Railway Traffic - Full Improved

August 17, 2017

1 Railway Traffic Time Series Clustering

This notebook presents an analysis on Railway Traffic Time Series Data. The data was collected through the planitmetro web site (http://planitmetro.com/data), i.e the Washington Metropolitan Area Transit Authority data.

This data has been cleaned up -stations which did not have any information about time were removed from the database. The dataset consists of over 28000 tuples, each representing a group of 5 tuples for a single station, identifying the number of average rides each day at 5 distinct times of the day (AM_PEAK, PM_PEAK, MIDDAY, LAATE NIGHT PEAK, EVENING). The data is accumulated for a period of approximately 6 years from Sept 2010 to Jan 2016.

To understand the 'distance' or correlation between stations, we use a algorithm called Sales Pattern Distance described here. The basic idea is to increase the distance between two stations based on *the overall variation between the %change in Passenger Density*. For example, if a Station A has 2 data values (Passenger Density) - 4000 & 5000, it means an increase of 25%. Similarly, Station B having 2 data values - 400 & 500, *also* has an increase of 25%. Thus, both these stations have the same variation and thus could belong to the same cluster.

Initially, we pre-process the data and compute the distance matrix.

```
In [1]: %matplotlib inline
        import pandas as pd
        import numpy as np
        from sklearn.cluster import AgglomerativeClustering
        import matplotlib.pyplot as plt
        import seaborn as sns
        import scipy.spatial.distance as ssd
        # compute_distance_matrix is a function that calculates a distance matrix between train
        # on change in % passenger density.
        import compute_distance_matrix as cdm
```

```
In [2]: data = pd.read_excel('../maindb.xlsx', 'Sheet1')
```

```
In [3]: data.head(10)
```

```
Out[3]:                          Station   Year  Passengerdensity
        0          Addison RoadAM Peak  20109              2303
        1          Addison RoadEvening  20109               211
        2  Addison RoadLate Night Peak  20109                 5
```

```
3          Addison RoadMidday  20109              748
4          Addison RoadPM Peak  20109              399
5             AnacostiaAM Peak  20109             3141
6             AnacostiaEvening  20109              604
7     AnacostiaLate Night Peak  20109               20
8              AnacostiaMidday  20109             1860
9             AnacostiaPM Peak  20109             1664
```

In [4]:
```
df = data.groupby(['Station','Year'])['Passengerdensity'].mean().to_frame().reset_index(
stations = df['Station'].unique()
```

In [5]:
```
di_matrix = cdm.extract_data(df)
```

```
Distance matrix computation complete.
```

In [6]:
```
#di_matrix
```

Now that we have computed the distance matrix, we split the data into test and training sets and apply Agglomerative Clustering.

