Comparison of Neighborhoods in New York and Toronto

Introduction

In this Notebook I have tried to solve a problem , suppose a friend of yours came to you and he wants to shift from New York to Toronto and he does not know in which neighborhood he should move . He is a very choosy guy and is afraid to move to a unfamiliar neighborhood. Here in this neighborhood i tried to solve his problem by comparing the neighborhoods of both cities and giving him a list of options to choose from and this makes his decision easy because now he can move in a neighborhood with similar features and traits as he was having in his current neighborhood in New York.

1. Importing Revelent Libraries

In [135]:

```
# library to handle data in a vectorized manner
import numpy as np

# library for data analsysis
import pandas as pd
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

# library to handle JSON files
import json

# convert an address into latitude and longitude values
from geopy.geocoders import Nominatim

# library to handle requests
import requests

# tranform JSON file into a pandas dataframe
from pandas.io.json import json_normalize

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors
import matplotlib.pyplot as plt
import seaborn as sbs
sbs.set()

# import k-means from clustering stage
from sklearn.cluster import KMeans

# map rendering library
import folium

#web servers data reciving library
import wget

#Library used to query a website
import urllib.request

# Webscrappiing library for parsing websites
from bs4 import BeautifulSoup
print('Libraries imported.')
```

```
Libraries imported.
```

2. Data Gathering and data Wrangling

2.1 Data Accusition

Web Scrapping For Toronto Data

As there is no specific dataset on postal codes of toronto I will get data from Wikipedia for that purpose i have to use web scrapping . I have done it by using BeautifulSoup Library

In [2]:

```
# set the url in a variable
url="https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M"

# request html file from url
page=urllib.request.urlopen(url)
```

In [3]:

```
#parsing the html and storing it in a new variable soup
soup=BeautifulSoup(page)

#seeing the nested structure of html
print(soup.prettify())
```

```
<!DOCTYPE html>
<html class="client-nojs" dir="ltr" lang="en">
 <head>
  <meta charset="utf-8"/>
  <title>
   List of postal codes of Canada: M - Wikipedia
  </title>
  <script>
   document.documentElement.className="client-js";RLCONF={"wgBreakFrame
s":!1,"wgSeparatorTransformTable":["",""],"wgDigitTransformTable":
["",""],"wgDefaultDateFormat":"dmy","wgMonthNames":["","January","Februar
y","March","April","May","June","July","August","September","October","Nov
ember","December"],"wgRequestId":"0906c2a3-efbb-4789-961b-f63b6aed2219","w
gCSPNonce":!1,"wgCanonicalNamespace":"","wgCanonicalSpecialPageName":!1,"w
gNamespaceNumber":0,"wgPageName":"List_of_postal_codes_of_Canada:_M","wgTi
tle":"List of postal codes of Canada: M","wgCurRevisionId":960187814,"wgRe
visionId":960187814,"wgArticleId":539066,"wgIsArticle":!0,"wgIsRedirect":!
1,"wgAction":"view","wgUserName":null,"wgUserGroups":["*"],"wgCategories":
["Articles with short description","Communications in Ontario","Postal cod
```

In [4]:

```
#checking for all avilible tables on website
all_tables=soup.find_all('table')
all_tables
```

Out[4]:

```
[<table class="wikitable sortable">
 <tbody><tr>
 <th>Postal Code
 </th>
 <th>Borough
 </th>
 <th>Neighborhood
 </th></tr>
 <tr>
 <td>M1A
 </td>
 <td>Not assigned
 </td>
 <td>Not assigned
 </td></tr>
 <tr>
 <td>M2A
 </td>
```

In [5]:

```
# defining the table that we need only
right_table=soup.find('table', {'class':'wikitable sortable'})
right_table
```

Out[5]:

```
<table class="wikitable sortable">
<tbody><tr>
<th>Postal Code
</th>
<th>Borough
</th>
<th>Neighborhood
</th></tr>
<tr>
<td>M1A
</td>
<td>Not assigned
</td>
<td>Not assigned
</td></tr>
<tr>
<td>M2A
</td>
```

In [6]:

```
#Generate lists
A=[]
B=[]
C=[]
for row in right_table.findAll("tr"):
    cells = row.findAll('td')
    if len(cells)==3:
        A.append(cells[0].find(text=True))
        B.append(cells[1].find(text=True))
        C.append(cells[2].find(text=True))
#Removing escape Sequence "\n" from lists
A = [x.replace('\n', '') for x in A]
B = [x.replace('\n', '') for x in B]
C = [x.replace('\n', '') for x in C]
```

Converting the Scrapped data in Pandas Dataframe

In [7]:

```
#creating new data frame with column names an pushing data from lists A,B and C
df=pd.DataFrame(A,columns=['Postal Code'])
df["Borough"]=B
df["Neighborhood"]=C
df.head()
```

Out[7]:

	Postal Code	Borough	Neighborhood
0	M1A	Not assigned	Not assigned
1	M2A	Not assigned	Not assigned
2	M3A	North York	Parkwoods
3	M4A	North York	Victoria Village
4	M5A	Downtown Toronto	Regent Park, Harbourfront

Downloading New York Data

In [8]:

```
a=wget.download('https://cocl.us/new_york_dataset/newyork_data.json')
print('Data downloaded!')
```

```
Data downloaded!
```

Load and explore the data

In [9]:

```
# Loading data
with open(a) as json_data:
    newyork_data = json.load(json_data)
```

In [10]:

```
newyork_data
```

Out[10]:


```
{'type': 'FeatureCollection',
 'totalFeatures': 306,
 'features': [{'type': 'Feature',
   'id': 'nyu_2451_34572.1',
   'geometry': {'type': 'Point',
    'coordinates': [-73.84720052054902, 40.89470517661]},
   'geometry_name': 'geom',
   'properties': {'name': 'Wakefield',
    'stacked': 1,
    'annoline1': 'Wakefield',
    'annoline2': None,
    'annoline3': None,
    'annoangle': 0.0,
    'borough': 'Bronx',
    'bbox': [-73.84720052054902,
     40.89470517661,
     -73.84720052054902,
     40.89470517661]}},
```


In [11]:

```
# Extracting data
neighborhoods_data = newyork_data['features']

# define the dataframe columns
column_names = ['Borough', 'Neighborhood', 'Latitude', 'Longitude']

# instantiate the dataframe
NY_neighborhoods = pd.DataFrame(columns=column_names)

# defining loop for filling the data in new dataframe
for data in neighborhoods_data:
    borough = neighborhood_name = data['properties']['borough']
    neighborhood_name = data['properties']['name']

    neighborhood_latlon = data['geometry']['coordinates']
    neighborhood_lat = neighborhood_latlon[1]
    neighborhood_lon = neighborhood_latlon[0]

    NY_neighborhoods = NY_neighborhoods.append({'Borough': borough,
                                          'Neighborhood': neighborhood_name,
                                          'Latitude': neighborhood_lat,
                                          'Longitude': neighborhood_lon}, ignore_index=True
```

In [12]:

```
NY_neighborhoods.head()
```

Out[12]:

	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

In [139]:

```
NY_neighborhoods.to_csv('C:/Users/camar/Desktop/projects/Machine-Learning-Unsupervised-/Dat
```

In [13]:

```
NY_neighborhoods.shape
```

Out[13]:

```
(306, 4)
```

2.2 Data Wrangling

In [14]:

```
#Creating a checkpoint
Raw_data=df.copy()
Raw_data.head()
Raw_data.shape
```

Out[14]:

```
(180, 3)
```

In [136]:

```
# Removing rows with "Not assigned" Borough of Toronto Data
cleaned_df=Raw_data.drop(df.loc[df['Borough']=='Not assigned'].index)
cleaned_df.reset_index(drop=True,inplace=True)
cleaned_df.head(5)
```

Out[136]:

	Postal Code	Borough	Neighborhood
0	M3A	North York	Parkwoods
1	M4A	North York	Victoria Village
2	M5A	Downtown Toronto	Regent Park, Harbourfront
3	M6A	North York	Lawrence Manor, Lawrence Heights
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government

In [137]:

```
#grouping columns with unique Postal code and combining duplicate Postal codes
grp_df=cleaned_df.groupby(["Postal Code","Borough"]).agg({"Neighborhood":",".join}).reset_i
grp_df.head(5)
```

Out[137]:

	Postal Code	Borough	Neighborhood
0	M1B	Scarborough	Malvern, Rouge
1	M1C	Scarborough	Rouge Hill, Port Union, Highland Creek
2	M1E	Scarborough	Guildwood, Morningside, West Hill
3	M1G	Scarborough	Woburn
4	M1H	Scarborough	Cedarbrae

In [17]:

```
#checking shape of dataframe
print(grp_df.shape)
```

```
(103, 3)
```

In [18]:

```
#Confirming that dataframe is correct " Extracting Postal code for M5A"
grp_df.loc[grp_df['Postal Code']=='M5A']
```

Out[18]:

	Postal Code	Borough	Neighborhood
53	M5A	Downtown Toronto	Regent Park, Harbourfront

In [19]:

```
#Checking if the unique values of postal code are equall to number of rows in data frame
grp_df["Postal Code"].nunique()
```

Out[19]:

```
103
```

Longitude and langitude values for Postal codes

In [20]:

```
#getting csv file containing lon, lat , values
Coordinates=pd.read_csv("http://cocl.us/Geospatial_data/Geospatial_Coordinates.csv")
Coordinates.head()
```

Out[20]:

	Postal Code	Latitude	Longitude
0	M1B	43.806686	-79.194353
1	M1C	43.784535	-79.160497
2	M1E	43.763573	-79.188711
3	M1G	43.770992	-79.216917
4	M1H	43.773136	-79.239476

In [21]:

```
# Creating new dataframe with the Coordinates included
DF_LL=grp_df.copy()
DF_LL["Latitude"]=Coordinates["Latitude"]
DF_LL["Longitude"]=Coordinates["Longitude"]
DF_LL.head()
```

Out[21]:

	Postal Code	Borough	Neighborhood	Latitude	Longitude
0	M1B	Scarborough	Malvern, Rouge	43.806686	-79.194353
1	M1C	Scarborough	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497
2	M1E	Scarborough	Guildwood, Morningside, West Hill	43.763573	-79.188711
3	M1G	Scarborough	Woburn	43.770992	-79.216917
4	M1H	Scarborough	Cedarbrae	43.773136	-79.239476

In [22]:

```
#Checking if values are correctly assigned to Postal Code
DF_LL.loc[grp_df['Postal Code']=='M5G']
```

Out[22]:

	Postal Code	Borough	Neighborhood	Latitude	Longitude
57	M5G	Downtown Toronto	Central Bay Street	43.657952	-79.387383

In [140]:

```
DF_LL.to_csv('C:/Users/camar/Desktop/projects/Machine-Learning-Unsupervised-/Data/Toronto_C
```

Creating DataFrame With Toronto Neighbourhoods

Toronto=DF_LL.loc[grp_df['Borough'].str.contains('Toronto')].reset_index(drop=True) Toronto.head()

In [23]:

```
DF_LL.shape
```

Out[23]:

```
(103, 5)
```

3. Maping of Neighbourhoods In Toronto And New York

Getting Geospatial data of Toronto

In [24]:

```
address_Tor = 'Toronto'

geolocator_Tor = Nominatim(user_agent="TN_explorer")
location_Tor = geolocator_Tor.geocode(address_Tor)
latitude_Tor = location_Tor.latitude
longitude_Tor = location_Tor.longitude
print('The geograpical coordinate of Toronto are {}, {}.'.format(latitude_Tor, longitude_To
```

```
The geograpical coordinate of Toronto are 43.6534817, -79.3839347.
```

Getting Geospatial data of New York

In [25]:

```
address_NY = 'New York City, NY'

geolocator_NY = Nominatim(user_agent="ny_explorer")
location_NY = geolocator_NY.geocode(address_NY)
latitude_NY = location_NY.latitude
longitude_NY = location_NY.longitude
print('The geograpical coordinate of New York City are {}, {}.'.format(latitude_NY, longitu
```

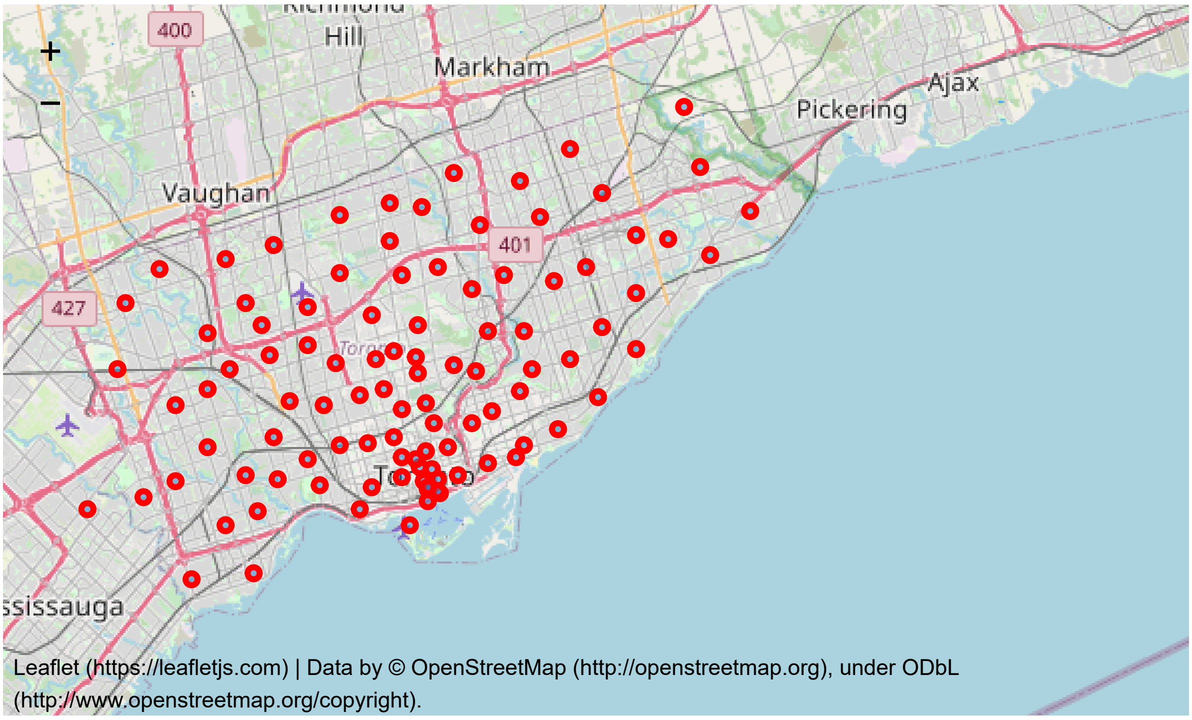
```
The geograpical coordinate of New York City are 40.7127281, -74.0060152.
```

Visualization of Toronto and its Neighbourhoods

In [26]:

```
# map of Toronto using latitude and longitude values
map_Toronto = folium.Map(location=[latitude_Tor, longitude_Tor], zoom_start=10)

# add markers to map
for lat, lng, label in zip(DF_LL['Latitude'], DF_LL['Longitude'], DF_LL['Neighborhood']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=3,
        popup=label,
        color='red',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.5,
        parse_html=False).add_to(map_Toronto)

map_Toronto
```

Out[26]:

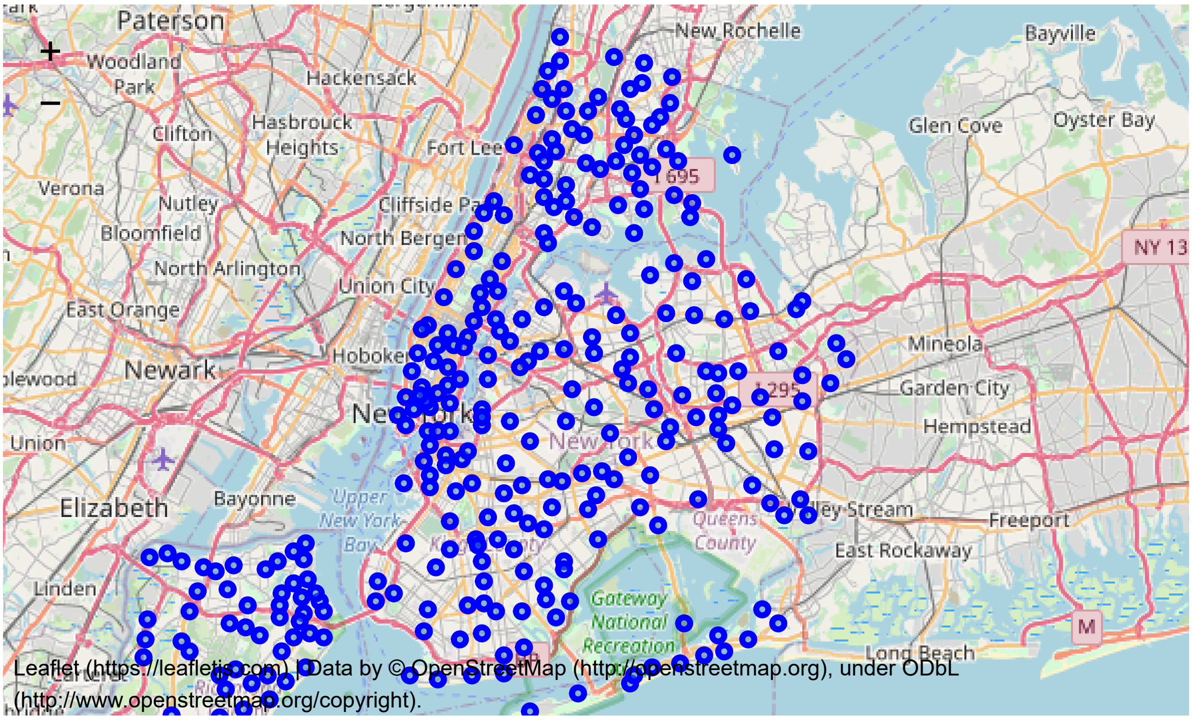


Visualization of New York and its Neighbourhoods

In [27]:

```
# map of New York using latitude and longitude values
map_New_York = folium.Map(location=[latitude_NY, longitude_NY], zoom_start=10)

# add markers to map
for lat, lng, label in zip(NY_neighborhoods['Latitude'], NY_neighborhoods['Longitude'], NY_
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=3,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.5,
        parse_html=False).add_to(map_New_York)

map_New_York
```

Out[27]:



Foresquare Credentials

In [28]:

```
CLIENT_ID = 'MCZFAP1NVEMUKKN15OHGOVFV5VH3X43VYUFXNQO5YJGYC1MP' # your Foursquare ID
CLIENT_SECRET = 'PKNLGKBDCEAOBWURJZEAVB30ATNRP1MJGTAVQC3ITJKWKRVT' # your Foursquare Secret
VERSION = '20200604' # Foursquare API version
LIMIT = 100 # limit of number of venues returned by Foursquare API
```

4. Exploring The Neighbourhoods in Toronto and New York

Creating a function that returns near venues for All the neighbourhoods in given place using Foresquare API

In [29]:

```
def getNearbyVenues(names, latitudes, longitudes, radius=500):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_secret={}&
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        venues_list.append([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame([item for venue_list in venues_list for item in venue_list
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

Creating a new dataframes for Veneus

In [31]:

```
# taking venues for Toronto
Toronto_venues = getNearbyVenues(names=DF_LL['Neighborhood'],
                                   latitudes=DF_LL['Latitude'],
                                   longitudes=DF_LL['Longitude']
                                  )
```

```
Malvern, Rouge
Rouge Hill, Port Union, Highland Creek
Guildwood, Morningside, West Hill
Woburn
Cedarbrae
Scarborough Village
Kennedy Park, Ionview, East Birchmount Park
Golden Mile, Clairlea, Oakridge
Cliffside, Cliffcrest, Scarborough Village West
Birch Cliff, Cliffside West
Dorset Park, Wexford Heights, Scarborough Town Centre
Wexford, Maryvale
Agincourt
Clarks Corners, Tam O'Shanter, Sullivan
Milliken, Agincourt North, Steeles East, L'Amoreaux East
Steeles West, L'Amoreaux West
Upper Rouge
Hillcrest Village
Fairview, Henry Farm, Oriole
```

In [37]:

```
# taking venues for New York
NY_venues = getNearbyVenues(names=NY_neighborhoods['Neighborhood'],
                                   latitudes=NY_neighborhoods['Latitude'],
                                   longitudes=NY_neighborhoods['Longitude']
                                  )
```

```
Wakefield
Co-op City
Eastchester
Fieldston
Riverdale
Kingsbridge
Marble Hill
Woodlawn
Norwood
Williamsbridge
Baychester
Pelham Parkway
City Island
Bedford Park
University Heights
Morris Heights
Fordham
East Tremont
West Farms
```

Size of new dataframe

In [38]:

```
print(Toronto_venues.shape)
Toronto_venues.head()
```

(2115, 7)

Out[38]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Malvern, Rouge	43.806686	-79.194353	Wendy's	43.807448	-79.199056	Fast Food Restaurant
1	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497	Royal Canadian Legion	43.782533	-79.163085	Bar
2	Guildwood, Morningside, West Hill	43.763573	-79.188711	RBC Royal Bank	43.766790	-79.191151	Bank
3	Guildwood, Morningside, West Hill	43.763573	-79.188711	G & G Electronics	43.765309	-79.191537	Electronics Store
4	Guildwood, Morningside, West Hill	43.763573	-79.188711	Big Bite Burrito	43.766299	-79.190720	Mexican Restaurant

In [39]:

```
print(NY_venues.shape)
NY_venues.head()
```

(9933, 7)

Out[39]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Wakefield	40.894705	-73.847201	Lollipops Gelato	40.894123	-73.845892	Dessert Shop
1	Wakefield	40.894705	-73.847201	Carvel Ice Cream	40.890487	-73.848568	Ice Cream Shop
2	Wakefield	40.894705	-73.847201	Walgreens	40.896528	-73.844700	Pharmacy
3	Wakefield	40.894705	-73.847201	Rite Aid	40.896649	-73.844846	Pharmacy
4	Wakefield	40.894705	-73.847201	Dunkin'	40.890459	-73.849089	Donut Shop

checking for unique values in veneus df

In [40]:

```
print('There are {} uniques categories.'.format(len(Toronto_venues['Venue Category'].unique
print('There are {} uniques categories.'.format(len(NY_venues['Venue Category'].unique())))
```

```
There are 269 uniques categories.
There are 425 uniques categories.
```

5. Grouping Data And Dealing with Catagorical variables

Dealing with catagorical data through "one hot encoding" Dummie Variables

In [41]:

```
# one hot encoding Toronto
Toronto_onehot = pd.get_dummies(Toronto_venues[['Venue Category']], prefix="", prefix_sep="

# add neighborhood column back to dataframe
Toronto_onehot['Neighborhood'] = Toronto_venues['Neighborhood']

Toronto_onehot.head()
```

Out[41]:

	Accessories Store	Afghan Restaurant	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antique Shop	Aquarium	Ga
0	0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	

In [42]:

```
# move neighborhood column to the first column
Col='Neighborhood'
first_col=Toronto_onehot.pop('Neighborhood')
Toronto_onehot.insert(0, Col, first_col)
Toronto_onehot.head()
```

Out[42]:

	Neighborhood	Accessories Store	Afghan Restaurant	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antique Shop
0	Malvern, Rouge	0	0	0	0	0	0	0	0	0
1	Rouge Hill, Port Union, Highland Creek	0	0	0	0	0	0	0	0	0
2	Guildwood, Morningside, West Hill	0	0	0	0	0	0	0	0	0
3	Guildwood, Morningside,	0	0	0	0	0	0	0	0	0

In [43]:

```
# one hot encoding New York
NY_onehot = pd.get_dummies(NY_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
NY_onehot['Neighborhood'] = NY_venues['Neighborhood']

NY_onehot.head()
```

Out[43]:

	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	Airport Terminal	American Restaurant	Animal Shelter	Antique Shop	Arca
0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	

In [44]:

```
# move neighborhood column to the first column
Col_1='Neighborhood'
first_col=NY_onehot.pop('Neighborhood')
NY_onehot.insert(0, Col_1, first_col)
NY_onehot.head()
```

Out[44]:

	Neighborhood	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	Airport Terminal	American Restaurant	Animal Shelter
0	Wakefield	0	0	0	0	0	0	0
1	Wakefield	0	0	0	0	0	0	0
2	Wakefield	0	0	0	0	0	0	0
3	Wakefield	0	0	0	0	0	0	0
4	Wakefield	0	0	0	0	0	0	0

Grouping the veneus according to there neighbourhoods

In [143]:

```
Toronto_grouped=Toronto_onehot.groupby("Neighborhood").mean().reset_index()
Toronto_grouped.head()
```

Out[143]:

	Neighborhood	Accessories Store	Afghan Restaurant	Airport	Airport Food Court	Airport Lounge	Airport Service	Airport Terminal	Ameri Restaur
0	Agincourt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000
1	Alderwood, Long Branch	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000
2	Bathurst Manor, Wilson Heights, Downsview North	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000
3	Bayview Village	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000
4	Bedford Park, Lawrence Manor East	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.043

In [ ]:

```
Toronto_grouped.to_csv('C:/Users/camar/Desktop/projects/Machine-Learning-Unsupervised-/Data
```

In [47]:

```
NY_grouped=NY_onehot.groupby("Neighborhood").mean().reset_index()
NY_grouped.head()
```

Out[47]:

	Neighborhood	Accessories Store	Adult Boutique	Afghan Restaurant	African Restaurant	Airport Terminal	American Restaurant	Animal Shelter
0	Allerton	0.0	0.0	0.0	0.0	0.0	0.000000	0.0
1	Annadale	0.0	0.0	0.0	0.0	0.0	0.090909	0.0
2	Arden Heights	0.0	0.0	0.0	0.0	0.0	0.000000	0.0
3	Arlington	0.0	0.0	0.0	0.0	0.0	0.200000	0.0
4	Arrochar	0.0	0.0	0.0	0.0	0.0	0.000000	0.0

In [144]:

```
NY_grouped.to_csv('C:/Users/camar/Desktop/projects/Machine-Learning-Unsupervised-/Data/NY_G
```

In [48]:

```
print(Toronto_grouped.shape)
print(NY_grouped.shape)
```

```
(94, 269)
(300, 425)
```

6. Merging datasets For Cluster Analysis

In [50]:

```
# creating lists of columns and Combining them together
L1 = list(NY_grouped.columns)
L2 = list(Toronto_grouped.columns)
L=list(set(L1).intersection(L2))

#mearging the two data sets
Merged_df=pd.merge(NY_grouped,Toronto_grouped, on=L,how='outer')
# deleting the columns that are not common in both data sets
cols = [col for col in Merged_df.columns if col not in L]
Merged_df=Merged_df.drop(cols,axis=1)
Merged_df.head()
```

Out[50]:

	Neighborhood	Accessories Store	Afghan Restaurant	Airport Terminal	American Restaurant	Antique Shop	Art Gallery	Art Museum	Cr S
0	Allerton	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	
1	Annadale	0.0	0.0	0.0	0.090909	0.0	0.0	0.0	
2	Arden Heights	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	
3	Arlington	0.0	0.0	0.0	0.200000	0.0	0.0	0.0	
4	Arrochar	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	

In [145]:

```
Merged_df.shape
```

Out[145]:

```
(394, 237)
```

In [141]:

```
Merged_df.to_csv('C:/Users/camar/Desktop/projects/Machine-Learning-Unsupervised-/Data/Newyo
```

7. Feature Extraction and Dimensionality Reduction

7.1 Missing Value Ratio

In [54]:

```
Merged_df.isnull().sum()/len(Merged_df)*100
```

Out[54]:

```
Neighborhood                    0.0
Accessories Store               0.0
Afghan Restaurant               0.0
Airport Terminal                0.0
American Restaurant             0.0
Antique Shop                    0.0
Art Gallery                     0.0
Art Museum                      0.0
Arts & Crafts Store             0.0
Asian Restaurant                0.0
Athletics & Sports              0.0
Auto Garage                     0.0
BBQ Joint                       0.0
Baby Store                      0.0
Bagel Shop                      0.0
Bakery                          0.0
Bank                            0.0
Bar                             0.0
```

7.2 Low Variance Filter

In [55]:

```
Merged_df.var()
```

Out[55]:

```
Accessories Store               5.874894e-05
Afghan Restaurant               1.399574e-05
Airport Terminal                4.382188e-05
American Restaurant             1.311999e-03
Antique Shop                    1.516048e-05
Art Gallery                     1.035233e-04
Art Museum                      1.066197e-04
Arts & Crafts Store             1.950155e-04
Asian Restaurant                4.170344e-04
Athletics & Sports              6.196938e-04
Auto Garage                     1.017557e-04
BBQ Joint                       6.472628e-05
Baby Store                      9.028462e-06
Bagel Shop                      9.994741e-04
Bakery                          1.150949e-03
Bank                            1.393480e-03
Bar                             4.192805e-03
Baseball Field                  5.594778e-03
```

7.3 High Correlation filter

In [56]:

```
Merged_df.corr()
```

Out[56]:

	Accessories Store	Afghan Restaurant	Airport Terminal	American Restaurant	Antique Shop	Art Gallery	Art Museum	Arts & Crafts Store	R
Accessories Store	1.000000	-0.010134	-0.008271	-0.023816	-0.018314	-0.032178	-0.009297	-0.015419	-
Afghan Restaurant	-0.010134	1.000000	-0.005623	-0.025490	-0.012451	-0.015193	-0.006321	-0.002679	-
Airport Terminal	-0.008271	-0.005623	1.000000	-0.023259	-0.010162	-0.017856	-0.005159	-0.008556	-
American Restaurant	-0.023816	-0.025490	-0.023259	1.000000	0.046325	0.031728	-0.021028	-0.021721	
Antique Shop	-0.018314	-0.012451	-0.010162	0.046325	1.000000	0.291213	-0.011422	0.147827	-

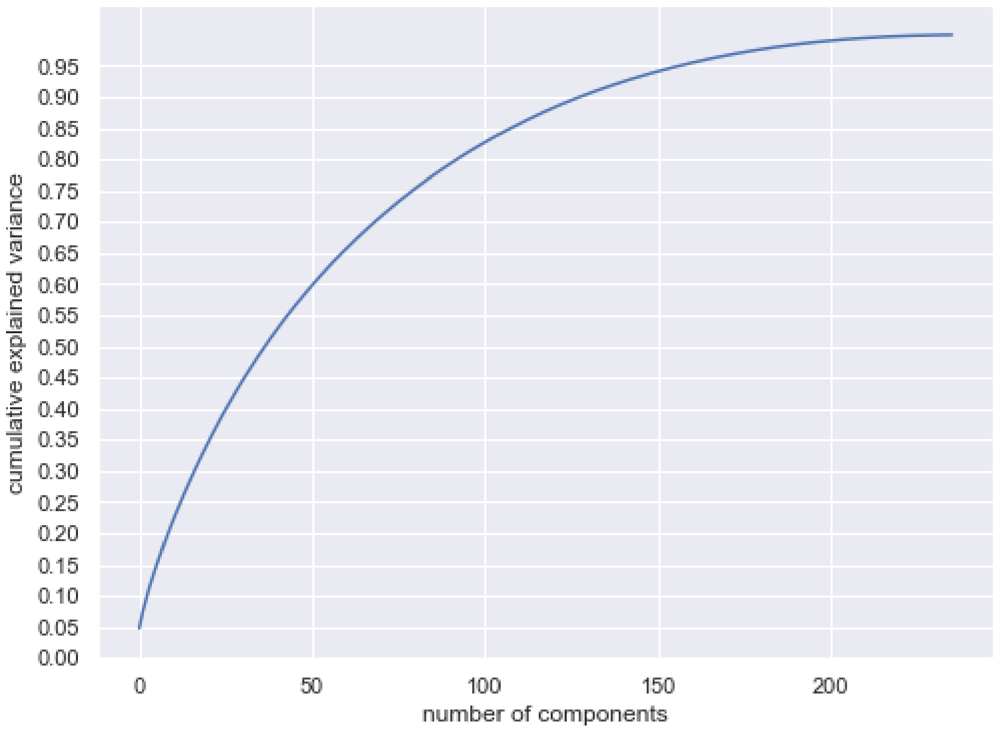
7.4 Principal Component Analysis

In [68]:

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler

neigh_name = Merged_df['Neighborhood']
df_grouped_clustering = Merged_df.drop('Neighborhood', 1)

scaler = MinMaxScaler(feature_range=[0, 1])
data_rescaled = scaler.fit_transform(df_grouped_clustering)

pca = PCA().fit(data_rescaled)
plt.figure(figsize=(8,6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.yticks(np.arange(0, 1.0, step=0.05))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
```

Out[68]:

```
Text(0, 0.5, 'cumulative explained variance')
```



In [73]:

```
# Lowering the dimentionality to 170 features
pca = PCA(n_components=170)
dataset = pca.fit_transform(data_rescaled)
```

In [74]:

```
print(dataset.shape)
print(Merged_df.shape)
pca
```

```
(394, 170)
(394, 237)
```

Out[74]:

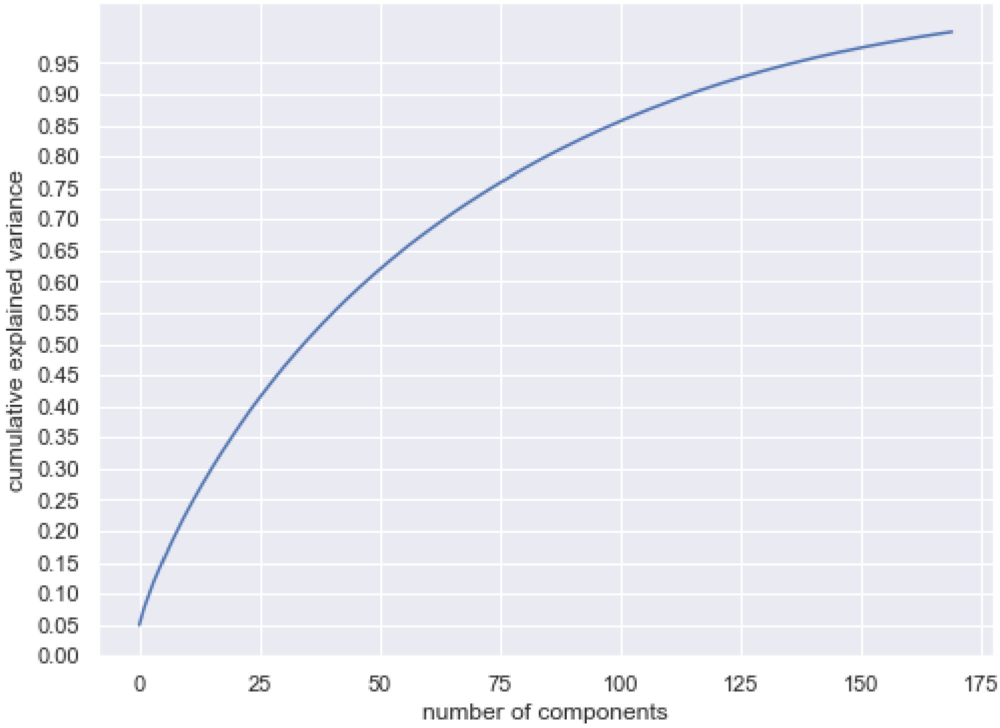
```
PCA(copy=True, iterated_power='auto', n_components=170, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

In [75]:

```
pca = PCA().fit(dataset)
plt.figure(figsize=(8,6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.yticks(np.arange(0, 1.0, step=0.05))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
```

Out[75]:

```
Text(0, 0.5, 'cumulative explained variance')
```



8. Clustering The Data

8.1 Finding optimal number of clusters

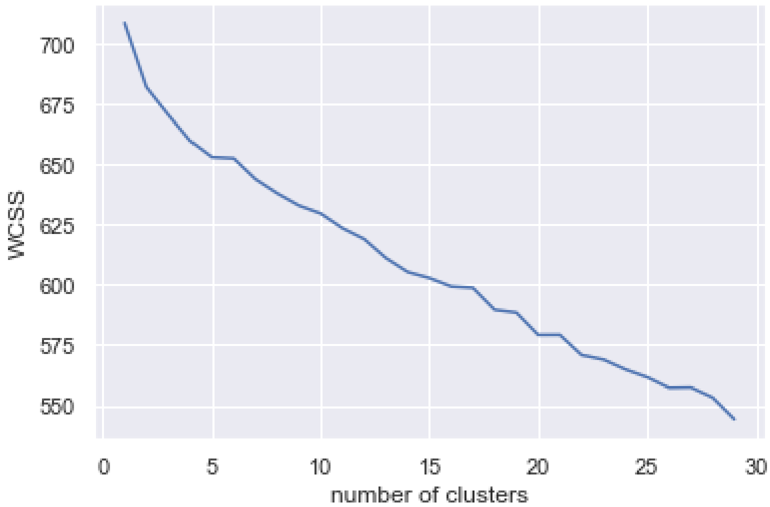
8.1.1 Elbow Method

In [77]:

```
# Creating a list for within cluster sum of squares and appending values
wcss=[]
for i in range(1,30):
    kmeans=KMeans(i)
    kmeans.fit(dataset)
    wcss_iter=kmeans.inertia_
    wcss.append(wcss_iter)
```

In [78]:

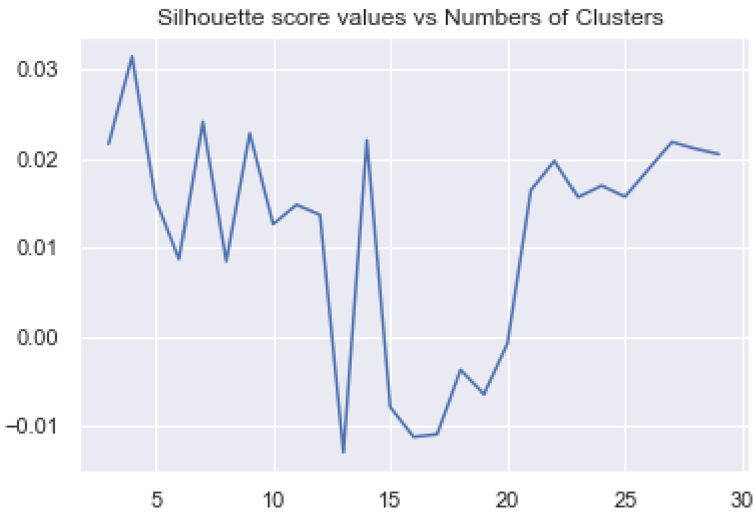
```
#ploting
num_clust=range(1,30)
plt.plot(num_clust,wcss)
plt.xlabel("number of clusters")
plt.ylabel("WCSS")
plt.show()
```



8.1.2 The Silhouette Method

In [81]:

```
import sklearn
obs = dataset.copy()
silhouette_score_values=[]
NumberOfClusters=range(3,30)

for i in NumberOfClusters:

    classifier=KMeans(i,init='k-means++', n_init=10, max_iter=300, tol=0.0001, random_state
    classifier.fit(obs)
    labels= classifier.predict(obs)
    silhouette_score_values.append(sklearn.metrics.silhouette_score(obs,labels ,metric='euc

plt.plot(NumberOfClusters, silhouette_score_values)
plt.title("Silhouette score values vs Numbers of Clusters ")
plt.show()

Optimal_NumberOf_Components=NumberOfClusters[silhouette_score_values.index(max(silhouette_s
print("Optimal number of components is:")
print(Optimal_NumberOf_Components)
```




```
Optimal number of components is:
4
```

8.1.3 Gap Statistic

In [113]:

```
from gap_statistic import OptimalK
optimalK = OptimalK(n_jobs=5, parallel_backend='multiprocessing')
n_clusters = optimalK(obs, cluster_array=np.arange(3, 7))

print('Optimal clusters: ', n_clusters)
optimalK.gap_df.head()
```

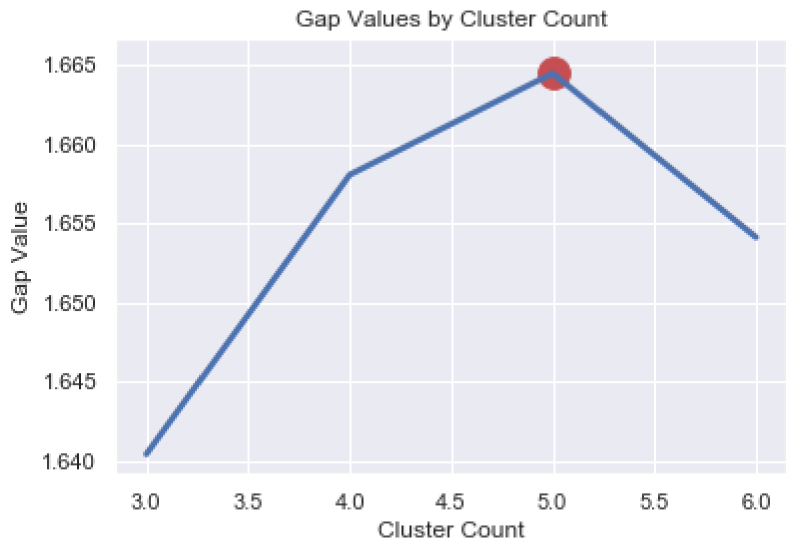
```
Optimal clusters:  5
```

Out[113]:

	n_clusters	gap_value	gap*	ref_dispersion_std	sk	sk*	diff	
0	3.0	1.640398	2861.040440	19.971700	0.006492	3303.725426	-0.021713	32
1	4.0	1.658045	2837.588983	10.766309	0.003550	3276.589111	0.008827	32
2	5.0	1.664449	2818.692808	7.035551	0.002338	3254.756241	0.009955	32
3	6.0	1.654093	2791.082542	14.586533	0.004875	3222.908525	NaN	

In [114]:

```
plt.plot(optimalK.gap_df.n_clusters, optimalK.gap_df.gap_value, linewidth=3)
plt.scatter(optimalK.gap_df[optimalK.gap_df.n_clusters == n_clusters].n_clusters,
            optimalK.gap_df[optimalK.gap_df.n_clusters == n_clusters].gap_value, s=250, c='
plt.grid(True)
plt.xlabel('Cluster Count')
plt.ylabel('Gap Value')
plt.title('Gap Values by Cluster Count')
plt.show()
```



8.2 K-Mean Clustering

In [116]:

```
k= 5


# run k-means clustering
kmeans = KMeans(n_clusters=k, init='k-means++', n_init=10, max_iter=300, tol=0.0001, verbos

# check cluster labels generated for each row in the dataframe
centroids = kmeans.cluster_centers_
labels = kmeans.labels_
```

In [117]:

```
#Creating a new data frame with clusters
Merged_with_clusters = Merged_df.copy()
Merged_with_clusters.insert(1, 'Cluster_Labels', kmeans.labels_)
Merged_with_clusters.head()
```

Out[117]:

	Neighborhood	Cluster_Labels	Accessories Store	Afghan Restaurant	Airport Terminal	American Restaurant	Antique Shop	A Galle
0	Allerton	1	0.0	0.0	0.0	0.000000	0.0	(
1	Annadale	1	0.0	0.0	0.0	0.090909	0.0	(
2	Arden Heights	1	0.0	0.0	0.0	0.000000	0.0	(
3	Arlington	1	0.0	0.0	0.0	0.200000	0.0	(
4	Arrochar	1	0.0	0.0	0.0	0.000000	0.0	(

8.3 Merging Data with respective Clusters

In [118]:

```
# Extracting neighbourhood and cluster colum from dataframe
df_cluster_neighborhood = Merged_with_clusters[['Cluster_Labels', 'Neighborhood']]
Toronto_merged = DF_LL[['Neighborhood', 'Latitude', 'Longitude']]
Toronto_merged = Toronto_merged.merge(df_cluster_neighborhood, on = 'Neighborhood', how = '
NY_merged =NY_neighborhoods[['Neighborhood', 'Latitude', 'Longitude']]
NY_merged = NY_merged.merge(df_cluster_neighborhood, on = 'Neighborhood', how = 'left')
Toronto_merged.dropna(inplace=True)
NY_merged.dropna(inplace=True)
print(Toronto_merged.shape)
print(NY_merged.shape)
```

```
(99, 4)
(305, 4)
```

In [125]:

```
Toronto_merged.head()
```

Out[125]:

	Neighborhood	Latitude	Longitude	Cluster_Labels
0	Malvern, Rouge	43.806686	-79.194353	3.0
1	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497	0.0
2	Guildwood, Morningside, West Hill	43.763573	-79.188711	0.0
3	Woburn	43.770992	-79.216917	0.0
4	Cedarbrae	43.773136	-79.239476	1.0

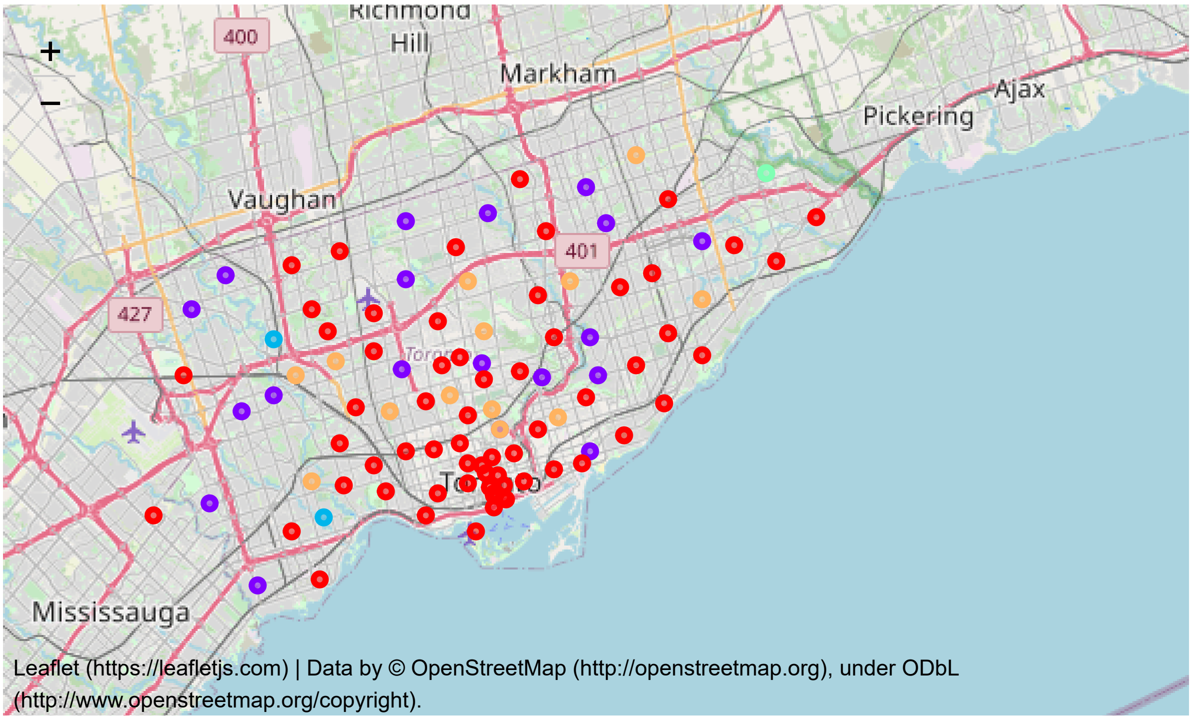
9. Visualization of Clusters on Map

9.1 Visualizing clusters of neighborhoods in Toronto

In [132]:

```
# create map
map_clusters = folium.Map(location=[latitude_Tor, longitude_Tor], zoom_start=10)

# set color scheme for the clusters
x = np.arange(k)
ys = [i + x + (i*x)**2 for i in range(k)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(Toronto_merged['Latitude'], Toronto_merged['Longitude'],T
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=3,
        popup=label,
        color=rainbow[int(cluster)-1],
        fill=True,
        fill_color=rainbow[int(cluster)-1],
        fill_opacity=0.5).add_to(map_clusters)

map_clusters
```

Out[132]:



9.2 Visualizing clusters of neighborhoods in NY

In [133]:

```
# create map
map_clusters_NY = folium.Map(location=[latitude_NY, longitude_NY], zoom_start=10)

# set color scheme for the clusters
x = np.arange(k)
ys = [i + x + (i*x)**2 for i in range(k)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(NY_merged['Latitude'], NY_merged['Longitude'],NY_merged['
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius=3,
        popup=label,
        color=rainbow[int(cluster)-1],
        fill=True,
        fill_color=rainbow[int(cluster)-1],
        fill_opacity=0.5).add_to(map_clusters_NY)

map_clusters_NY
```

Out[133]: