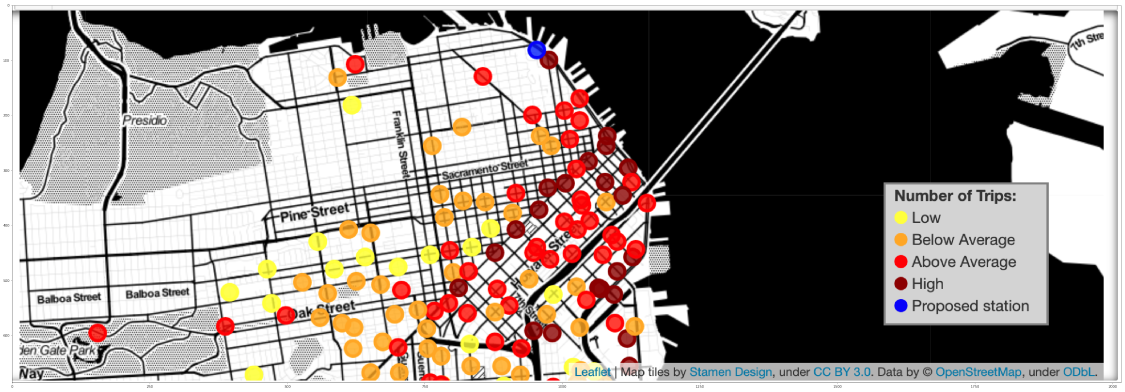
In [496]:
```
import folium

plt.figure(figsize=(15,10))
m = folium.Map(location=[37.786375, -122.404904], tiles='Stamen Toner', zoom_start=1

mapping_data.apply(lambda row:folium.CircleMarker(location=[row["start_station_latit
            row["start_station_longitude"]], radius=7,\
            color=row['marker_color'], fill=True, fill_opacity=0.8\
            ).add_to(m), axis=1)
legend_html =   '''
                <div style="position: fixed;
                            bottom: 50px; right: 50px; width: 150px; height: 130px;
                            border:2px solid grey; z-index:9999; font-size:14px;
                            background-color:lightgrey;
                            ">  <b>Number of Trips:</b><br>
                                <i class="fa fa-circle" style="color:yellow"></
                                <i class="fa fa-circle" style="color:orange"></
                                <i class="fa fa-circle" style="color:red"></i> 
                                <i class="fa fa-circle" style="color:darkred"><
                                <i class="fa fa-circle" style="color:blue"></i>
                </div>
                </div>
                </div>
                '''

m.get_root().html.add_child(folium.Element(legend_html))
m
```

Out[496]: <folium.folium.Map at 0x16e4a4470>

```
<Figure size 1080x720 with 0 Axes>
```

In case the html map does not render properly, here is a png snapshot of what it should look like:

```
In [477]: import matplotlib.image as mpimg

          plt.figure(figsize = (100,20))
          img=mpimg.imread('lyft_stations_screen_shot.png')
          imgplot = plt.imshow(img)
```



1.0.1 That was the final product. Now let's back up and show how we got to this point.

2 1. Introduction and Motivation

Bike shares are great, but you may be wondering why there isn't a station near your house or a busy part of town. You may want to propose a new station. A simple way to evaluate whether your proposed station will be viable, and have enough users, is to compare to existing stations. Since bike share bikes are often used for getting to or from public transit, the distance to BART and Muni will also be considered.

The Lyft Baywheels bike share provides data for trips taken using their bikes. The data includes the station names, locations, and number of trips started and finished there. From this data I calculated the number of trips per station per week and found which stations are more or less popular. I also calculated how far the stations are from public transit. I fed this into a machine learning model to predict the popularity of a proposed station location.

3 2. Let's read in all the csv's and append them into one dataframe

3.0.1 The website for getting data is the Lyft Baywheels site:

https://s3.amazonaws.com/baywheels-data/index.html

```
In [5]: df_201907= pd.read_csv('201907-baywheels-tripdata.csv')
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/IPython/core/inte
  interactivity=interactivity, compiler=compiler, result=result)
```

```
In [6]: df_201906= pd.read_csv('201906-baywheels-tripdata.csv')
```

```
In [8]: df_201905= pd.read_csv('201905-baywheels-tripdata.csv')
```

```
In [9]: df_201904 = pd.read_csv('201904-fordgobike-tripdata.csv')
```

```
In [10]: df_201903 = pd.read_csv('201903-fordgobike-tripdata.csv')
```

```
In [11]: df_201902 = pd.read_csv('201902-fordgobike-tripdata.csv')
```

```
In [12]: df_201901 = pd.read_csv('201901-fordgobike-tripdata.csv')
```

```
In [13]: df_201812 = pd.read_csv('201812-fordgobike-tripdata.csv')
```

```
In [14]: df_201811 = pd.read_csv('201811-fordgobike-tripdata.csv')
```

```
In [15]: df_201810 = pd.read_csv('201810-fordgobike-tripdata.csv')
```

```
In [16]: df_201809 = pd.read_csv('201809-fordgobike-tripdata.csv')
```

```
In [17]: df_201808 = pd.read_csv('201808-fordgobike-tripdata.csv')
```

```
In [18]: df_201807 = pd.read_csv('201807-fordgobike-tripdata.csv')
```

```
In [19]: df_201806 = pd.read_csv('201806-fordgobike-tripdata.csv')
```

```
In [20]: df_201805 = pd.read_csv('201805-fordgobike-tripdata.csv')
```

```
In [21]: df_201804 = pd.read_csv('201804-fordgobike-tripdata.csv')
```

```
In [22]: df_201803 = pd.read_csv('201803-fordgobike-tripdata.csv')
```

```
In [23]: df_201802 = pd.read_csv('201802-fordgobike-tripdata.csv')
```

```
In [24]: df_201801 = pd.read_csv('201801-fordgobike-tripdata.csv')
```

```
In [25]: df_2017 = pd.read_csv('2017-fordgobike-tripdata.csv')
```

```
In [529]: df = df_201907.append(df_201906, sort=True)
          df = df.append(df_201905, sort=True)
          df = df.append(df_201904, sort=True)
          df = df.append(df_201903, sort=True)
          df = df.append(df_201902, sort=True)
          df = df.append(df_201901, sort=True)
          df = df.append(df_201812, sort=True)
          df = df.append(df_201811, sort=True)
          df = df.append(df_201810, sort=True)
          df = df.append(df_201809, sort=True)
          df = df.append(df_201808, sort=True)
          df = df.append(df_201807, sort=True)
          df = df.append(df_201806, sort=True)
          df = df.append(df_201805, sort=True)
          df = df.append(df_201804, sort=True)
          df = df.append(df_201803, sort=True)
          df = df.append(df_201802, sort=True)
          df = df.append(df_201801, sort=True)
```

```
In [530]: df = df.append(df_2017, sort=True)
```

4 3. Let's get some data for Muni and Bart station locations

I am assuming that the proximity to public transit makes the bike docking stations more popular.

4.1 3.1 Muni stops

```
In [28]: muni_stops = pd.read_csv('sfmta_transit/stops.txt')
         muni_stops.head()
```

```
Out[28]:     stop_lat  stop_code    stop_lon  stop_url  stop_id  stop_desc  \
         0  37.792357      14026 -122.421010       NaN     4026        NaN
         1  37.793826      14027 -122.409591       NaN     4027        NaN
         2  37.793653      14024 -122.410823       NaN     4024        NaN
         3  37.794682      14025 -122.402770       NaN     4025        NaN
         4  37.792526      14022 -122.419589       NaN     4022        NaN

                        stop_name  location_type  zone_id
         0          Clay St & Polk St              0      NaN
         1        Clay St & Powell St              0      NaN
         2         Clay St & Mason St              0      NaN
         3    Clay St & Montgomery St              0      NaN
         4        Clay St & Larkin St              0      NaN
```

4.2 3.2 BART stops

```
In [29]: bart= [[-122.27145,37.803768],[-122.419694,37.765062],[-122.268602,37.80835],\
               [-122.418143,37.75247],[-122.270062,37.852803],[-122.447506,37.721585],\
               [-122.126514,37.696924], [-122.075602,37.690746],[-122.414123,37.779732],\
               [-122.196869,37.753661],[-122.466233,37.684638],[-122.029095,37.973737],\
               [-122.469081,37.706121],[-122.268133,37.870104],[-122.316794,37.925086],\
               [-121.899179,37.701687],[-122.39702,37.792874],[-121.976608,37.557465],\
               [-122.224175,37.774836],[-122.433817,37.733064],[-122.087018,37.669723],\
               [-122.12463,37.893176],[-122.26518,37.797027],[-122.26704,37.829065],\
               [-122.386702,37.600271],[-122.401066,37.789405],[-122.28344,37.873967],\
               [-122.024653,38.003193],[-122.212191,37.713238],[-122.183791,37.878361],\
               [-122.056012,37.928468],[-121.945154,38.018914],[-122.298904,37.902632],\
               [-122.407974,37.784471],[-122.353099,37.936853],[-122.251371,37.844702],\
               [-122.160844,37.721947],[-122.416287,37.637761],[-122.392409,37.615966],\
               [-122.057189,37.634375],[-122.44396,37.664245],[-122.017388,37.59063],\
               [-121.939313,37.502171],[-122.067527,37.905522],[-121.92824,37.699756],\
               [-122.29514,37.804872],[-121.7799352782858,37.9952478246996],\
               [-121.8889731954402,38.01681081863409]]
```

```
In [30]: bart = pd.DataFrame(bart)
         bart.columns = ['long','lat']
         bart.head()
```

```
Out[30]:          long        lat
         0 -122.271450  37.803768
```

```
1 -122.419694  37.765062
2 -122.268602  37.808350
3 -122.418143  37.752470
4 -122.270062  37.852803
```

4.3 3.3 Calculating the distance of each stop from BART and Muni

```
In [481]: from geopy.distance import geodesic

          def distance_calc(origin, destination):

              return geodesic(origin, destination).miles
```

```
In [32]: def bart_dist(df):
             station = (df.start_station_latitude, df.start_station_longitude)
             bart_df = list(zip(bart.lat, bart.long))

             distances = [distance_calc(station, entry) for entry in bart_df]
             return min(distances)
```

```
In [33]: def muni_dist(df):
             station = (df.start_station_latitude, df.start_station_longitude)
             muni_df = list(zip(muni_stops.stop_lat, muni_stops.stop_lon))

             distances = [distance_calc(station, entry) for entry in muni_df]
             return min(distances)
```

4.3.1 We need to filter for only San Francisco because proximity to BART and Muni is only valid here

Our original dataset includes the East Bay and San Jose, but we just want to look at San Francisco. We want to be West of -122.368535 (less than) and North of 37.702170 (greater than)

```
In [181]: df = df[df['start_station_latitude'] > 37.702170 ]
```

```
In [182]: df = df[df['start_station_longitude'] < -122.368535]
```

4.3.2 Dataframe of just the station id's, coordinates, and distances to BART and Muni

We can join this to other dataframes later, it avoids recalculating distances.

```
In [36]: coords_only = df.groupby('start_station_id').agg({'start_station_latitude':'min','sta
```

```
In [482]: coords_only['min_bart_dist'] = coords_only.apply(bart_dist, axis=1)
          coords_only['min_muni_dist'] = coords_only.apply(muni_dist, axis=1)
```

5 4. Let's look at some time data

```
In [531]: df['start_time'] = pd.to_datetime(df['start_time'])
```

```
In [532]: df.set_index('start_time', inplace=True)
```

5.1 4.1 Weekly sampling

```
In [533]: weekly = df.groupby('start_station_id').resample('W').count()

In [534]: weekly = weekly[['bike_id']]

In [535]: weekly.columns = ['trip_count']

In [536]: weekly.head()

Out[536]:                                   trip_count
          start_station_id start_time
          3.0              2017-07-02          111
                           2017-07-09          191
                           2017-07-16          218
                           2017-07-23          346
                           2017-07-30          290

In [537]: weekly.reset_index(inplace=True)

In [538]: weekly['start_time'] = pd.to_datetime(weekly['start_time'])

In [539]: weekly['month'] = weekly.start_time.dt.month
          weekly['year'] = weekly.start_time.dt.year
```

Now joining the coordinate and distance data back to our weekly trip counts.

```
In [540]: joined_weekly = weekly.join(coords_only, on='start_station_id', how='left')

In [541]: joined_weekly.reset_index().head()

Out[541]:    index  start_station_id start_time  trip_count  month  year  \
          0      0               3.0 2017-07-02         111      7  2017
          1      1               3.0 2017-07-09         191      7  2017
          2      2               3.0 2017-07-16         218      7  2017
          3      3               3.0 2017-07-23         346      7  2017
          4      4               3.0 2017-07-30         290      7  2017

             start_station_latitude  start_station_longitude  min_bart_dist  \
          0               37.786375              -122.404904       0.213256
          1               37.786375              -122.404904       0.213256
          2               37.786375              -122.404904       0.213256
          3               37.786375              -122.404904       0.213256
          4               37.786375              -122.404904       0.213256

             min_muni_dist
          0       0.014029
          1       0.014029
          2       0.014029
          3       0.014029
          4       0.014029
```

5.2 4.2 Plotting weekly trips

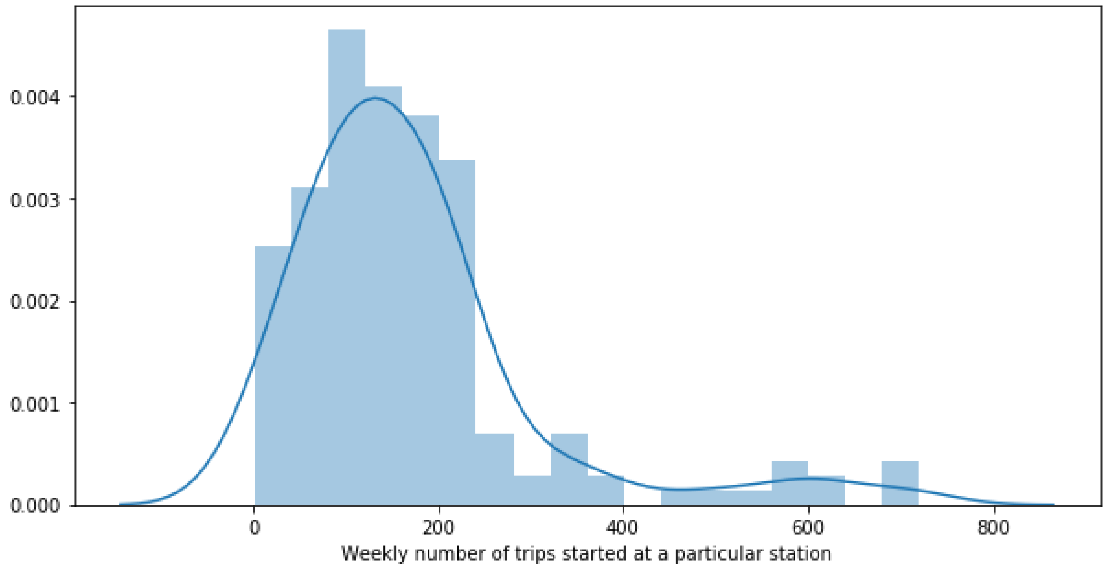
Here let's average all the trips per station over the entire timeframe so we can put them on a map with one colored marker.

```
In [542]: weekly_markers = joined_weekly.groupby('start_station_id')['trip_count'].mean()

In [543]: weekly_markers = pd.DataFrame(weekly_markers)

In [544]: weekly_markers['normalized_trip_count'] = weekly_markers.trip_count/ weekly_markers.t

In [545]: weekly_markers.normalized_trip_count.describe()

Out[545]: count    388.000000
          mean       1.000000
          std        1.116897
          min        0.009584
          25%        0.257491
          50%        0.657130
          75%        1.416971
          max        6.946962
          Name: normalized_trip_count, dtype: float64

In [546]: weekly_markers['marker_color'] = weekly_markers['normalized_trip_count'].apply(color_

In [547]: weekly_markers.head()

Out[547]:                   trip_count  normalized_trip_count marker_color
          start_station_id
          3.0               574.590909               5.506844      darkred
          4.0               120.600000               1.155823          red
          5.0               474.763636               4.550106      darkred
          6.0               587.927273               5.634659      darkred
          7.0               167.027778               1.600784      darkred

In [432]: def color_selector(size):
              """This function assigns a color to station markers on the map.
              Based on the normalized number of trips from that station."""

              if size <0.5:
                  color = 'yellow'
              elif size >0.5 and size < 1:
                  color = 'orange'
              elif size >1 and size < 1.5:
                  color = 'red'
              elif size > 1.5:
                  color = 'darkred'
              else:
                  color = 'black'
              return color
```

5.3 4.3 Weekly Trip Count Histogram

In [548]:
```
import numpy as np
plt.figure(figsize=(10, 5))
sns.distplot(markers_joined['trip_count'])
plt.xlabel('Weekly number of trips started at a particular station')
```

Out[548]:
```
Text(0.5, 0, 'Weekly number of trips started at a particular station')
```



5.4 4.4 Daily Sampling

Let's also look at daily sampling. Perhaps knowing they day of the week can help us make a better model.

In [188]:
```
daily = df.groupby('start_station_id').resample('D').count()
```

In [189]:
```
daily = daily[['bike_id']]
daily.columns = ['trip_count']
```

In [190]:
```
daily.reset_index(inplace=True)
```

In [191]:
```
daily.head()
```

Out[191]:

	start_station_id	start_time	trip_count
0	3.0	2017-06-29	22
1	3.0	2017-06-30	23
2	3.0	2017-07-01	27
3	3.0	2017-07-02	39
4	3.0	2017-07-03	28

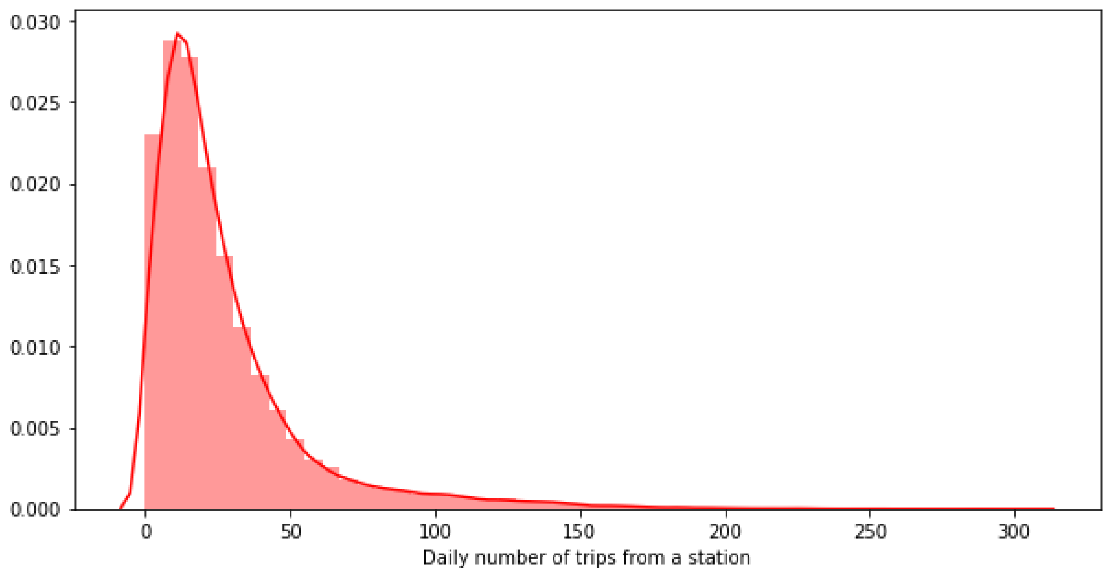
```
In [192]: daily['start_time'] = pd.to_datetime(daily['start_time'])

In [193]: daily['month'] = daily.start_time.dt.month
          daily['day'] = daily.start_time.dt.weekday_name
          daily['year'] = daily.start_time.dt.year

In [194]: daily.head(1)

Out[194]:    start_station_id start_time  trip_count  month       day  year
          0               3.0 2017-06-29          22      6  Thursday  2017
```

Now, joining the station coordinates and distances to transit back to the time data.

```
In [195]: daily_coords = daily.join(coords_only, on='start_station_id', how='left')

In [196]: daily_coords.head()

Out[196]:    start_station_id start_time  trip_count  month       day  year  \
          0               3.0 2017-06-29          22      6  Thursday  2017
          1               3.0 2017-06-30          23      6    Friday  2017
          2               3.0 2017-07-01          27      7  Saturday  2017
          3               3.0 2017-07-02          39      7    Sunday  2017
          4               3.0 2017-07-03          28      7    Monday  2017

             start_station_latitude  start_station_longitude  min_bart_dist  \
          0               37.786375              -122.404904       0.342934
          1               37.786375              -122.404904       0.342934
          2               37.786375              -122.404904       0.342934
          3               37.786375              -122.404904       0.342934
          4               37.786375              -122.404904       0.342934

             min_muni_dist
          0       0.022524
          1       0.022524
          2       0.022524
          3       0.022524
          4       0.022524
```

5.5 4.5 Daily Trip Count Histogram

```
In [197]: plt.figure(figsize=(10,5))
          sns.distplot(daily_coords['trip_count'], color='red')
          plt.xlabel('Daily number of trips from a station')

Out[197]: Text(0.5, 0, 'Daily number of trips from a station')
```



6 5. Let's get into some machine learning

Let's build a model that takes into account the station coordinates, distance from public transit, and some time variable to predict station popularity.

It turns out that the weekly data was superior to daily data for training the model. That is what is shown in this section.

The transformer below, will help us select which columns of the dataframe we want to feed into which part of the model.

In [140]:
```
import numpy as np
from sklearn import base

class ColumnSelectTransformer(base.BaseEstimator, base.TransformerMixin):

    def __init__(self, columns):
        self.columns = columns

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X[self.columns].values
```

6.1 5.1 Let's separate out the label (y value) data and separate out a test set

In [277]:
```
usage = joined_weekly['trip_count'].values
data = joined_weekly
```

```
In [278]: from sklearn.utils import shuffle

          data, usage = shuffle(data, usage)
```

```
In [279]: from sklearn.model_selection import  train_test_split

          X_train, X_test, y_train, y_test = train_test_split(data, usage, test_size=0.1, rand
```

6.2 5.2 Models that we'll be using:

- **K-nearest-neighbors:** The principle behind nearest neighbor methods is to find a predefined number of training samples closest in distance to the new point, and predict the label from these. Neighbors-based regression can be used in cases where the data labels are continuous rather than discrete variables. The label assigned to a query point is computed based on the mean of the labels of its nearest neighbors.
- **Ridge regression:** This model solves a regression model where the loss function is the linear least squares function and regularization is given by the l2-norm.
- **Random forest regression:** A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting

```
In [201]: from sklearn.neighbors import KNeighborsRegressor
          from sklearn.linear_model import Ridge
          from sklearn.ensemble import RandomForestRegressor

          linreg = linear_model.Ridge()
          knn = KNeighborsRegressor()
          tree = RandomForestRegressor()
```

6.3 5.3 This is for clustering the coordinates:

```
In [280]: from sklearn.pipeline import Pipeline

          coord_pipe = Pipeline([('cst', ColumnSelectTransformer(['start_station_latitude', 's
                                 ('knn', KNeighborsRegressor())
                                 ])
```

6.3.1 Let's do some cross validation/ grid search to find the best hyperparameters:

```
In [281]: from sklearn import model_selection

          gs_coord = model_selection.GridSearchCV(
              coord_pipe,
              {"knn__n_neighbors": range(10, 100)},
              cv=5)
          gs_coord.fit(X_train, y_train)
          print (gs_coord.best_params_)

{'knn__n_neighbors': 37}
```

```
In [282]: gs_coord.score(X_test, y_test)
```

```
Out[282]: 0.7081739085071528
```

6.4 5.4 This is for the distance information:

```
In [514]: dist_pipe = Pipeline([('cst', ColumnSelectTransformer(['min_bart_dist', 'min_muni_di
                                ('tree', RandomForestRegressor())
              ])
```

```
In [515]: gs_dist = model_selection.GridSearchCV(
              dist_pipe,
              {"tree__n_estimators": [90, 140, 150, 160, 170]},
              cv=5)
          gs_dist.fit(X_train, y_train)
          print (gs_dist.best_params_)
```

```
{'tree__n_estimators': 150}
```

```
In [516]: gs_dist.score(X_test, y_test)
```

```
Out[516]: 0.7217002316330802
```

6.5 5.5 This is for the time series information:

```
In [523]: from sklearn.preprocessing import OneHotEncoder

          time_pipe = Pipeline([
                                      ('cst',ColumnSelectTransformer(['year', 'month'])),
                                      ('ohe', OneHotEncoder(categories='auto')),
                                      ('tree', RandomForestRegressor())
              ])
```

```
In [524]: gs_time = model_selection.GridSearchCV(
              time_pipe,
              {"tree__n_estimators": [90, 140, 150, 160, 170]},
              cv=5)
          gs_time.fit(X_train, y_train)
          print (gs_time.best_params_)
```

```
{'tree__n_estimators': 160}
```

```
In [525]: gs_time.score(X_test, y_test)
```

```
Out[525]: 0.05905515969991437
```

While this prediction score of 6% may seem insignificant, when the time aspect of the prediction is removed the impact is actually closer to a 10% loss in accuracy. The month and year data is worth keeping.

6.6 5.6 Let's combine the time and spatial data into our final model:

Our previous estimators need to be converted to transformers. They will all be combined in a feature union and fed into a new pipe with a linear estimator to weight the 3 models appropriately.

```
In [152]: class EstimatorTransformer(base.BaseEstimator, base.TransformerMixin):

              def __init__(self, estimator):
                  self.estimator = estimator

              def fit(self, X, y):
                  self.estimator.fit(X,y)
                  return self

              def transform(self, X):
                  result = self.estimator.predict(X)
                  mid = np.array(result)
                  final = mid.reshape(-1,1)
                  return final
```

```
In [302]: time_trans = EstimatorTransformer(gs_time)
          dist_trans = EstimatorTransformer(gs_dist)
          coord_trans = EstimatorTransformer(gs_coord)
```

```
In [506]: from sklearn.pipeline import FeatureUnion

          union = FeatureUnion([('time', time_trans),
                                ('space', space_trans),
                                ('coords', coord_trans)
              ])
```

6.6.1 Here is the full model:

```
In [507]: full_model_pipe = Pipeline([('union', union), ('ridge', Ridge(alpha=10))])
          full_model_pipe.fit(X_train, y_train)
```

```
Out[507]: Pipeline(memory=None,
                   steps=[('union',
                           FeatureUnion(n_jobs=None,
                                        transformer_list=[('time',
                                                           EstimatorTransformer(estimator=GridS
```

```
                           transformer_weights=None, verbose=False)),
                ('ridge',
                 Ridge(alpha=10, copy_X=True, fit_intercept=True, max_iter=None,
                       normalize=False, random_state=None, solver='auto',
                       tol=0.001))],
         verbose=False)
```

```
In [508]: full_model_pipe.score(X_test, y_test)
```

```
Out[508]: 0.8163848240868449
```

6.7 5.6 Let's put everything we've done above into one function:

This function will take coordinates for a proposed station and output a prediction.

```
In [526]: def coordinates_to_predictions(coordinates):
              """Takes in a list of coordinates, makes dataframe,
              calculates distances to public transit, predicts the avg number of trips per wee
              normalizes the prediction, prints out a prediction, and assigns a color to
              the marker for placing on the map.
              """
              ######### Making sure that we are in SF ###
              if  (coordinates[0] <= 37.692174) or (coordinates[0] >= 37.807073):
                  print('Your chosen address is not in San Francisco.  Please enter a valid ad
                  return None

              if  (coordinates[1] >= -122.351810) or (coordinates[1] <= -122.528495):
                  print('Your chosen address is not in San Francisco.  Please enter a valid ad
                  return None

              ########## Making a dataframe ###########
              """This will fill in info for a hypothetical full year.  We will average over al
              the predictions at the end."""

              d_f = pd.DataFrame()
              month = list(range(1,13))
              year = [2019]*12
              d_f['year'] = year
```

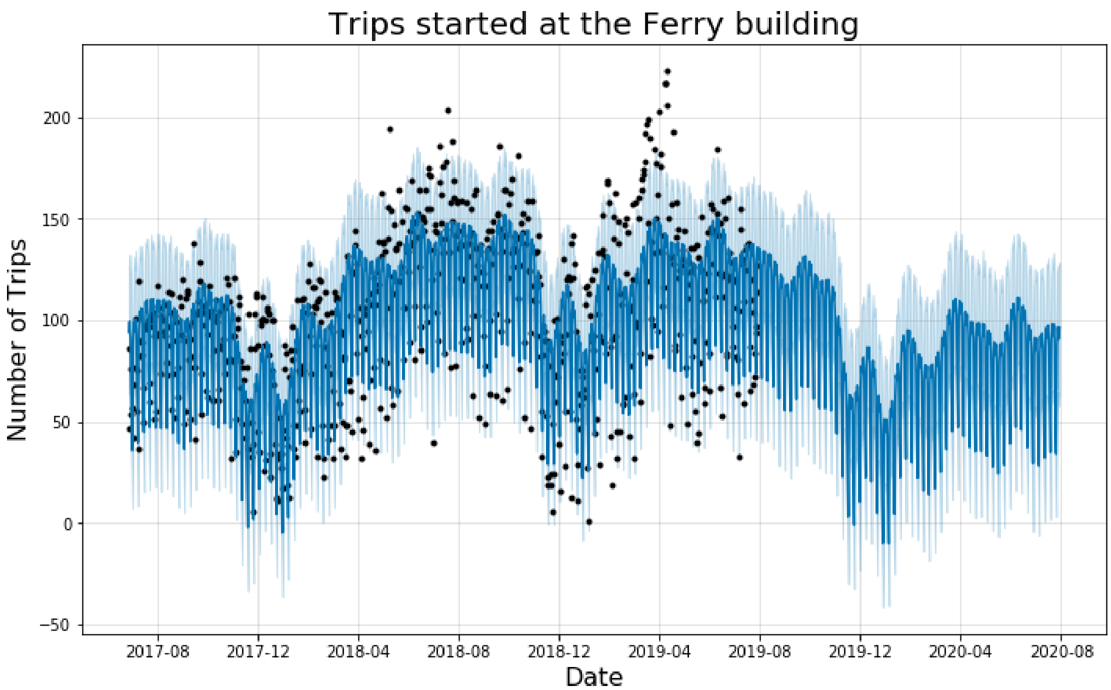
```
    d_f['month'] = month
    d_f['start_station_latitude'] = coordinates[0]
    d_f['start_station_longitude'] = coordinates[1]

    ########## Calculating distance to public transit...###########
    d_f['min_muni_dist'] = d_f.apply(muni_dist, axis=1)
    d_f['min_bart_dist'] = d_f.apply(bart_dist, axis=1)

    ########### Predicting number of trips per week...####################
    prediction = full_model_pipe.predict(d_f)
    d_f['prediction'] = pd.Series(prediction)

    weekly_trip_mean = weekly_markers.trip_count.mean()
    d_f['normalized_trip_count'] = d_f.prediction/weekly_trip_mean

    ######## Printing out stuff for the user ############
    print("The predicted number of trips per week, starting at this location, is:", 
    print("The normalized weekly trip count is: ", d_f.normalized_trip_count.mean())

    if d_f.normalized_trip_count.mean() < 1:
        print('The trip count is less than average, this may not be a good location.
    else:
        print('The trip count is more than average, this may be a good location.')

    ### A Dataframe of averages will be returned ########
    d_f_avg = pd.DataFrame()
    d_f_avg['start_station_latitude'] = [coordinates[0]]
    d_f_avg['start_station_longitude'] = coordinates[1]
    d_f_avg['trip_count'] = d_f.prediction.mean()
    d_f_avg['normalized_trip_count'] = d_f.normalized_trip_count.mean()
    d_f_avg['marker_color'] = 'blue'
    d_f_avg['min_muni_dist'] = d_f.min_muni_dist.mean()
    d_f_avg['min_bart_dist'] = d_f.min_bart_dist.mean()

    return d_f_avg
```

7 6. Using Prophet to look at a time series of one station

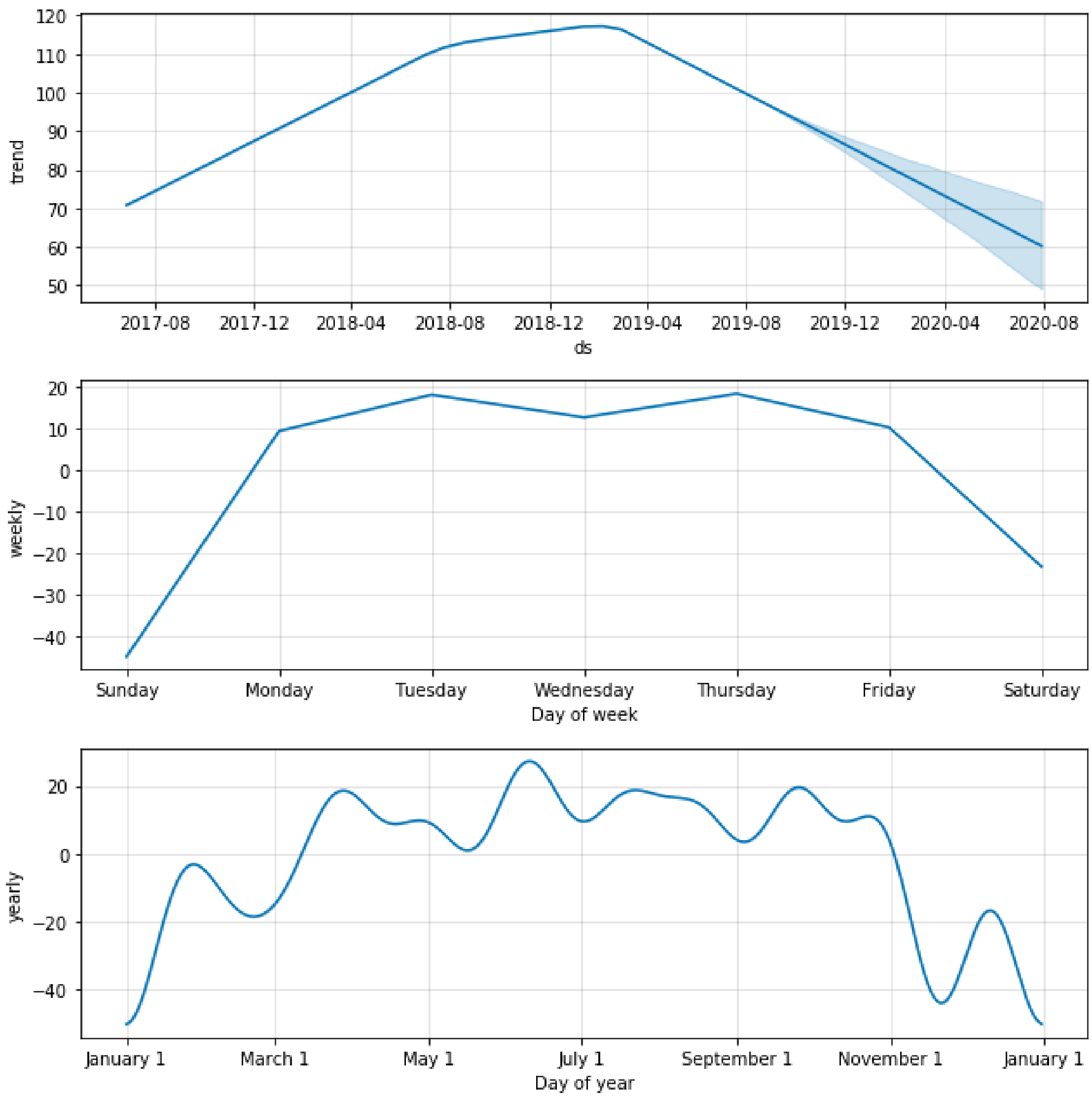
A slight side-track looking at a time series for just one station and using Prophet to predict future demand. The analysis will look at the San Francisco Ferry Building.

```
In [433]: from fbprophet import Prophet

In [434]: stations = df.groupby('start_station_name')

In [435]: ferry_building = stations.get_group('San Francisco Ferry Building (Harry Bridges Pla

In [436]: ferry_time = ferry_building.groupby('date')['date'].count()
```

```
In [437]: ferry_time = pd.DataFrame(ferry_time)
          ferry_time.head()
          ferry_time['DS'] = ferry_time.index

In [438]: ferry_time.columns = ['y','ds']

In [439]: ferry_time.head()

Out[439]:              y          ds
          date
          2017-06-28  47  2017-06-28
          2017-06-29  86  2017-06-29
          2017-06-30  76  2017-06-30
          2017-07-01  54  2017-07-01
          2017-07-02  57  2017-07-02

In [489]: m = Prophet(daily_seasonality=False)
          m.fit(ferry_time)

Out[489]: <fbprophet.forecaster.Prophet at 0x16e559518>

In [490]: future = m.make_future_dataframe(periods=365)

In [491]: forecast = m.predict(future)
          forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()

Out[491]:              ds       yhat  yhat_lower  yhat_upper
          1124 2020-07-26  34.218068    3.320309   66.697036
          1125 2020-07-27  88.174987   53.355814  122.837820
          1126 2020-07-28  96.632684   64.533279  126.674147
          1127 2020-07-29  90.853974   57.605654  127.383945
          1128 2020-07-30  96.245663   64.764603  128.532360

In [492]: fig1 = m.plot(forecast)
          plt.xlabel('Date', fontsize=16)
          plt.ylabel('Number of Trips', fontsize=16)
          plt.title('Trips started at the Ferry building', fontsize=20)

Out[492]: Text(0.5, 1.0, 'Trips started at the Ferry building')
```




```
In [493]: fig2 = m.plot_components(forecast)
```



This nicely captures the seasonal trend in ride numbers, where there is a drop-off in November-January. It also shows the drop-off in rides on the weekend as compared to weekdays, indicating that commuters are the primary users.