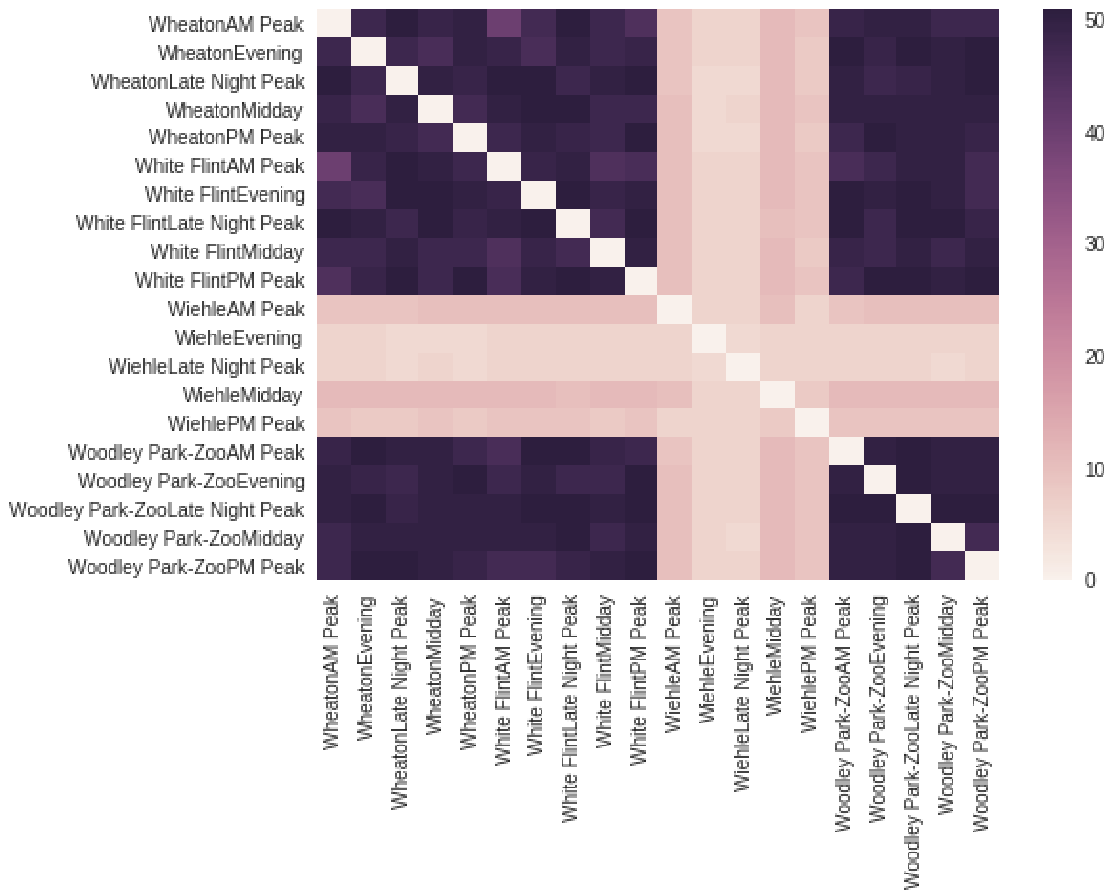
In [7]:
```
test_stations = stations[-20:]
mask = np.in1d(stations,test_stations)
training_stations = stations[np.where(~mask)]

# Create test and training data
test_data = df[df['Station'].isin(test_stations)]
train_data = df[df['Station'].isin(training_stations)]

# Print out sizes
print('Training data size: ', train_data.index.size)
print('Test data size: ', test_data.index.size)
```

```
Training data size:  21696
Test data size:  822
```

In [8]:
```
test_matrix = di_matrix.ix[di_matrix.index.isin(test_stations), di_matrix.columns.isin(t
train_matrix = di_matrix.ix[di_matrix.index.isin(training_stations), di_matrix.columns.i
```

We split the data into two halves, we keep 20 stations as test data, which is visualized using a heatmap below. We can see that there a couple of stations that are very similar in their growth/fall of % Passenger Density, shown in pink.

In [9]:
```
ax = sns.heatmap(test_matrix)
```

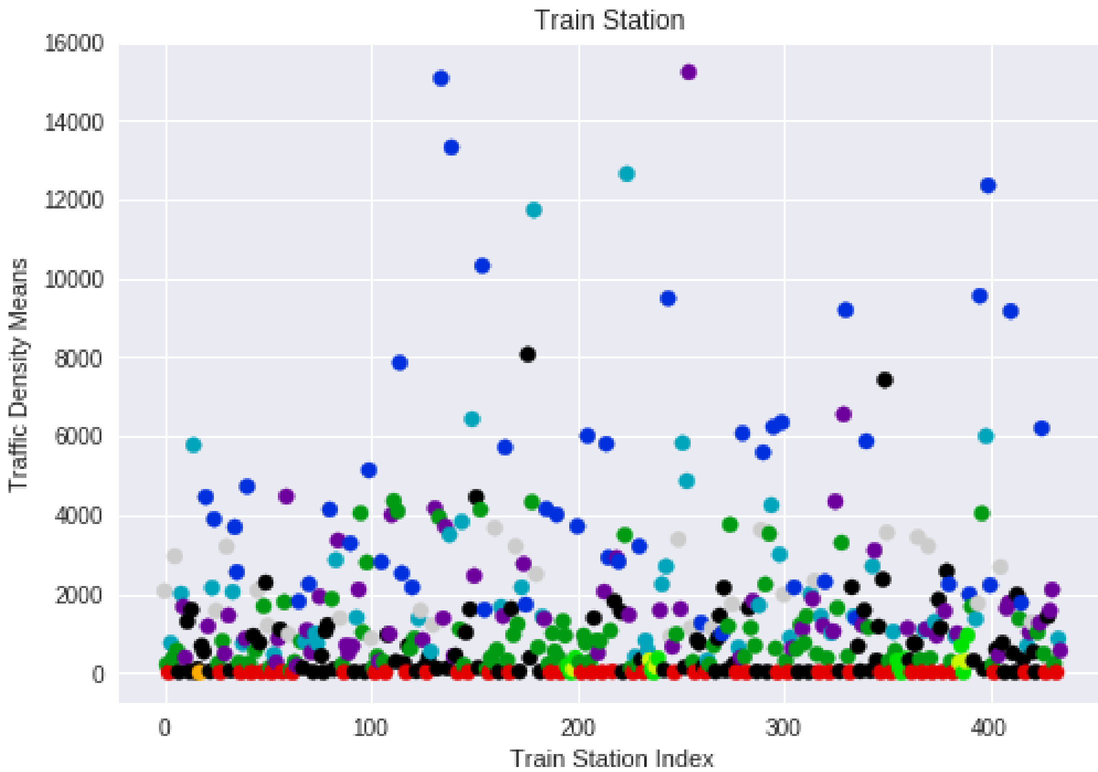



```
In [10]: # Calculate clusters using Agglomerative Clustering using Euclidean Distance Measure.
         # We keep the clusters at a fixed random number 10 for now.
         # Based on cluster evaluation, we can change this number.

         clustering = AgglomerativeClustering(n_clusters=int(10))
         clustering.fit(train_matrix)
```

```
Out[10]: AgglomerativeClustering(affinity='euclidean', compute_full_tree='auto',
                     connectivity=None, linkage='ward',
                     memory=Memory(cachedir=None), n_clusters=10,
                     pooling_func=<function mean at 0x7f5b1c030840>)
```

```
In [11]: Y = train_data.groupby('Station')['Passengerdensity'].mean().as_matrix()
         X = train_data.groupby('Station').mean().reset_index().index

         plt.scatter(X,Y, c=clustering.labels_, cmap=plt.cm.spectral)
         plt.title('Train Station ')
         plt.xlabel('Train Station Index')
         plt.ylabel('Traffic Density Means')
```

```
plt.rcParams["figure.figsize"] = [10,25]

plt.show()
```




```
In [12]: cluster = dict()
         for i in range(clustering.labels_.size):
             label = clustering.labels_[i]
             if label not in cluster:
                 cluster[label] = [training_stations[i]]
             else:
                 cluster[label].append(training_stations[i])

In [13]: st_clusters = pd.DataFrame(dict([ ('Cluster ' + str(k),pd.Series(v)) for k,v in cluster

In [14]: st_clusters

Out[14]:                                 0                                  1  \
         Cluster 0        AnacostiaLate Night Peak  Archives-Navy MemorialEvening
         Cluster 1               AnacostiaPM Peak  Archives-Navy MemorialAM Peak
         Cluster 2                BallstonAM Peak                 BallstonPM Peak
         Cluster 3            Addison RoadMidday                 AnacostiaMidday
         Cluster 4            Addison RoadEvening            Addison RoadPM Peak
```

Cluster 5	GreensboroAM Peak	GreensboroEvening
Cluster 6	GreensboroMidday	McLeanAM Peak
Cluster 7	Arlington CemeteryLate Night Peak	
Cluster 8	Addison RoadLate Night Peak	Benning RoadLate Night Peak
Cluster 9	Addison RoadAM Peak	AnacostiaAM Peak

	2 \
Cluster 0	Archives-Navy MemorialLate Night Peak
Cluster 1	BallstonEvening
Cluster 2	BethesdaPM Peak
Cluster 3	Archives-Navy MemorialPM Peak
Cluster 4	AnacostiaEvening
Cluster 5	GreensboroLate Night Peak
Cluster 6	McLeanMidday
Cluster 7	
Cluster 8	Braddock RoadLate Night Peak
Cluster 9	Benning RoadAM Peak

	3	4 \
Cluster 0	Archives-Navy MemorialMidday	Arlington CemeteryAM Peak
Cluster 1	Benning RoadPM Peak	BethesdaEvening
Cluster 2	Braddock RoadAM Peak	Branch AvenueAM Peak
Cluster 3	BallstonMidday	BethesdaMidday
Cluster 4	Benning RoadEvening	Benning RoadMidday
Cluster 5	GreensboroPM Peak	McLeanEvening
Cluster 6	Tysons CornerAM Peak	Tysons CornerMidday
Cluster 7		
Cluster 8	Branch AvenueLate Night Peak	BrooklandLate Night Peak
Cluster 9	BethesdaAM Peak	BrooklandAM Peak

