# BATTLE OF NEIGHBORHOOD

Capstone Project Report v1.0

DECEMBER 25, 2019

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| Title | Version | Date |
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| Battle of Neighborhood – Capstone Project Report | 1.0 | 25-Dec-2019 |

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# Purpose:

The purpose of this report is to provide the overview of the problem that we are trying to address through this final capstone project, data we are using to analyze and the methodology we follow to uncover the facts. This report also has the final conclusion from the author based on the insights derived from the data.

# Problem Background:

Being the land of opportunities, United States of America becomes the world's most welcoming place for work for the tech geeks around the world. People from different culture, ethnics move into USA for work, studies, business etc. The immigration of people goes up and up every year. People who migrate gets professionally settled over a period of time would like move up further to get settled in USA. The general problem for such people is to find a city/state which is financially affordable and with a better living standard. The better place to live is defined by the availability of residents with the same culture background, crime rate, Cost of living index, Poverty level, employment level, per capita income and the ongoing rental rate in the location. So, developing a model to cluster the locations based on these attributes will help the people to select the location.

# Description and Usage of data:

As part of this capstone project assignment, I am taking different cities in Montgomery County in Pennsylvania and trying to segment the cities by weighing them in terms of crime rate, rental cost, Cost of living index, Poverty level, Employment rate and per capita income. I am considering one another data to choose the better city is the availability of restaurants with different cuisines. For example, if a location is having multiple Indian Restaurants, then that neighborhood must have more Indian community. It is assumed that the restaurant's owner must have done the analysis on population with different ethnicity before to open the restaurants. These datas are used to analyze and build a model to cluster the cities to decide the better livelihood.

- Crime Rate: Needless to say. Cities with less crime rate will be a better place to live.
- Cost of Living Index: A measure of expenses in the neighborhood
- Poverty Level: This must be direct proportional to Crime Rate. More in Poverty lead to more in crime and turns up less likelihood place to live.
- Employment Level, Per Capita Income: Indirect proportional to crime rate and contributes significantly to decide the better neighborhood
- Ongoing rental rate/Real Estate cost: This is an important factor while choosing a place to live.

# Methodology Highlights:

In this analysis, we shall take different cities in Montgomery county in Pennsylvania and will estimate their goodness as livelihood.

1. Import the Montgomery county map
2. Import the different cities in the county from https://data.montgomerycountymd.gov/
3. Mark those cities in the Montgomery map
4. Fetch the availabilities of different restaurants using foursquare API
5. Analyze different cuisines available in different cities to decide different community presence
6. Finally cluster the cities based on the cost of living index, crime rate, employment rate, poverty rate and rental rate

Lets import the geo locations of different cities of Montgomery county into a dataframe and mark these cities in the geospatial map of Montgomery county.

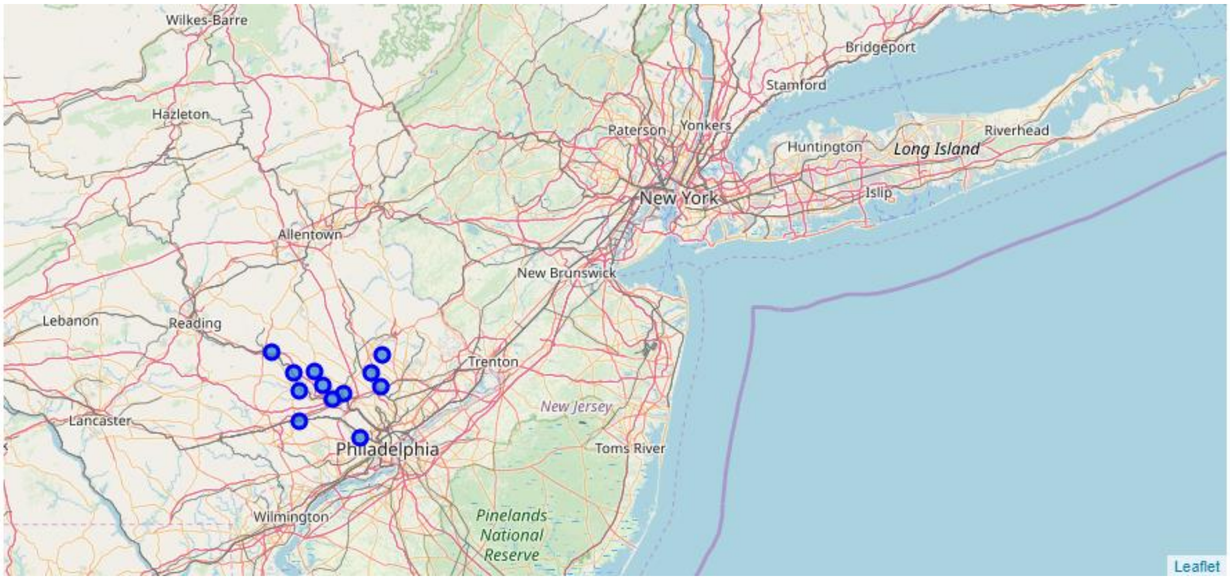
Refer the details code in the notebook:

https://github.com/paulchelladurai/Coursera_Capstone/blob/master/capstone%20project%20final%20(1).ipynb

```
#Import the geo locations of different cities in Montgomery County in the state of Pennsylvania and display it
Montgomerydf=pd.read_csv('pennsylvania.csv')
Montgomerydf
```

| | Latitude | Longitude | State | County | City | Name | RegionID |
|---|---|---|---|---|---|---|---|
| 0 | 40.248003 | -75.626843 | PA | Montgomery | Pottstown | Washington/Rosedale | 761971 |
| 1 | 40.184300 | -75.538000 | PA | Montgomery | Royersford | East End South | 761171 |
| 2 | 40.184365 | -75.226319 | PA | Montgomery | Lower Gwynedd | Spring House | 16311 |
| 3 | 40.143300 | -75.422800 | PA | Montgomery | Lower Providence | Downtown North | 761169 |
| 4 | 40.185700 | -75.451600 | PA | Montgomery | Collegeville | Beech/Wilson | 761168 |
| 5 | 40.130400 | -75.514900 | PA | Montgomery | Phoenixville | Downtown South | 761170 |
| 6 | 40.121500 | -75.339900 | PA | Montgomery | Norristown | North End | 761970 |
| 7 | 40.101300 | -75.383600 | PA | Montgomery | King Of Prussia | Dresher | 38234 |
| 8 | 40.139832 | -75.188891 | PA | Montgomery | Upper Dublin | Fort Washington | 24770 |
| 9 | 39.985409 | -75.272983 | PA | Montgomery | Wynnewood | Penn Wynne | 6460 |
| 10 | 40.036200 | -75.513800 | PA | Montgomery | Malvern | West End | 275966 |

Geo spatial map:




Let's then fetch all the restaurants available in these cities of Montgomery county using Foursquare API and move them to a dataframe. First few rows look as shown below.

```
Restaurantdf= Montgomery_venues[Montgomery_venues['Venue Category'].str.contains('Restaurant')]
print('There are {} venus for the food (holding Restaurants in their name)'.format(Restaurantdf.shape[0]))
Restaurantdf.head(10)
```

```
There are 224 venus for the food (holding Restaurants in their name)
```

| | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|
| 0 | Pottstown | 40.248003 | -75.626843 | McDonald's | 40.242988 | -75.619734 | Fast Food Restaurant |
| 3 | Pottstown | 40.248003 | -75.626843 | McDonald's | 40.252671 | -75.659760 | Fast Food Restaurant |
| 4 | Pottstown | 40.248003 | -75.626843 | Wendy's | 40.253671 | -75.660442 | Fast Food Restaurant |
| 5 | Pottstown | 40.248003 | -75.626843 | Arby's | 40.254643 | -75.661653 | Fast Food Restaurant |
| 6 | Pottstown | 40.248003 | -75.626843 | Burger King | 40.265440 | -75.628389 | Fast Food Restaurant |
| 11 | Pottstown | 40.248003 | -75.626843 | TGI Fridays | 40.234440 | -75.661947 | American Restaurant |
| 12 | Pottstown | 40.248003 | -75.626843 | Chili's Grill & Bar | 40.265175 | -75.650780 | Tex-Mex Restaurant |
| 13 | Pottstown | 40.248003 | -75.626843 | Boston Market | 40.254724 | -75.662670 | American Restaurant |
| 15 | Pottstown | 40.248003 | -75.626843 | Friendly's | 40.254824 | -75.659765 | Restaurant |
| 16 | Pottstown | 40.248003 | -75.626843 | Red Lobster | 40.254113 | -75.660487 | Seafood Restaurant |

