Lyft_Baywheels_capstone_2019

August 29, 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
```

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

```
In [387]: address = "1800 Montgomery St, San Francisco, CA 94111"
          #example: address = "1800 Montgomery St, San Francisco, CA 94111"
```

```
In [450]: geolocator = GoogleV3(api_key='')
          location = geolocator.geocode(address, timeout=10)
          print(location.address)
          print((location.latitude, location.longitude))
          proposed_station = [location.latitude, location.longitude]
```

```
1800 Montgomery St, San Francisco, CA 94111, USA
(37.80599309999999, -122.4051806)
```

```
In [447]: coordinate_predictions = coordinates_to_predictions(proposed_station)
```

```
The predicted number of trips per week, starting at this location, is: 612
The normalized weekly trip count is:  3.5846862505293022
The trip count is more than average, this may be a good location.
```

```
In [448]: import folium

          #tiles: Stamen Toner or Stamen Terrain or Stamen Watercolor
```

```
plt.figure(figsize=(15,10))
m = folium.Map(location=[37.786375, -122.404904], tiles='Stamen Toner', zoom_start=13
#m.save('map.html')

mapping_data.apply(lambda row:folium.CircleMarker(location=[row["start_station_latitu
            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
                                <i class="fa fa-circle" style="color:orange"></i
                                <i class="fa fa-circle" style="color:red"></i> A
                                <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[448]: <folium.folium.Map at 0x16a7afc18>

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

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

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 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:

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

In [2]: *#2019-07 data is new and contains e-bikes, save for testing*

```
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 [179]: df = df_201907.append(df_201906)
          df = df.append(df_201905)
          df = df.append(df_201904)
          df = df.append(df_201903)
          df = df.append(df_201902)
          df = df.append(df_201901)
          df = df.append(df_201812)
          df = df.append(df_201811)
```

```
df = df.append(df_201810)
df = df.append(df_201809)
df = df.append(df_201808)
df = df.append(df_201807)
df = df.append(df_201806)
df = df.append(df_201805)
df = df.append(df_201804)
df = df.append(df_201803)
df = df.append(df_201802)
df = df.append(df_201801)
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/pandas/core/frame
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=False'.

To retain the current behavior and silence the warning, pass 'sort=True'.

  sort=sort)
```

```
In [180]: 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	stop_name	location_type	zone_id
0	37.792357	14026	-122.421010	NaN	4026	NaN	Clay St & Polk St	0	NaN
1	37.793826	14027	-122.409591	NaN	4027	NaN	Clay St & Powell St	0	NaN
2	37.793653	14024	-122.410823	NaN	4024	NaN	Clay St & Mason St	0	NaN
3	37.794682	14025	-122.402770	NaN	4025	NaN	Clay St & Montgomery St	0	NaN
4	37.792526	14022	-122.419589	NaN	4022	NaN	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 [31]: # Haversine formula
         # Adapted from Wayne Dyck

         import math

         def distance_calc(origin, destination):

             or_lat, or_long = origin
             dest_lat, dest_long = destination
             radius = 6371 # km

             dlat = math.radians(dest_lat - or_lat)
             dlong = math.radians(dest_long - or_long)
             a = math.sin(dlat/2) * math.sin(dlat/2) + math.cos(math.radians(or_lat)) \
                 * math.cos(math.radians(dest_lat)) * math.sin(dlong/2) * math.sin(dlong/2)
             c = 2 * math.atan2(math.sqrt(a), math.sqrt(1-a))
```

```
            d = radius * c

            return d
```

```
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

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, but it avoids recalculating distances.

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

```
In [37]: 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 [186]: df['start_time'] = pd.to_datetime(df['start_time'])
```

```
In [184]: df['month'] = df.start_time.dt.month
          df['hour'] = df.start_time.dt.hour
          df['day'] = df.start_time.dt.weekday_name
          df['year'] = df.start_time.dt.year
          df['date'] = df.start_time.dt.date
```

```
In [187]: df.set_index('start_time', inplace=True)
```

6 4.1 Weekly sampling

```
In [74]: weekly = df.groupby('start_station_id').resample('W').count()

In [76]: weekly = weekly[['bike_id']]

In [77]: weekly.columns = ['trip_count']

