Prospects of a opening an Vegan Restaurant in Manhattan

As part of the IBM Data Science Capstone Project, I have decided to work on the problem on finding the best location to start a new Vegan restaurant in New York. Main objective of this section was to define the problem and discuss the ways in which the data can be found. The data will be got from different sources including the web, open source .CSV files and Four Square data. Analysis will be done on this data to find out which is the best neighbourhood suitable for starting a new vegan restaurant. In this report, the step-by-step process from explaining the problem, preparing the data, analysing, and thus deriving the conclusion will be discussed in detail.

Introduction: Description of the problem.

New York City has been described as the cultural, financial, and media capital of the world, significantly influencing commerce, entertainment, research, technology, education, politics, tourism, art, fashion, and sports. New York City is composed of five boroughs, each of which is a county of the State of New York. The five boroughs -
Brooklyn, Queens, Manhattan, the Bronx, and Staten Island.

New York City's food culture includes an array of international cuisines influenced by the city's immigrant history. The city is home to "nearly one thousand of the finest and most diverse haute cuisine restaurants in the world", according to Michelin. Hence it will be an easy choice to start a new Vegan Restaurant in New York, but with limited knowledge of the demographics starting a restaurant in an already overcrowded market will be futile.

Hence the criteria set by the clients to look for the best neighbourhood to start the restaurant will be as follows:

- *Most concentrated areas of Vegetarian/Vegan restaurants in Manhattan.*

Target audience:

1. Business personnel who wants to invest or open a Vegan restaurant or any other type of new restaurant in an already crowded New York market. This analysis will be a comprehensive guide to start or expand restaurants targeting the young to middle aged crowd.

2. Freelancer Chef who loves to have their own restaurant as a side-line.

Data:

Mainly two types of data will be used for this project.

1. The first one is the file containing the neighbourhoods of New York. Neighborhood has a total of 5 boroughs and 306 neighborhoods. In order to segement the neighborhoods and explore them, we will essentially need a dataset that contains the 5 boroughs and the neighborhoods that exist in each borough as well as the the latitude and logitude coordinates of each neighborhood.

Luckily, this dataset exists for free on the web. Here is the link to the dataset: https://geo.nyu.edu/catalog/nyu_2451_34572

a) And this will be converted to a DataFrame.

Assumptions made to a DataFrame of neighbourhoods in New York:

- Dataframe will consist of three columns: PostalCode, Borough, and Neighborhood

- Only the cells that have an assigned borough will be processed. Borough that is not assigned are ignored.
- More than one neighborhood can exist in one postal code area. These two rows will be combined into one row with the neighborhoods separated with a comma as shown in row 11 in the above table.
- If a cell has a borough but a Not assigned neighborhood, then the neighborhood will be the same as the borough.

b) Adding geographical coordinates to the neighborhoods

Next important step is adding the geographical coordinates to these neighborhoods. To do so we will be extracting the data present in the Geospatial Data csv file and combining it with the existing neighborhood dataframe by merging them both based on the postal code.

Neighbourhood level data from a variety of other sources are also available through the City's mapping application and here on the Open Data portal.

Each data point in this file is presented for the City's neighbourhoods, as well as for the City of Toronto as a whole. The data is sourced from several Census tables released by Statistics. The general Census Profile is the main source table for this data, but other Census tables have also been used to provide additional information.

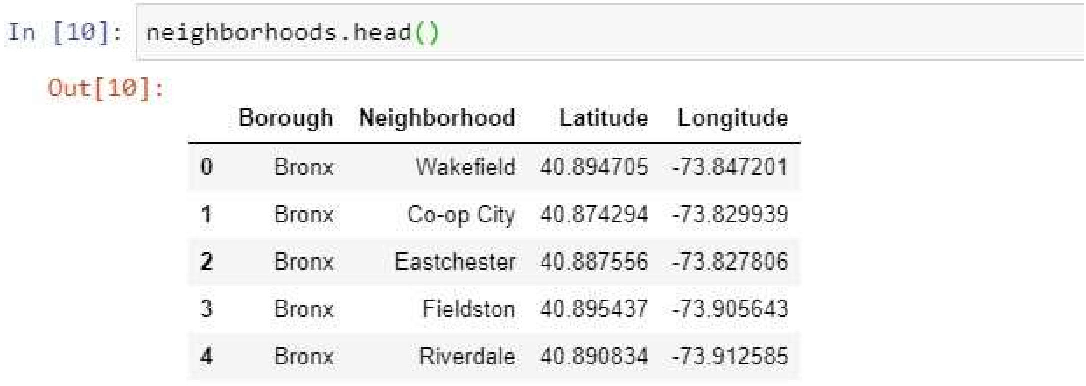
c) Scrap the distribution of population from Wikipedia

Another factor that can help us in deciding which neighborhood would be best option to open a restaurant is, the distribution of population based on the ethnic diversity for each neighborhood. As this helps us in identifying the neighborhoods which are densely populated with Indian crowd since that neighborhood would be an ideal place to open an Indian restaurant.

2) The other type of data is from FourSquare to get the location data of venues in the neighbourhoods. Foursquare API is very useful online application used my many developers & other applications like Uber etc. In this project we will use it to retrieve information about the places present in the neighborhoods of New York. The API returns a JSON file and we need to turn that into a data-frame. Here we will choose 100 popular spots for each neighbourhood within a radius of 1km.

Methodology:

We will first get all the data into a data frame as shown.

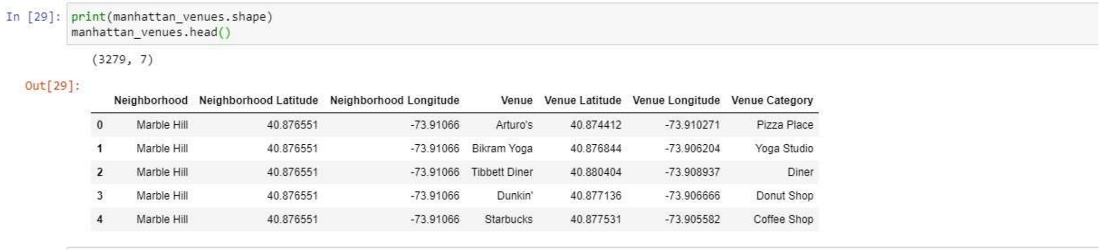


```
In [10]: neighborhoods.head()
```

Out[10]:

	Borough	Neighborhood	Latitude	Longitude
0	Bronx	Wakefield	40.894705	-73.847201
1	Bronx	Co-op City	40.874294	-73.829939
2	Bronx	Eastchester	40.887556	-73.827806
3	Bronx	Fieldston	40.895437	-73.905643
4	Bronx	Riverdale	40.890834	-73.912585

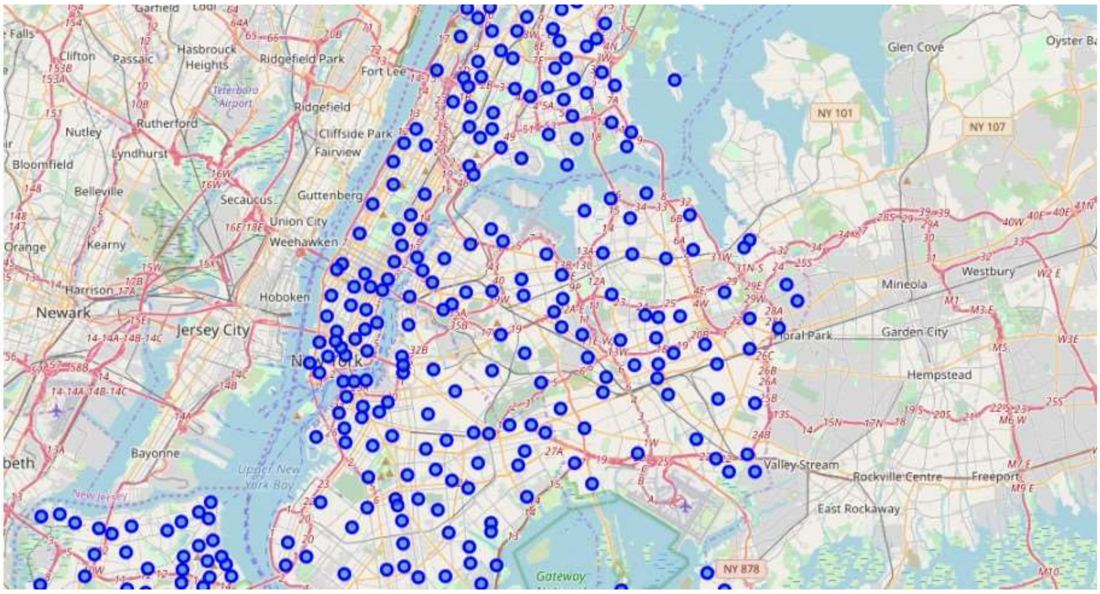
We will use geopy library for getting coordinates of Manhattan, New York for further use. Using FourSquare is very useful as it is very comprehensive and it powers location data for Apple, Uber etc. For this business problem I have used, the FourSquare API to retrieve information about the Venue, Venue category with the longitudes and latitudes. The call returns a JSON file and we need to turn that into a data-frame. Here I've chosen 100 popular spots for each neighborhoods within a radius of 500 meters. Below is the data-frame obtained from the JSON file that was returned by Foursquare



```
In [29]: print(manhattan_venues.shape)
         manhattan_venues.head()

           (3279, 7)

Out[29]:
```

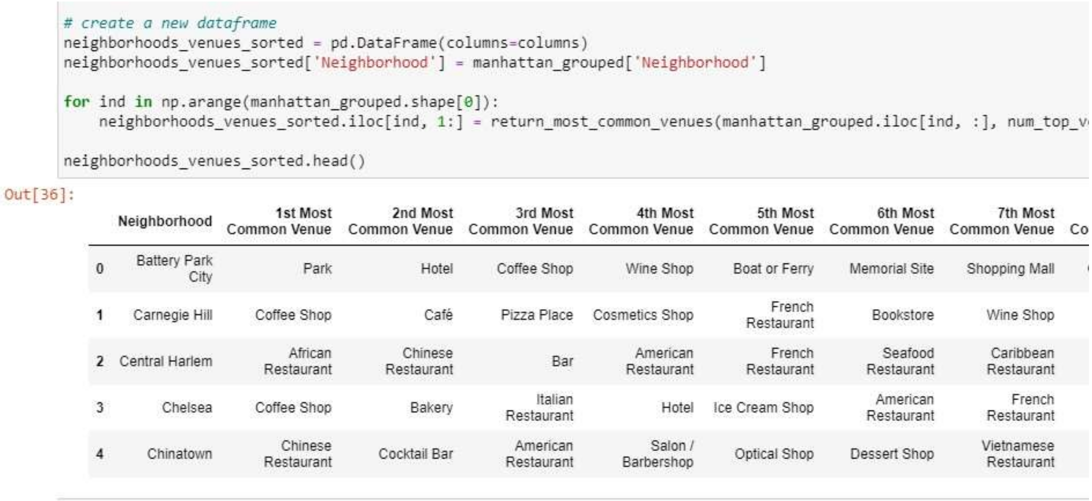
	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Marble Hill	40.876551	-73.91066	Arturo's	40.874412	-73.910271	Pizza Place
1	Marble Hill	40.876551	-73.91066	Bikram Yoga	40.876844	-73.906204	Yoga Studio
2	Marble Hill	40.876551	-73.91066	Tibbett Diner	40.880404	-73.908937	Diner
3	Marble Hill	40.876551	-73.91066	Dunkin'	40.877136	-73.906666	Donut Shop
4	Marble Hill	40.876551	-73.91066	Starbucks	40.877531	-73.905582	Coffee Shop

A folium map was created as shown below:



Exploratory Data Analysis:

There are 271 unique categories in which Vegetarian/Vegan is one of them. We will do one hot encoding for getting dummies of venue category. Then we will group venue using the groupby using neighborhoods.

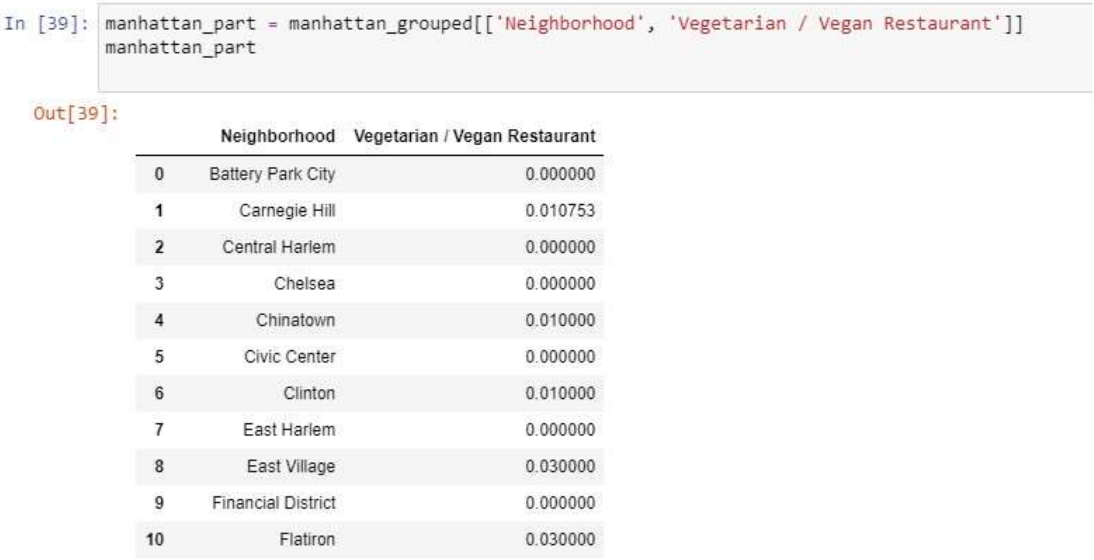


```
# create a new dataframe
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhood'] = manhattan_grouped['Neighborhood']

for ind in np.arange(manhattan_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(manhattan_grouped.iloc[ind, :], num_top_v

neighborhoods_venues_sorted.head()
```

Out[36]:

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	Co
0	Battery Park City	Park	Hotel	Coffee Shop	Wine Shop	Boat or Ferry	Memorial Site	Shopping Mall	
1	Carnegie Hill	Coffee Shop	Café	Pizza Place	Cosmetics Shop	French Restaurant	Bookstore	Wine Shop	
2	Central Harlem	African Restaurant	Chinese Restaurant	Bar	American Restaurant	French Restaurant	Seafood Restaurant	Caribbean Restaurant	
3	Chelsea	Coffee Shop	Bakery	Italian Restaurant	Hotel	Ice Cream Shop	American Restaurant	French Restaurant	
4	Chinatown	Chinese Restaurant	Cocktail Bar	American Restaurant	Salon / Barbershop	Optical Shop	Dessert Shop	Vietnamese Restaurant	

After this we will extract only Neighborhood and Vegan restaurant column for further analysis:

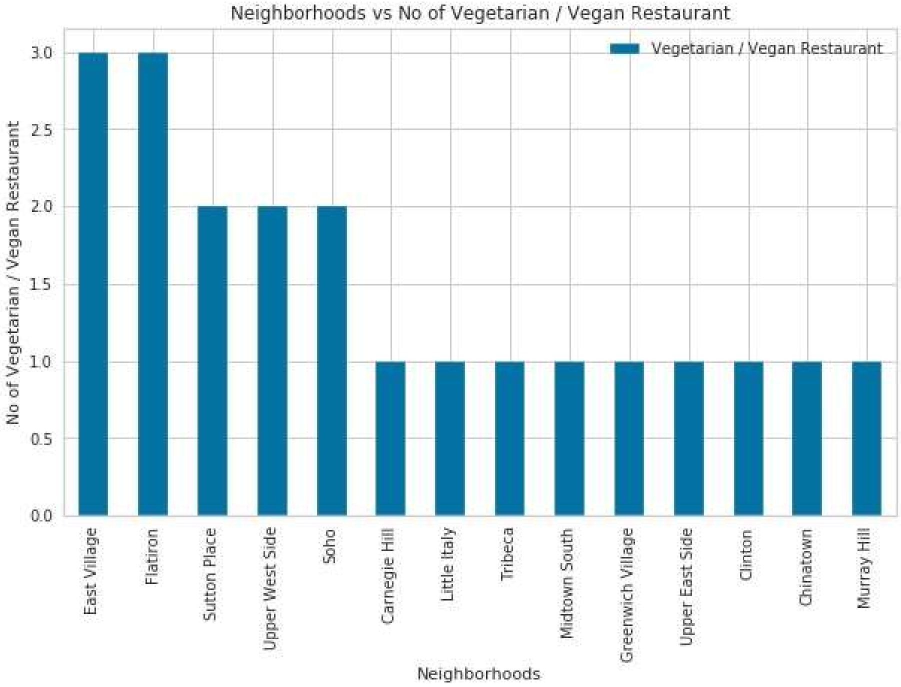


```
In [39]: manhattan_part = manhattan_grouped[['Neighborhood', 'Vegetarian / Vegan Restaurant']]
         manhattan_part
```

Out[39]:

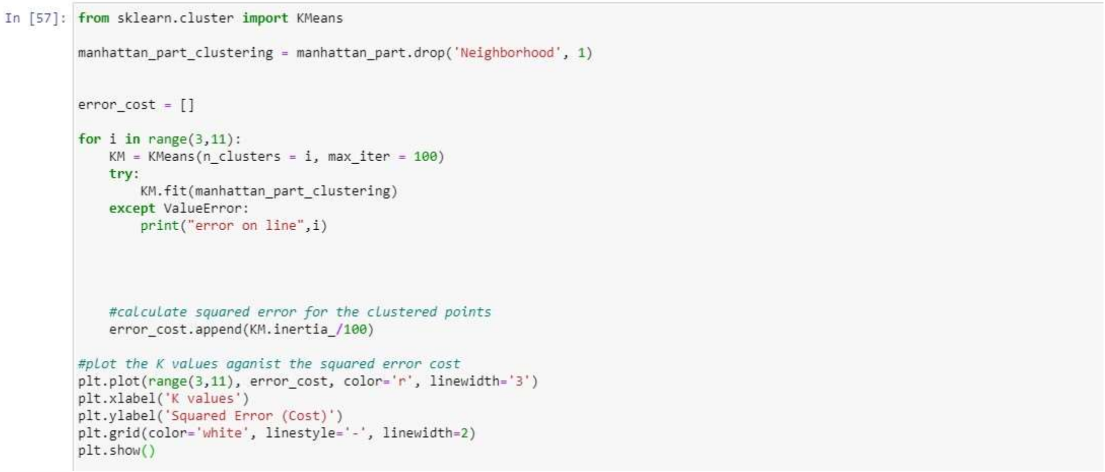
	Neighborhood	Vegetarian / Vegan Restaurant
0	Battery Park City	0.000000
1	Carnegie Hill	0.010753
2	Central Harlem	0.000000
3	Chelsea	0.000000
4	Chinatown	0.010000
5	Civic Center	0.000000
6	Clinton	0.010000
7	East Harlem	0.000000
8	East Village	0.030000
9	Financial District	0.000000
10	Flatiron	0.030000

Vegetarian restaurant vs neighbourhoods plot:



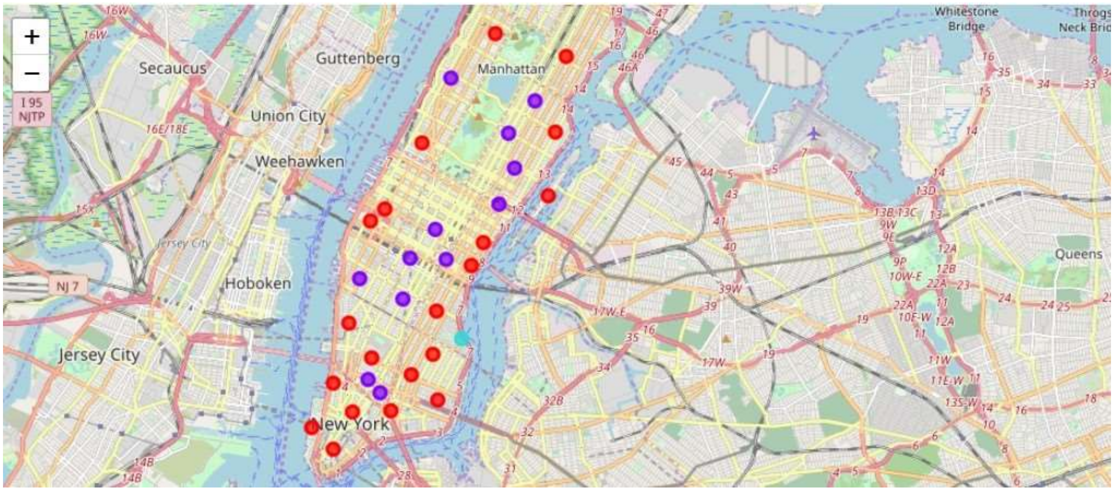
Clustering the Neighborhoods:

We will extract Vegan restaurant data from above table and fit this into the code for finding best value of K.

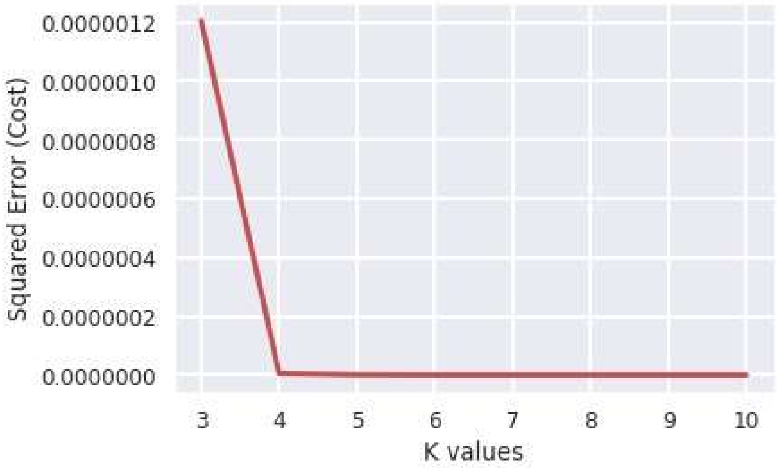


```
In [57]: from sklearn.cluster import KMeans

         manhattan_part_clustering = manhattan_part.drop('Neighborhood', 1)


         error_cost = []

         for i in range(3,11):
             KM = KMeans(n_clusters = i, max_iter = 100)
             try:
                 KM.fit(manhattan_part_clustering)
             except ValueError:
                 print("error on line",i)



             #calculate squared error for the clustered points
             error_cost.append(KM.inertia_/100)

         #plot the K values aganist the squared error cost
         plt.plot(range(3,11), error_cost, color='r', linewidth='3')
         plt.xlabel('K values')
         plt.ylabel('Squared Error (Cost)')
         plt.grid(color='white', linestyle='-', linewidth=2)
         plt.show()
```

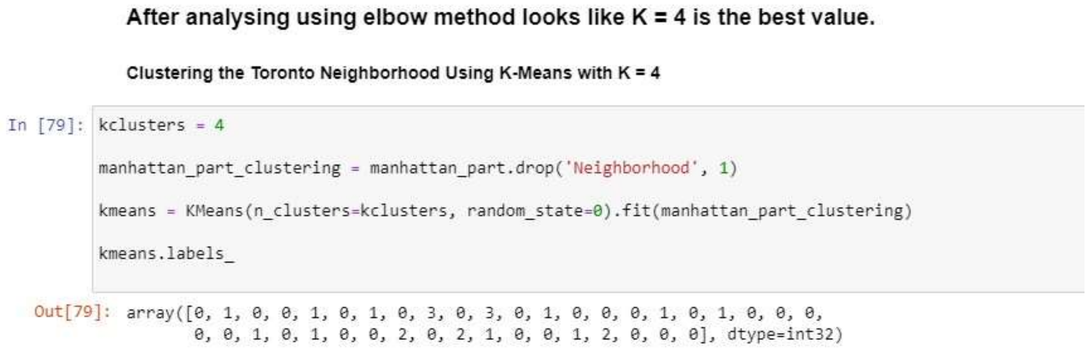
A folium map of the cluster is given:



Elbow chart for the best value of k:



From the above chart we can see that k=4 is the best value for our data set. Hence we can use it to cluster our neighbourhood.



After analysing using elbow method looks like K = 4 is the best value.

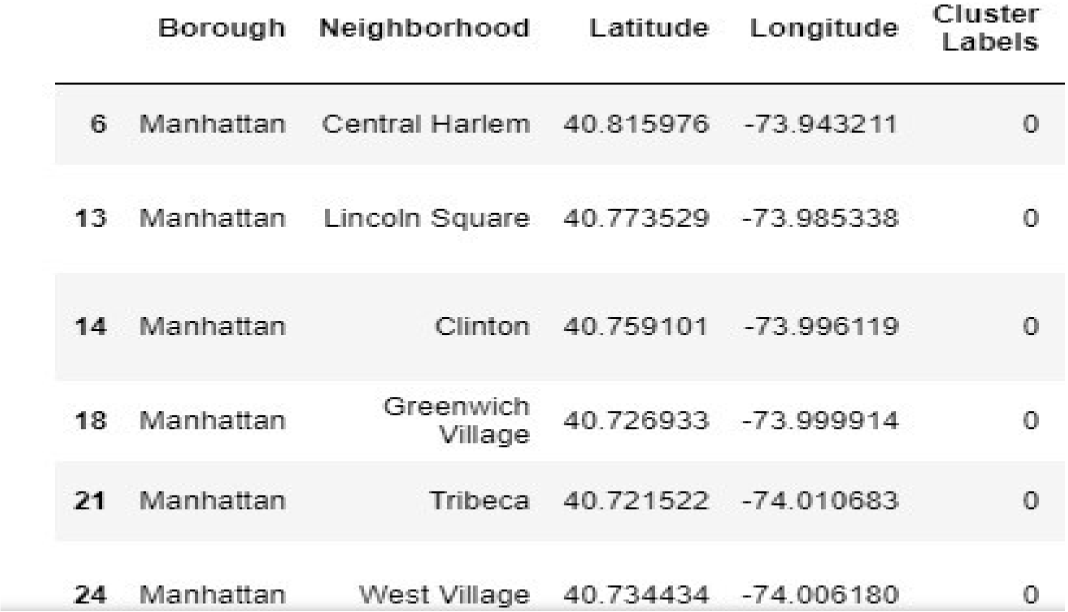
Clustering the Toronto Neighborhood Using K-Means with K = 4

```
In [79]: kclusters = 4

         manhattan_part_clustering = manhattan_part.drop('Neighborhood', 1)

         kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(manhattan_part_clustering)

         kmeans.labels_
```

```
Out[79]: array([0, 1, 0, 0, 1, 0, 1, 0, 3, 0, 3, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
                0, 0, 1, 0, 1, 0, 0, 2, 0, 2, 1, 0, 0, 1, 2, 0, 0, 0], dtype=int32)
```

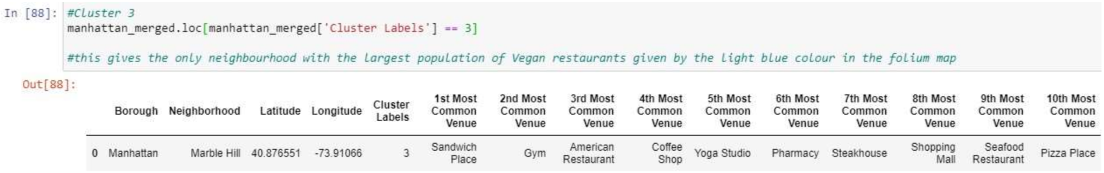
The cluster values are 0, 1, 2 and 3.

For cluster value of 0 the values of Boroughs are as follows they are shown as red dots on the above Folium map.



	Borough	Neighborhood	Latitude	Longitude	Cluster Labels
6	Manhattan	Central Harlem	40.815976	-73.943211	0
13	Manhattan	Lincoln Square	40.773529	-73.985338	0
14	Manhattan	Clinton	40.759101	-73.996119	0
18	Manhattan	Greenwich Village	40.726933	-73.999914	0
21	Manhattan	Tribeca	40.721522	-74.010683	0
24	Manhattan	West Village	40.734434	-74.006180	0

For cluster value of 3 the value of Boroughs are as follows it is shown as the light blue dot on the above Folium map.



```
In [88]: #Cluster 3
         manhattan_merged.loc[manhattan_merged['Cluster Labels'] == 3]

         #this gives the only neighbourhood with the largest population of Vegan restaurants given by the light blue colour in the folium map
```

Out[88]:

	Borough	Neighborhood	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Manhattan	Marble Hill	40.876551	-73.91066	3	Sandwich Place	Gym	American Restaurant	Coffee Shop	Yoga Studio	Pharmacy	Steakhouse	Shopping Mall	Seafood Restaurant	Pizza Place

Results and Discussion:

Results

We have reached the end of the analysis, in the result section we can document all the findings from above clustering & visualization of the data. In this project, as the business problem started with identifying a good neighborhood to open a new Vegan restaurant, we looked into all the neighborhoods in Manhattan, analysed spread of Vegan restaurants in those neighborhoods to come to conclusion about which neighborhood would be a better spot for opening a new Vegan restaurant. I have used data from web resources like Wikipedia, geospatial coordinates of Manhattan neighborhoods, and Foursquare API, to set up a very realistic data-analysis scenario. We have found out that there are 14 neighbourhoods have already got a least density of Vegan restaurants. they include:

1. Central Harlem
2. Lincoln Square
3. Clinton
4. Greenwich Village
5. Tribeca
6. West Village
7. Morning Heights
8. Gramercy
9. Battery Park City
10. Financial District
11. Noho
12. Civic Centre
13. Turtle bay
14. Hudson yards

So it would be a good idea to start in the above areas as they do not have enough Vegan restaurants and it will be a good business investment.

With a cluster value of 3, Marble Hill is the worst neighbourhood to open a new Vegan restaurant as this is already an over saturated area of vegan restaurants. We can then use the same project to analyse the best options for other restaurants and even other type of business establishments like gym, cinema, etc

Discussion

I really enjoyed doing this data analysis as it gave me the required ideas to work out the most suitable place to open a restaurant. and this can be used to analyse opening any type of restaurant. The biggest drawback is the clustering is based only on the information provided by Foursquare and the data is not up to date. Nevertheless, it certainly provides us with some good insights, preliminary information on possibilities and a head start into this business problem by setting the step stones properly. Furthermore, this may also potentially vary depending on the type of clustering techniques that we use to examine the data.

Conclusion:

As part of the IBM Data Science Capstone Project, I decided to work on the problem on finding the best location to start a new Vegan restaurant in New York. Analysis was done on this data to find out which is the best neighbourhood suitable for starting a new vegan restaurant. The datasets contents were manipulated and visualised using the different methods in Python. I also applied machine learning technique to predict the output given the data and used Folium to visualize it on a map. We can then use the same project to analyse the best options for other restaurants and even other type of business establishments like gym, cinema, etc. Hopefully, this project helps as an initial guidance to take head on more complex real-life challenges using data-science