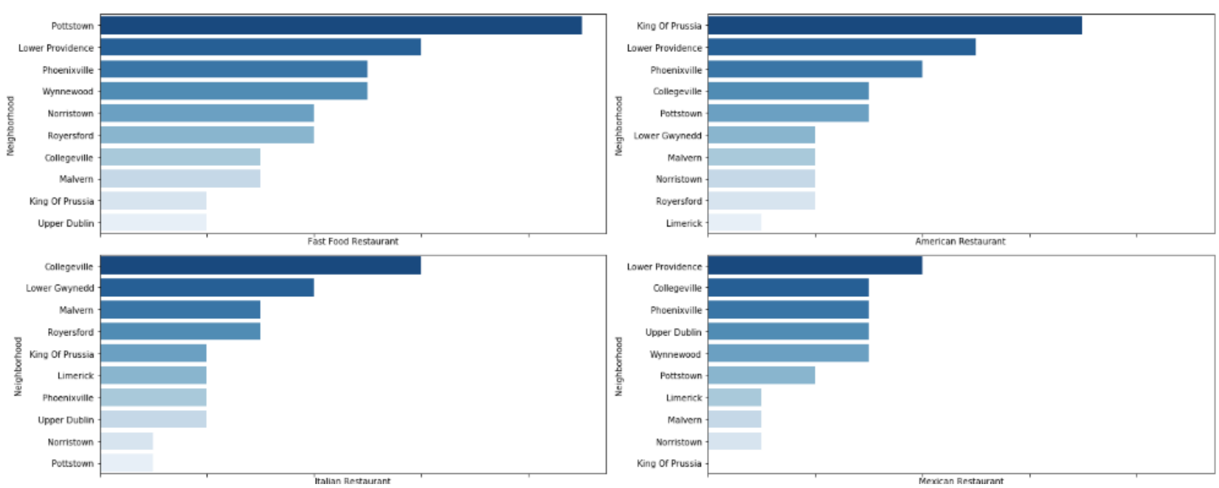
The top 10 restaurants from all these cities and their data description is as looks below:

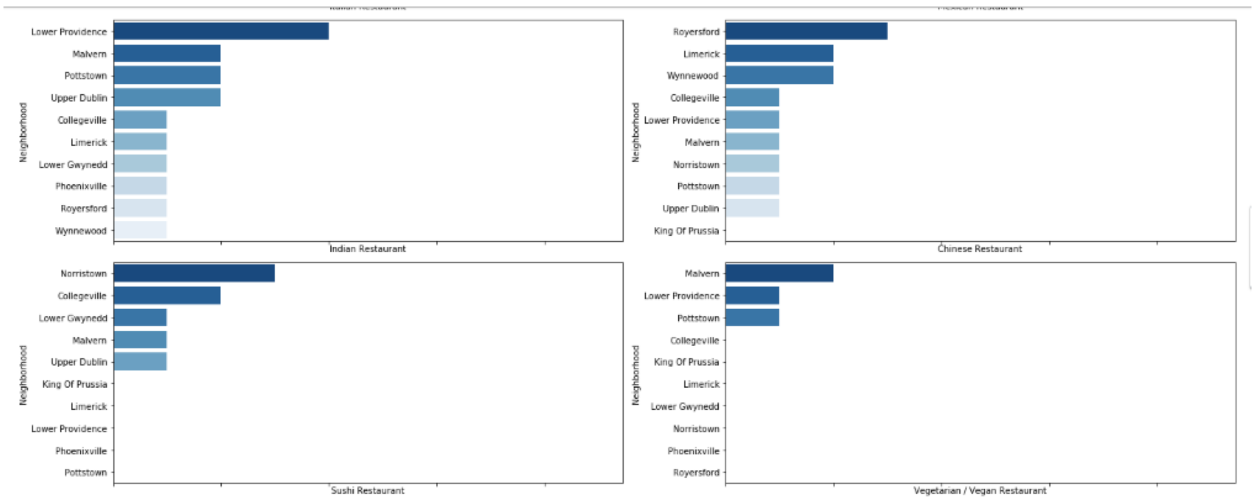
```
venue_counts_described = venue_counts.describe().transpose()
venue_top10 = venue_counts_described.sort_values('max', ascending=False)[0:10]
venue_top10
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Fast Food Restaurant** | 12.0 | 3.750000 | 2.301185 | 1.0 | 2.00 | 3.5 | 5.00 | 9.0 |
| **American Restaurant** | 12.0 | 2.750000 | 1.815339 | 1.0 | 1.75 | 2.0 | 3.25 | 7.0 |
| **Italian Restaurant** | 12.0 | 2.250000 | 1.602555 | 0.0 | 1.00 | 2.0 | 3.00 | 6.0 |
| **Mexican Restaurant** | 12.0 | 1.750000 | 1.422226 | 0.0 | 0.75 | 1.5 | 3.00 | 4.0 |
| **Indian Restaurant** | 12.0 | 1.333333 | 1.073087 | 0.0 | 1.00 | 1.0 | 2.00 | 4.0 |
| **Chinese Restaurant** | 12.0 | 1.083333 | 0.900337 | 0.0 | 0.75 | 1.0 | 1.25 | 3.0 |
| **Sushi Restaurant** | 12.0 | 0.666667 | 0.984732 | 0.0 | 0.00 | 0.0 | 1.00 | 3.0 |
| **Vegetarian / Vegan Restaurant** | 12.0 | 0.333333 | 0.651339 | 0.0 | 0.00 | 0.0 | 0.25 | 2.0 |
| **Thai Restaurant** | 12.0 | 0.333333 | 0.651339 | 0.0 | 0.00 | 0.0 | 0.25 | 2.0 |
| **Seafood Restaurant** | 12.0 | 0.583333 | 0.792961 | 0.0 | 0.00 | 0.0 | 1.00 | 2.0 |

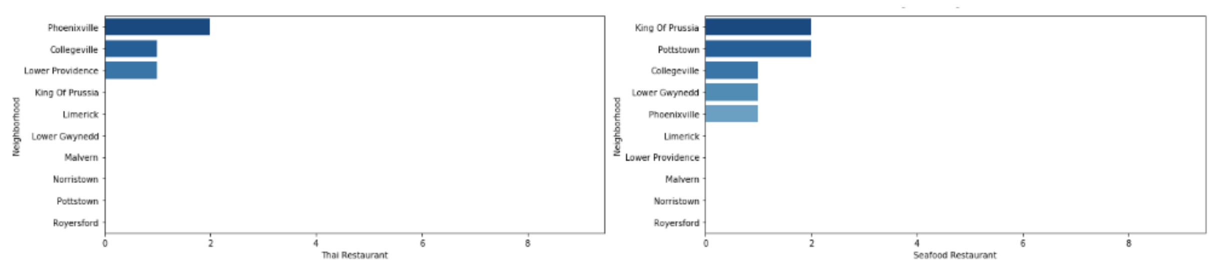
Based on our analysis, Fast Food restaurant are the most followed by American Restaurants. Over all the top 10 food categories gives us an idea that Montgomery county has the good mix of food ethnicity that includes American. Italian, Mexican, and other Asian countries

Now I'm trying to put the availability of different cuisines in the different locations…Let's see how the Horizontal bar chart comes in and then let's explore it in group chart



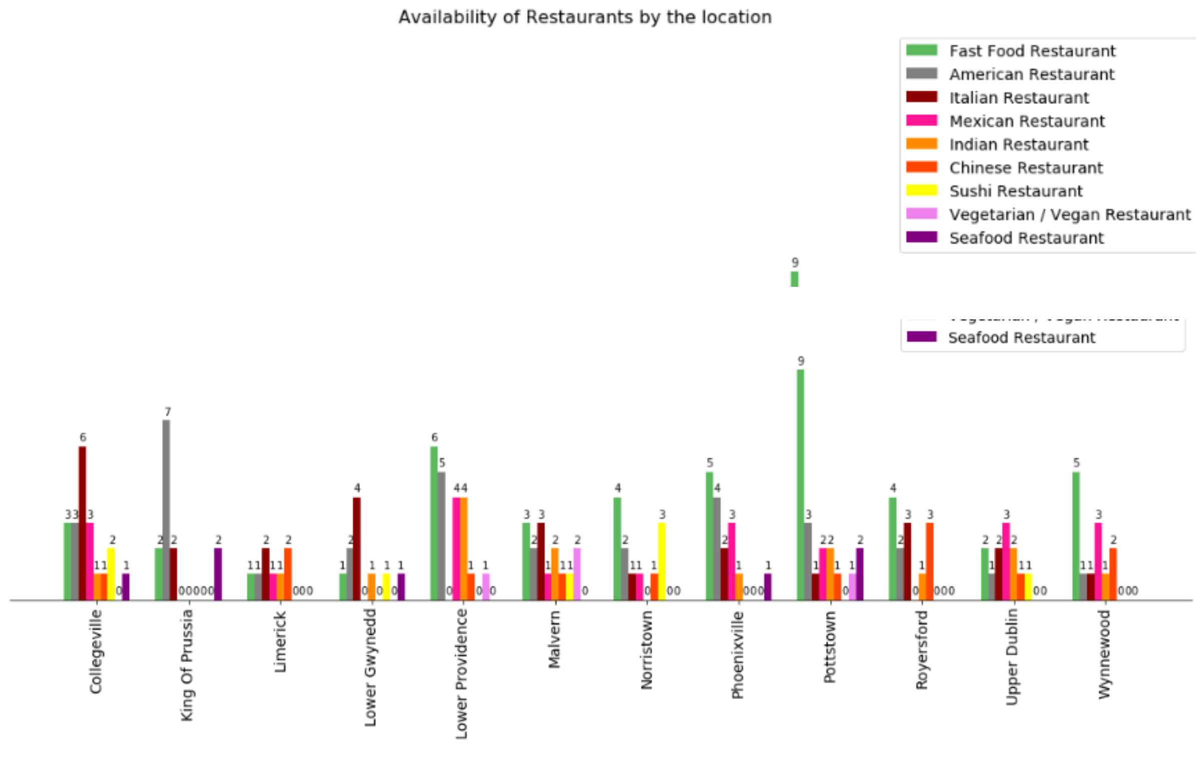


Lower Providence
Malvern
Pottstown
Upper Dublin
Collegeville
Limerick
Lower Gwynedd
Phoenixville
Royersford
Wynnewood
Neighborhood
Indian Restaurant
Royersford
Limerick
Wynnewood
Collegeville
Lower Providence
Malvern
Norristown
Pottstown
Upper Dublin
King Of Prussia
Neighborhood
Chinese Restaurant
Norristown
Collegeville
Lower Gwynedd
Malvern
Upper Dublin
King Of Prussia
Limerick
Lower Providence
Phoenixville
Pottstown
Neighborhood
Sushi Restaurant
Malvern
Lower Providence
Pottstown
Collegeville
King Of Prussia
Limerick
Lower Gwynedd
Norristown
Phoenixville
Royersford
Neighborhood
Vegetarian / Vegan Restaurant

Phoenixville
Collegeville
Lower Providence
King Of Prussia
Limerick
Lower Gwynedd
Malvern
Norristown
Pottstown
Royersford
Neighborhood
0
2
4
6
8
Thai Restaurant
King Of Prussia
Pottstown
Collegeville
Lower Gwynedd
Phoenixville
Limerick
Lower Providence
Malvern
Norristown
Royersford
Neighborhood
0
2
4
6
8
Seafood Restaurant

**Group Chart:**




Fast food restaurants, American Restaurants, Italian and Mexican Restaurants are common across locations. Indian, Chines Restaurants are more in some locations.

# Clustering and Segmenting the Cities:

Now lets cluster and segment the Cities by Cost of Living, Crime Rate, employment rate, Poverty rate and Rental rate into 2 groups.

```
# Modules
import matplotlib.pyplot as plt
from matplotlib.image import imread
from sklearn.datasets.samples_generator import (make_blobs,
                                                make_circles,
                                                make_moons)
from sklearn.cluster import KMeans, SpectralClustering
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_samples, silhouette_score

%matplotlib inline
sns.set_context('notebook')
plt.style.use('fivethirtyeight')
from warnings import filterwarnings
filterwarnings('ignore')

pdf=pd.read_csv('pennsylvania_Metadata.csv')

Citydf=pdf['City']
Montgomerypdf=pdf.drop('City',axis=1)

from sklearn.cluster import KMeans
# Standardize the data
X_std = StandardScaler().fit_transform(Montgomerypdf)

# Run Local implementation of kmeans
km = KMeans(init="k-means++",n_clusters=2, n_init=50).fit(X_std)
print('The labels out of Kmeans: ', km.labels_)
centroids=km.cluster_centers_
print('The centroids that come out of clustering: ',centroids)

#Insert the cluster Label in the parent daaframe
try:
    pdf.drop('Cluster Labels', axis=1)
except:
    pdf.insert(0, 'Cluster Labels', km.labels_)
# Merge the dataframes that holdes the clustered data and the geospatial data of cities in the montgomery county
finalpdf=pd.merge(pdf, Montgomerydf, on='City')
print('\n\n\nFinal dataframe with the clustered data (refer cluster lable column) and Geospatial data of cities looks as follows \n')
finalpdf
```

The cluster outputs attributes are as follows:

```
The labels out of Kmeans:  [1 1 0 0 0 0 1 0 0 0 0 1]
The centroids that come out of clustering:  [[ 0.57767656  0.14431655 -0.55347007  0.57942639 -0.585853    0.43813729]
 [-1.15535313 -0.2886331   1.10694013 -1.15885278  1.171706   -0.87627458]]
```

The Geospatial map with the clustered cities marked:

Lets see the cities in Cluster – 0

```
cluster_0 = finalpdf.loc[finalpdf['Cluster Labels'] == 0, finalpdf.columns[1:12]]
cluster_0
```

| | City | Income per capita | Unemployment rate | Poverty level | Cost of living index | Crime per 100k peopl | Mean rental rate | Latitude | Longitude | State | County |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Lower Gwynedd | 35755 | 0.05 | 0.10 | 111 | 832 | 1350 | 40.184365 | -75.226319 | PA | Montgomery |
| 3 | Lower Providence | 43387 | 0.02 | 0.05 | 131 | 688 | 1200 | 40.143300 | -75.422800 | PA | Montgomery |
| 4 | Collegeville | 33510 | 0.03 | 0.02 | 124 | 966 | 1300 | 40.185700 | -75.451600 | PA | Montgomery |
| 5 | Phoenixville | 32881 | 0.05 | 0.09 | 113 | 1317 | 1300 | 40.130400 | -75.514900 | PA | Montgomery |
| 7 | King Of Prussia | 44934 | 0.04 | 0.07 | 124 | 800 | 1600 | 40.101300 | -75.383600 | PA | Montgomery |
| 8 | Upper Dublin | 45745 | 0.03 | 0.01 | 135 | 638 | 1400 | 40.139832 | -75.188891 | PA | Montgomery |
| 9 | Wynnewood | 54087 | 0.03 | 0.03 | 137 | 645 | 1400 | 39.985409 | -75.272983 | PA | Montgomery |
| 10 | Malvern | 48086 | 3.50 | 0.11 | 132 | 684 | 1700 | 40.036200 | -75.513800 | PA | Montgomery |

Lets see the cities in Cluster – 1

```
cluster_1 = finalpdf.loc[finalpdf['Cluster Labels'] == 1, finalpdf.columns[1:12]]
cluster_1
```

| | City | Income per capita | Unemployment rate | Poverty level | Cost of living index | Crime per 100k peopl | Mean rental rate | Latitude | Longitude | State | County |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Pottstown | 23346 | 0.06 | 0.22 | 94 | 4325 | 1050 | 40.248003 | -75.626843 | PA | Montgomery |
| 1 | Royersford | 28169 | 0.06 | 0.13 | 110 | 2184 | 1300 | 40.184300 | -75.538000 | PA | Montgomery |
| 6 | Norristown | 21986 | 0.07 | 0.22 | 103 | 2214 | 900 | 40.121500 | -75.339900 | PA | Montgomery |
| 11 | Limerick | 24380 | 0.03 | 0.11 | 96 | 1917 | 1300 | 40.238400 | -75.184329 | PA | Montgomery |

The final dataframe with the cluster labels and geospatial data

| | Cluster Labels | City | Income per capita | Unemployment rate | Poverty level | Cost of living index | Crime per 100k peopl | Mean rental rate | Latitude | Longitude | State | County | Name | RegionID |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Pottstown | 23346 | 0.06 | 0.22 | 94 | 4325 | 1050 | 40.248003 | -75.626843 | PA | Montgomery | Washington/Rosedale | 761971 |
| 1 | 1 | Royersford | 28169 | 0.06 | 0.13 | 110 | 2184 | 1300 | 40.184300 | -75.538000 | PA | Montgomery | East End South | 761171 |
| 2 | 0 | Lower Gwynedd | 35755 | 0.05 | 0.10 | 111 | 832 | 1350 | 40.184365 | -75.226319 | PA | Montgomery | Spring House | 16311 |
| 3 | 0 | Lower Providence | 43387 | 0.02 | 0.05 | 131 | 688 | 1200 | 40.143300 | -75.422800 | PA | Montgomery | Downtown North | 761169 |
| 4 | 0 | Collegeville | 33510 | 0.03 | 0.02 | 124 | 966 | 1300 | 40.185700 | -75.451600 | PA | Montgomery | Beech/Wilson | 761168 |
| 5 | 0 | Phoenixville | 32881 | 0.05 | 0.09 | 113 | 1317 | 1300 | 40.130400 | -75.514900 | PA | Montgomery | Downtown South | 761170 |
| 6 | 1 | Norristown | 21986 | 0.07 | 0.22 | 103 | 2214 | 900 | 40.121500 | -75.339900 | PA | Montgomery | North End | 761970 |
| 7 | 0 | King Of Prussia | 44934 | 0.04 | 0.07 | 124 | 800 | 1600 | 40.101300 | -75.383600 | PA | Montgomery | Dresher | 38234 |
| 8 | 0 | Upper Dublin | 45745 | 0.03 | 0.01 | 135 | 638 | 1400 | 40.139832 | -75.188891 | PA | Montgomery | Fort Washington | 24770 |
| 9 | 0 | Wynnewood | 54087 | 0.03 | 0.03 | 137 | 645 | 1400 | 39.985409 | -75.272983 | PA | Montgomery | Penn Wynne | 6460 |
| 10 | 0 | Malvern | 48086 | 3.50 | 0.11 | 132 | 684 | 1700 | 40.036200 | -75.513800 | PA | Montgomery | West End | 275966 |
| 11 | 1 | Limerick | 24380 | 0.03 | 0.11 | 96 | 1917 | 1300 | 40.238400 | -75.184329 | PA | Montgomery | Maple Glen | 19189 |

# Discussion and insights of Analysis:

By looking at the group chart by restaurants, we can conclude that Fast food restaurants, American Restaurants, Italian and Mexican Restaurants are wide spread across all the cities which is as expected. The Indian Restaurants are more in Lower Providence city and Sushi Restaurants are more in Collegeville.

The cities Pottstown, Royersford, Norristown and Limerick are clustered into one group. The other cities are clustered into group 0. Again, we can observe that the cities in Cluster-1 has more crime rate and less per capita income. we can see the uniqueness. On the other end, the cities in Cluster-0 has less crime rate and the other factors are good compared to cities in cluster-1.

# Conclusion:

Lets assume a Indian looking for the better city to settle, he or she will prefer to choose Lower providence since it is in cluster-0 with less crime rate and other better factors. The city Lower Providence also has more Indian Restaurants and as per our initial assumption, more Indian Restaurant means more Indians in the city.

In case if a real estate house looks for a new location to start a housing project, it will choose a city from Cluster-0.

The same analysis can further be enhanced to find better counties in the state or the better state in the country by following the same approach.

# End User/Beneficiary:

This analysis will be beneficial for anyone who wish to choose a location to buy house/get settled. This model/analysis can also be used by real estate business house' to understand the customer preferences on locations.

### Data References:


1. https://data.opendatasoft.com/
2. https://foursquare.com/
3. https://data.montgomerycountymd.gov/
4. Google Geo Locator