In [253]: weekly.head()
```

Out[253]:

start_station_id	start_time	trip_count
3.0	2017-07-02	111
	2017-07-09	191
	2017-07-16	218
	2017-07-23	346
	2017-07-30	290

```
In [256]: weekly.reset_index(inplace=True)

In [257]: weekly['start_time'] = pd.to_datetime(weekly['start_time'])

In [258]: 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 [267]: joined_weekly = weekly.join(coords_only, on='start_station_id', how='left')

In [268]: joined_weekly.reset_index().head()
```

Out[268]:

	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	0.342934	
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

6.1 Plotting weekly trips

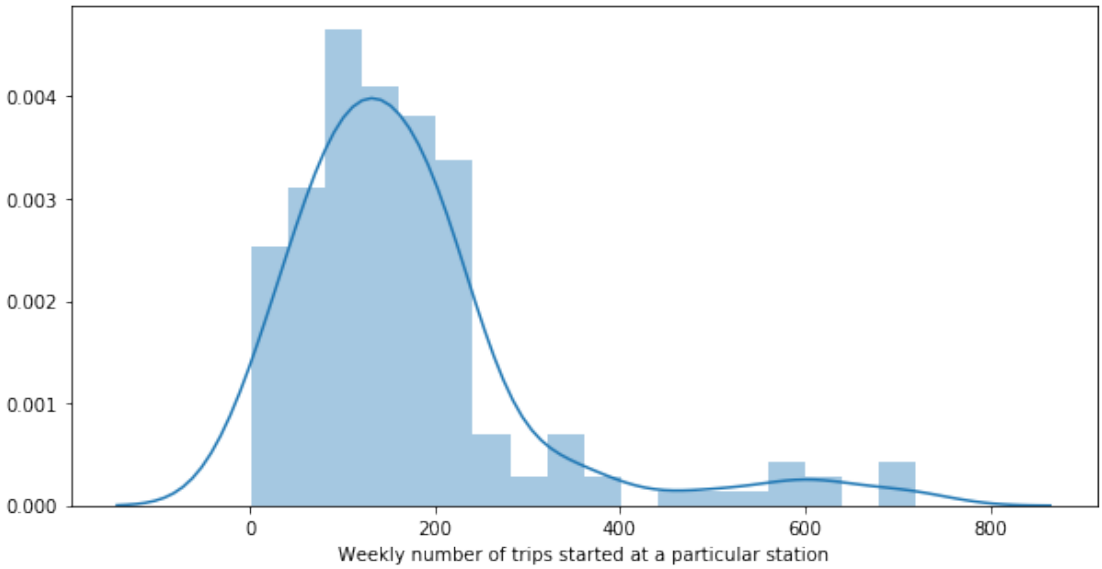
Here let's average all the trips per station over the entire timeframe so we can put them on a map with one colored marker.

```
In [270]: weekly_markers = joined_weekly.groupby('start_station_id')['trip_count'].mean()

In [271]: weekly_markers = pd.DataFrame(weekly_markers)

In [272]: weekly_markers['normalized_trip_count'] = weekly_markers.trip_count/ weekly_markers.t

In [273]: weekly_markers.normalized_trip_count.describe()

Out[273]: count    178.000000
          mean       1.000000
          std        0.804264
          min        0.012440
          25%        0.511454
          50%        0.840007
          75%        1.203739
          max        4.208897
          Name: normalized_trip_count, dtype: float64

In [274]: weekly_markers['marker_color'] = weekly_markers['normalized_trip_count'].apply(color_

In [276]: weekly_markers.head()

Out[276]:                   trip_count  normalized_trip_count marker_color
          start_station_id
          3.0               576.847619               3.376852      darkred
          4.0               122.009524               0.714241       orange
          5.0               474.828571               2.779635      darkred
          6.0               594.885714               3.482447      darkred
          8.0               200.961905               1.176426          red

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
```

6.2 Weekly Trip Count Histogram

```
In [428]: 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[428]: Text(0.5, 0, 'Weekly number of trips started at a particular station')
```



7 4.2 Daily Sampling