	5	6 \
Cluster 0	Arlington CemeteryEvening	Arlington CemeteryMidday
Cluster 1	Braddock RoadPM Peak	Capitol HeightsPM Peak
Cluster 2	ClarendonAM Peak	Cleveland ParkAM Peak
Cluster 3	Braddock RoadMidday	Capitol HeightsMidday
Cluster 4	Braddock RoadEvening	Branch AvenueEvening
Cluster 5	McLeanLate Night Peak	McLeanPM Peak
Cluster 6		
Cluster 7		
Cluster 8	Capitol HeightsLate Night Peak	Capitol SouthLate Night Peak
Cluster 9	Capitol HeightsAM Peak	CheverlyAM Peak

	7	8 \
Cluster 0	Arlington CemeteryPM Peak	BallstonLate Night Peak
Cluster 1	Capitol SouthAM Peak	Capitol SouthPM Peak
Cluster 2	Columbia HeightsAM Peak	Court HouseAM Peak
Cluster 3	ClarendonMidday	Cleveland ParkMidday
Cluster 4	Branch AvenuePM Peak	BrooklandMidday

```
Cluster 5        Spring HillAM Peak              Spring HillEvening
Cluster 6
Cluster 7
Cluster 8    CheverlyLate Night Peak  Congress HeightsLate Night Peak
Cluster 9    Congress HeightsAM Peak                   DeanwoodAM Peak

                                   9           ...              \
Cluster 0     BethesdaLate Night Peak          ...
Cluster 1             CheverlyPM Peak          ...
Cluster 2         Crystal CityPM Peak          ...
Cluster 3       Cleveland ParkPM Peak          ...
Cluster 4      Capitol HeightsEvening          ...
Cluster 5  Spring HillLate Night Peak          ...
Cluster 6                                      ...
Cluster 7                                      ...
Cluster 8     DeanwoodLate Night Peak          ...
Cluster 9       Eastern MarketPM Peak          ...

                              82                        83  \
Cluster 0  Van Dorn StreetMidday      Van Ness-UDCEvening
Cluster 1
Cluster 2
Cluster 3
Cluster 4       TwinbrookEvening  U Street-CardozoEvening
Cluster 5
Cluster 6
Cluster 7
Cluster 8
Cluster 9

                                 84                      85  \
Cluster 0  Van Ness-UDCLate Night Peak           ViennaEvening
Cluster 1
Cluster 2
Cluster 3
Cluster 4         Union StationEvening  Van Dorn StreetEvening
Cluster 5
Cluster 6
Cluster 7
Cluster 8
Cluster 9

                              86                 87  \
Cluster 0  ViennaLate Night Peak      ViennaMidday
Cluster 1
Cluster 2
Cluster 3
Cluster 4          ViennaPM Peak  WaterfrontMidday
```

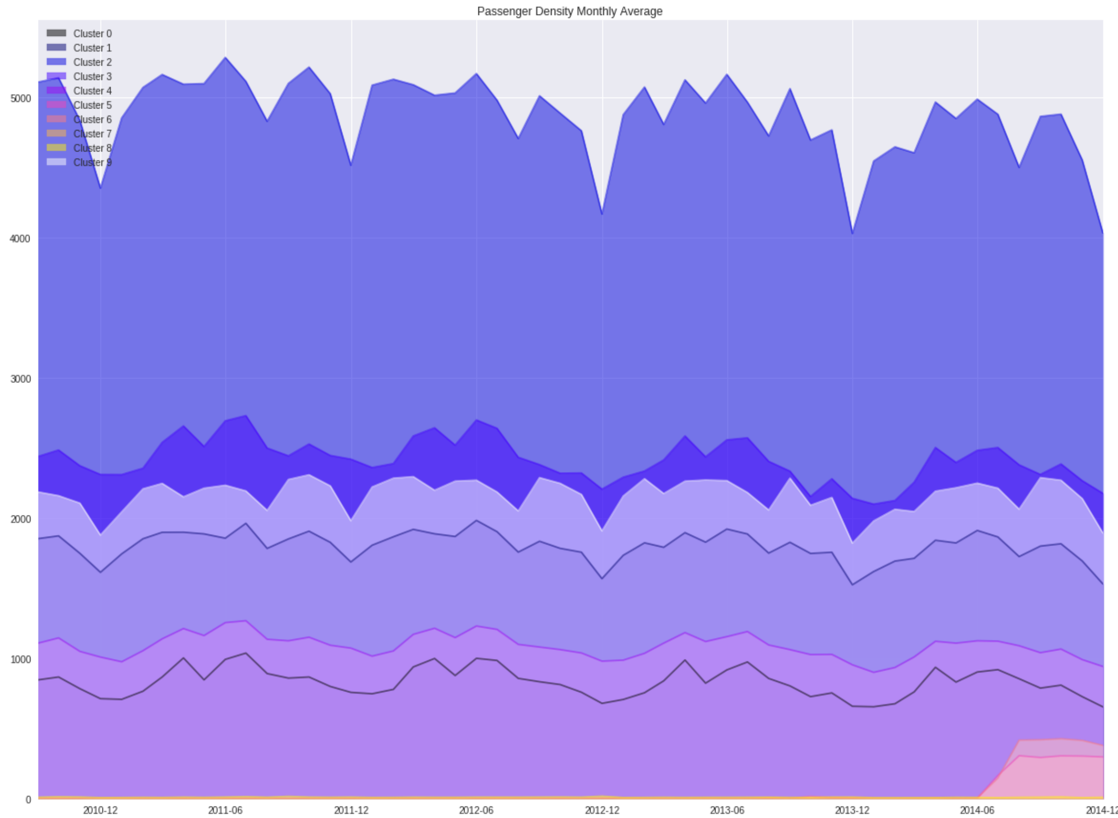
```
Cluster 5
Cluster 6
Cluster 7
Cluster 8
Cluster 9

                                   88                        89  \
Cluster 0  Virginia Square-GMUEvening        WaterfrontEvening
Cluster 1
Cluster 2
Cluster 3
Cluster 4    West Falls ChurchEvening  West HyattsvilleEvening
Cluster 5
Cluster 6
Cluster 7
Cluster 8
Cluster 9

                                  90                        91
Cluster 0  WaterfrontLate Night Peak  West Falls ChurchMidday
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6
Cluster 7
Cluster 8
Cluster 9

[10 rows x 92 columns]
```

In [15]:
```
st_clusters.to_excel('Training Data Set Clusters.xlsx', 'Sheet1')
```

In [16]:
```
# Find cluster center by mean of Passenger Density
cluster_means = dict()
for index, row in st_clusters.iterrows():
    traffic = train_data[train_data['Station'].isin(row)]
    traffic['Year'] = train_data.apply(lambda row: cdm.year_format(row['Year']), axis=1
    cluster_means[index] = traffic.groupby('Year')['Passengerdensity'].mean()

cdf = pd.DataFrame(cluster_means).fillna(value=0)
```

```
/home/ishaan/.pyenv/versions/3.6.0/lib/python3.6/site-packages/ipykernel/__main__.py:5: SettingW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

```
In [17]: cdf.plot.area(stacked=False, figsize=[20,15], title='Passenger Density Monthly Average'

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5adff900f0>
```



As can be seen from the plot above of Passenger Density Mean vs Time, separate clusters have different curves. However, cluster 5 & 6 (purple-pink shades with ~1000 passenger density mean) appear very similar. They are differentiated only by the few instances where their individual % change in passenger densities vary a lot. For example, stations in cluster 5 have a greater increase in Passenger Density around April 2011 as compared to Cluster 6 (seen as a *sharper peak*).

The clustering itself is based on grouping stations with *similar* variations.

```
In [18]: cluster_centers = dict()

         # Find cluster center by mean of Passenger Density

         for index, row in st_clusters.iterrows():
             traffic = train_data[train_data['Station'].isin(row)]
             traffic['Year'] = train_data.apply(lambda row: cdm.year_format(row['Year']), axis=1
             cluster_centers[index] = dict()
             cluster_centers[index]['center'] = traffic['Passengerdensity'].mean()
             cluster_centers[index]['count'] = row[row != ''].size

         cluster_centers
```

```
/home/ishaan/.pyenv/versions/3.6.0/lib/python3.6/site-packages/ipykernel/__main__.py:7: SettingW
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

Out[18]:
```
{'Cluster 0': {'center': 829.55948149696837, 'count': 92},
 'Cluster 1': {'center': 1801.4004342431763, 'count': 62},
 'Cluster 2': {'center': 4873.0797275641025, 'count': 48},
 'Cluster 3': {'center': 2415.5432692307691, 'count': 48},
 'Cluster 4': {'center': 1088.6399572649573, 'count': 90},
 'Cluster 5': {'center': 254.60204081632654, 'count': 15},
 'Cluster 6': {'center': 221.06, 'count': 5},
 'Cluster 7': {'center': 1.1428571428571428, 'count': 1},
 'Cluster 8': {'center': 8.6396321070234112, 'count': 46},
 'Cluster 9': {'center': 2162.2348901098903, 'count': 28}}
```

In [19]:
```
# plot cluster centers
data_points = pd.DataFrame(cluster_centers).T.reset_index()

Y = data_points['center'].values
X = range(data_points.index.size)

plt.scatter(X,Y, s=data_points['count']*50, c=X, cmap=plt.cm.spectral)
plt.title('Train Station Cluster Centers')
plt.xlabel('Cluster Number')
plt.ylabel('Passenger Density Mean')

plt.show()
```


Train Station Cluster Centers
5000
4000
3000
2000
1000
0
Passenger Density Mean
0
2
4
6
8
Cluster Number

The above scatter plot shows the sizes of the clusters and the order of the Passenger Densities of the stations within each cluster. Considering a mean of Passenger Density would seem counter intuitive since stations with different order of density can still be in the same cluster. However, it can be noted from the earlier time series plot that stations with similar orders tend to be in the same cluster.

Moreover, we can see that Cluster 7 (the tiny orange point) is an outlier. It consists of only 1 station, and displays behaviour that is anomalous with respect to other stations.

2 Predictive Analysis

Now that we have created the clusters, we evaluate our clustering method (agglomerative) by comparing it to BIRCH, and measuring cluster dispersion to find out the optimum no of clusters (remember, we had initially taken 10 clusters as default).

```
In [20]: # Predict clusters for test data
         predict_labels = clustering.fit_predict(test_matrix)
         print("Agglomerative Clustering:" + str(list(predict_labels)))

         # Compare the clustering with Birch
         from sklearn.cluster import Birch
         brc = Birch(branching_factor=50, n_clusters=10, threshold=0.5, compute_labels=True)
         brc.fit(train_matrix)
         print('BIRCH Clustering:\t ' + str(list(brc.fit_predict(test_matrix))))
```

```
Agglomerative Clustering:[2, 4, 0, 4, 9, 2, 8, 1, 1, 2, 3, 3, 3, 3, 3, 7, 0, 6, 5, 5]
BIRCH Clustering:         [2, 4, 0, 4, 9, 2, 8, 1, 1, 2, 3, 3, 3, 3, 3, 7, 0, 6, 5, 5]
```

```
In [21]: pred_cluster = dict()
         for i in range(predict_labels.size):
             label = predict_labels[i]
             if label not in pred_cluster:
                 pred_cluster[label] = [test_stations[i]]
             else:
                 pred_cluster[label].append(test_stations[i])
```

```
In [22]: print('Predicted Clusters:\n')
         for k, v in pred_cluster.items():
             if v:
                 for station in v:
                     print(str(station) + "  =>  " + str(k))
```

```
Predicted Clusters:

WheatonAM Peak  =>  2
White FlintAM Peak  =>  2
```

```
White FlintPM Peak  =>  2
WheatonEvening  =>  4
WheatonMidday  =>  4
WheatonLate Night Peak  =>  0
Woodley Park-ZooEvening  =>  0
WheatonPM Peak  =>  9
White FlintEvening  =>  8
White FlintLate Night Peak  =>  1
White FlintMidday  =>  1
WiehleAM Peak  =>  3
WiehleEvening  =>  3
WiehleLate Night Peak  =>  3
WiehleMidday  =>  3
WiehlePM Peak  =>  3
Woodley Park-ZooAM Peak  =>  7
Woodley Park-ZooLate Night Peak  =>  6
Woodley Park-ZooMidday  =>  5
Woodley Park-ZooPM Peak  =>  5
```

2.1 Cluster Evaluation

2.1.1 Silhoutte Score

The Silhouette Coefficient is defined for each sample and is composed of two scores:
a: The mean distance between a sample and all other points in the same class.
b: The mean distance between a sample and all other points in the next nearest cluster.
The Silhouette Coefficient s for a single sample is then given as:

$$s = \frac{b - a}{max(a, b)}$$

The Silhouette Coefficient for a set of samples is given as the mean of the Silhouette Coefficient for each sample.

In [23]:
```
from sklearn import metrics
from sklearn.metrics import pairwise_distances

print('Test data score: ' + str(metrics.silhouette_score(test_matrix, predict_labels, m
print('Training data score: ' + str(metrics.silhouette_score(train_matrix, clustering.f
```

```
Test data score: 0.241376574604
Training data score: 0.0526737648439
```

The score is bounded between -1 for incorrect clustering and +1 for highly dense clustering. Scores around zero indicate overlapping clusters.

A 0.2 cluster score isn't great for the test data and it shows we have overlapping clusters in the training data itself. This is possible, and we figured this was happening when we plotted

Passenger Density means with Time and saw that a few plot lines were very similar even though the passenger densities were in different orders of magnitude.

We now try the Calinski-Harabaz Index

2.1.2 Calinski-Harabaz Index

For k clusters, the Calinski-Harabaz score s is given as the ratio of the between-clusters dispersion mean and the within-cluster dispersion:

$$s(k) = \frac{\mathrm{Tr}(B_k)}{\mathrm{Tr}(W_k)} \times \frac{N-k}{k-1}$$

where B_K is the between group dispersion matrix and W_K is the within-cluster dispersion matrix defined by:

$$W_k = \sum_{q=1}^{k} \sum_{x \in C_q} (x - c_q)(x - c_q)^T$$

$$B_k = \sum_q n_q (c_q - c)(c_q - c)^T$$

with N be the number of points in our data, C_q be the set of points in cluster q, c_q be the center of cluster q, c be the center of E, n_q be the number of points in cluster q.

```
In [24]: print('Test Data: ' + str(metrics.calinski_harabaz_score(test_matrix, predict_labels)))
         print('Training Data: ' + str(metrics.calinski_harabaz_score(train_matrix, clustering.f
```

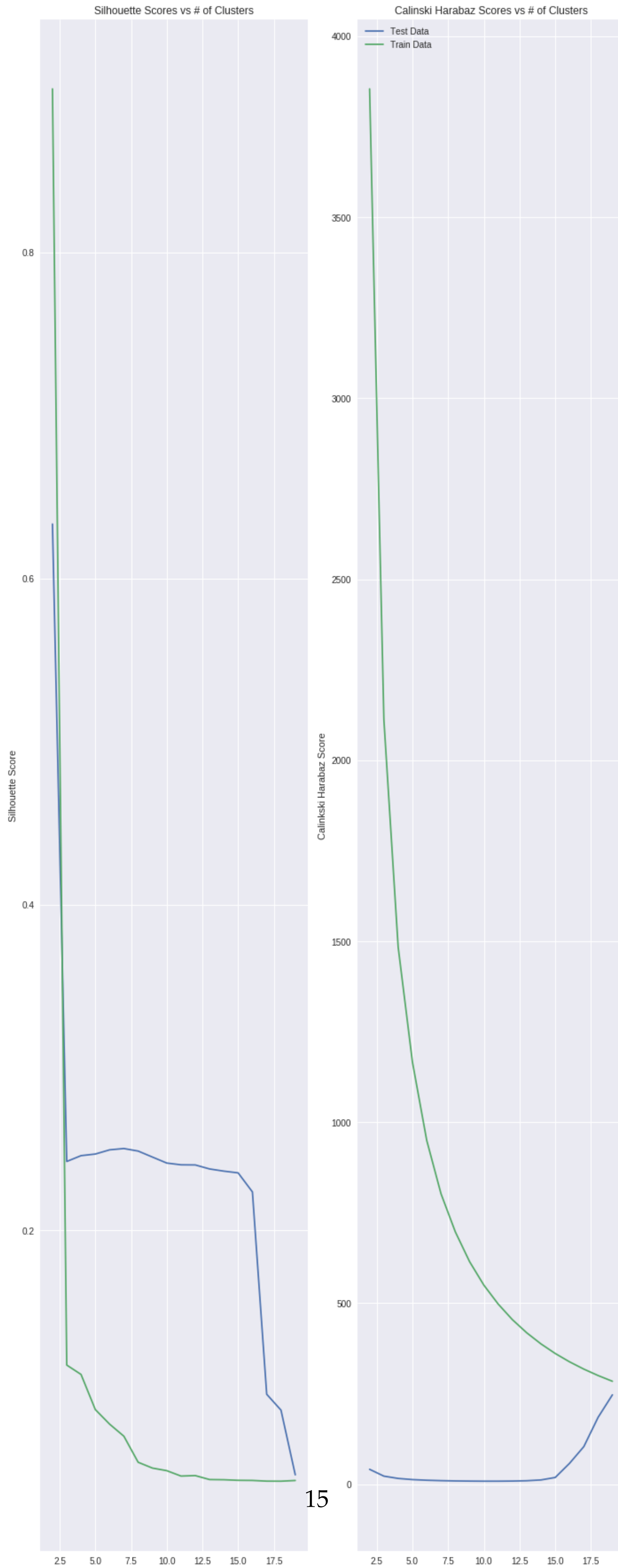
```
Test Data: 8.51233238295
Training Data: 550.117797116
```

We see here that the training data has higher score than the test data. This implies that even though the clusters are overlapping, they are sufficiently dense. This may be happening due to the small number of final clusters (fixed at 10). We now increase the value and see how the scores change.

```
In [25]: test_sil = list()
         train_sil = list()
         test_cal = list()
         train_cal = list()
         for i in range(2,20):
             trial = AgglomerativeClustering(n_clusters=int(i))
             trial.fit(train_matrix)
             test_sil.append(metrics.silhouette_score(test_matrix, trial.fit_predict(test_matrix
             train_sil.append(metrics.silhouette_score(train_matrix, trial.fit_predict(train_mat
             test_cal.append(metrics.calinski_harabaz_score(test_matrix, trial.fit_predict(test_
             train_cal.append(metrics.calinski_harabaz_score(train_matrix, trial.fit_predict(tra
```

```
In [26]: sil_plot = plt.subplot(1,2,1)
         sil_plot.plot(range(2,20),test_sil, label='Test Data')
```

```
sil_plot.plot(range(2,20),train_sil, label='Train Data')

sil_plot.set_title('Silhouette Scores vs # of Clusters')
sil_plot.set_xlabel('# of Clusters')
sil_plot.set_ylabel('Silhouette Score')

cal_plot = plt.subplot(1,2,2)
cal_plot.plot(range(2,20),test_cal, label='Test Data')
cal_plot.plot(range(2,20),train_cal, label='Train Data')

cal_plot.set_title('Calinski Harabaz Scores vs # of Clusters')
cal_plot.set_xlabel('# of Clusters')
cal_plot.set_ylabel('Calinkski Harabaz Score')

plt.tight_layout()
plt.legend(loc='upper left')
plt.show()
```


Silhouette Scores vs # of Clusters
Silhouette Score
0.8
0.6
0.4
0.2
2.5
5.0
7.5
10.0
12.5
15.0
17.5
# of Clusters
Calinski Harabaz Scores vs # of Clusters
Test Data
Train Data
Calinkski Harabaz Score
4000
3500
3000
2500
2000
1500
1000
500
0

2.2 Intuition and Analysis

As can bee seen from the graphs, the Silhouette score drops with increase in the number of clusters. That is, increasing the number of clusters leads to overlapping. Moreover, while training data becomes almost constant at large no of clusters, the test data sharply decreases.

One of the reasons could be that since the data itself is dispersed in a certain way, increasing the number of clusters may actually lead to sparse overlapping clusters after a certain point. The BIRCH algorithm which I briefly use detects 20 clusters within the data with a threshold of 0.5.

As for the Calinski Harabaz score, increasing the number of clusters seem to exponentially increase the score for test data, while monotonically decreasing training data score. That is, as the number of clusters k increases, $B(k)$ increases and $W(k)$ decreases. Since the Calinski Harabaz score is monotonically increasing/decreasing for training and test data, it may not be a reliable measure in this scenario.

In conclusion, a smaller number of clusters (~5) may be the best for this particular set of data. We see that at 2 clusters, the score sharply increases for both measures. Keep in mind that the data itself is clustered based on *Change in the Passenger Density growth/fall*, so even if a Station A has a Passenger Density of 4000 and Station B has a density of 400, they can be in the same cluster if these numbers grow/fall *by the same amount*.