```
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()
```

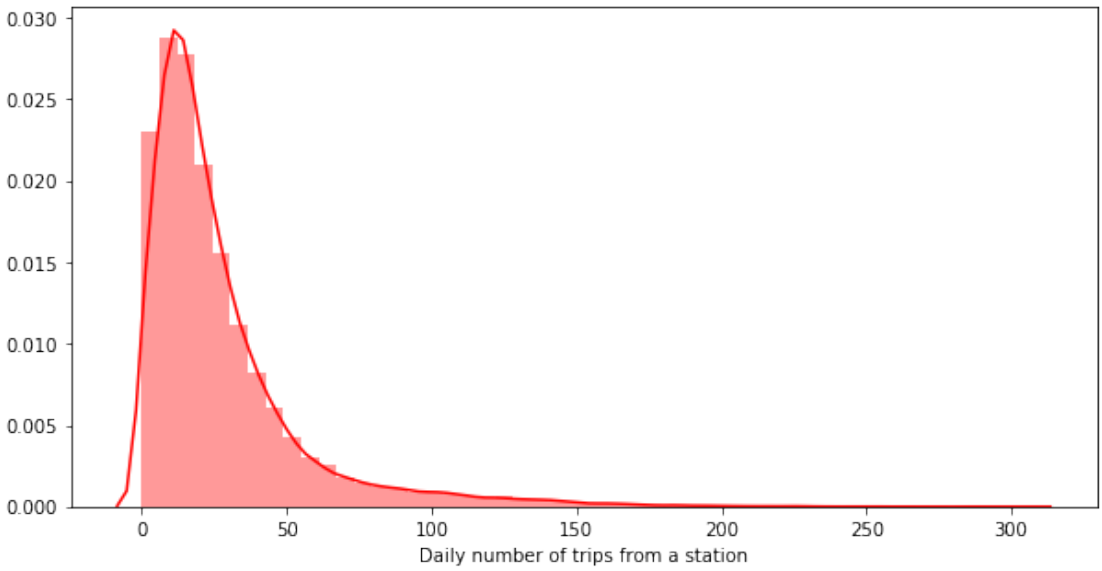
```
Out[191]:    start_station_id start_time  trip_count
          0               3.0 2017-06-29          22
          1               3.0 2017-06-30          23
          2               3.0 2017-07-01          27
          3               3.0 2017-07-02          39
          4               3.0 2017-07-03          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

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')
```



8 5. Let's get into some machine learning

```
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
```

8.0.1 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,
                                                              random_state=0)
```

8.0.2 Models to choose from:

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

          linreg = linear_model.Ridge(alpha=0.1)
          knn = KNeighborsRegressor()
          tree = RandomForestRegressor()
```

8.0.3 This is for clustering the coordinates:

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

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

In [281]:
          gs_coord = model_selection.GridSearchCV(
              coord_pipe,
              {"knn__n_neighbors": range(10, 100)},#can do one hyperparameter at a time or mor
              cv=5)
          gs_coord.fit(X_train, y_train) #this is an estimator
          print (gs_coord.best_params_)
```

```
{'knn__n_neighbors': 37}
```

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

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

8.0.4 This is for the distance information:

```
In [283]: from sklearn.pipeline import Pipeline

          dist_pipe = Pipeline([('cst', ColumnSelectTransformer(['min_bart_dist', 'min_muni_dis
                                ('tree', RandomForestRegressor())
              ])

In [284]: from sklearn import model_selection

          #"tree__max_depth": range(1,100)
          #"tree__n_estimators": [20,25,30,50,100]---25

          gs_dist = model_selection.GridSearchCV(
              dist_pipe,
              {"tree__n_estimators": [90, 140, 150, 160, 170]},#can do one hyperparameter at a
```

```
            cv=5)
        gs_dist.fit(X_train, y_train) #this is an estimator
        print (gs_dist.best_params_)
```

```
{'tree__n_estimators': 90}
```

```
In [285]: gs_dist.score(X_test, y_test)
```

```
Out[285]: 0.7228086453369806
```

8.0.5 This is for the time series information:

```
In [299]: from sklearn.preprocessing import OneHotEncoder

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

```
In [300]: #"linreg__alpha": range(0, 10)

        gs_time = model_selection.GridSearchCV(
            time_pipe,
            {"tree__n_estimators": [90, 140, 150, 160, 170]},#can do one hyperparameter at a
            cv=5)
        gs_time.fit(X_train, y_train) #this is an estimator
        print (gs_time.best_params_)
```

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

```
In [301]: gs_time.score(X_test, y_test)
```

```
Out[301]: 0.05897159383837624
```

8.0.6 Let's combine the time and spatial data:

```
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 [335]:
```
from sklearn.pipeline import FeatureUnion

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

In [336]:
```
full_model_pipe = Pipeline([('union', union), ('ridge', Ridge(alpha=10))])
full_model_pipe.fit(X_train, y_train)
```

Out[336]:
```
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 [337]: full_model_pipe.score(X_test, y_test)

Out[337]: 0.8168617828478962

In [430]: 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 = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
              year = [2019, 2019, 2019, 2019, 2019, 2019, 2019, 2018, 2018, 2018, 2018, 2018]
              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.
```

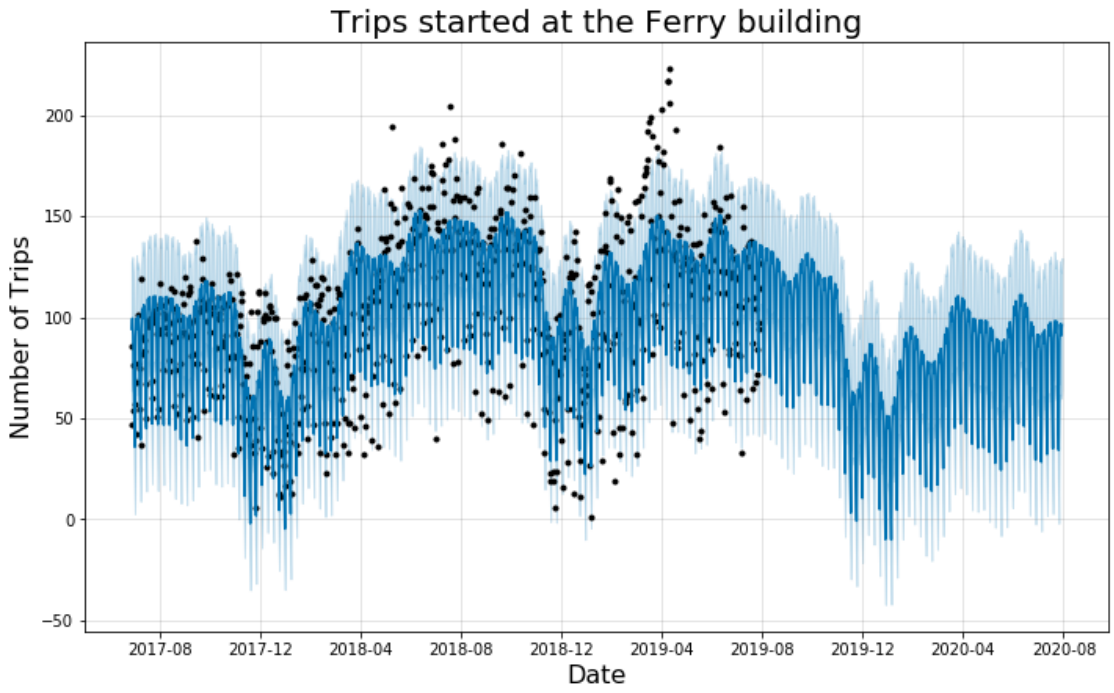
```
        else:
            print('The trip count is more than average, this may be a good location.')

        ### 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
```

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

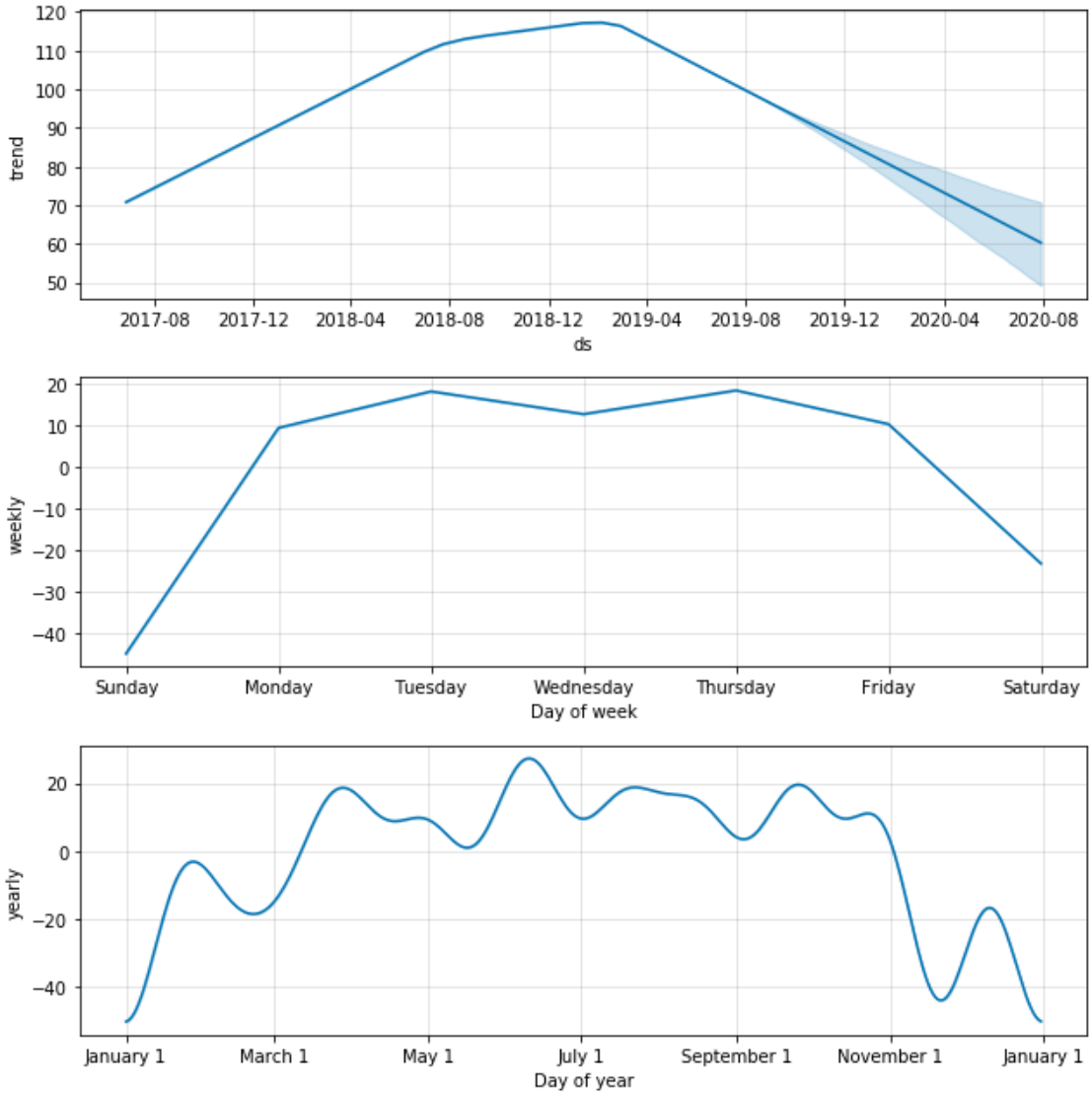
A slight side-track looking at a time series for just one station and using Prophet to predict future demand. The analysis will look at the San Francisco Ferry Building.

```
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 [440]: m = Prophet()
          m.fit(ferry_time)

INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to overrid
```

```
Out[440]: <fbprophet.forecaster.Prophet at 0x1689acb70>

In [443]: future = m.make_future_dataframe(periods=365)

In [444]: forecast = m.predict(future)
          forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()

Out[444]:             ds       yhat  yhat_lower  yhat_upper
          1124 2020-07-26  34.218068   -1.895765   66.835199
          1125 2020-07-27  88.174987   58.005279  123.137589
          1126 2020-07-28  96.632684   61.904080  127.949962
          1127 2020-07-29  90.853974   59.888146  122.397748
          1128 2020-07-30  96.245663   64.562764  129.273255

In [445]: 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[445]: Text(0.5, 1.0, 'Trips started at the Ferry building')
```




```
In [446]: fig2 = m.plot_components(forecast)
```


trend
120
110
100
90
80
70
60
50
2017-08
2017-12
2018-04
2018-08
2018-12
2019-04
2019-08
2019-12
2020-04
2020-08
ds
weekly
20
10
0
−10
−20
−30
−40
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week
yearly
20
0
−20
−40
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year

In [ ]: