Capstone Project Report: Battle of Neighborhoods

Applied Data Science by Coursera/ IBM

IBM Data Science Professional Certificate

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Introduction

Moving to a new city, state or country - is no easy task and one probably will feel the effect of change. Sometimes the effect of change could gradually lead us to culture shock! This might result to pack up and head back to home. Before doing so, let's have a look how data science (tools and methodology) can help us to find some similarities/ dissimilarities in neighborhoods.

Considering relocation, people usually tend to explore the places before moving and that involves so many aspects including **neighborhood analysis**. This requires a search algorithm that usually returns the requested features such as population rate, median housing price, school ratings, crime rates, weather conditions, recreational facilities and many more. Wouldn't it be nice to have an application (one platform) that could spit out an extensive analysis of all these features for a neighborhood or a comparative analysis between neighborhoods by just sending out the names of the neighborhoods?

In this project the above mentioned user need will be taken as main idea to develop the model. I will be focusing on **neighborhood analysis** in the city of our choice.

This Project aims to help the stakeholders take a better decision on choosing the best neighborhood out of many neighborhoods in the city of **Toronto** based on the distribution of various facilities in and around that neighborhood. For example, this project would compare 2 or more randomly chosen neighborhoods and analyze the top 10 most common venues in each of those two neighborhoods based on the number of visits by people in each of those places. I will use K-means clustering unsupervised machine learning algorithm to cluster the venues based on the place category such as restaurants, park, coffee shop, gym etc. This would help to understand better, the similarities and dissimilarities between/ among the chosen neighborhoods to retrieve more insights and to conclude which neighborhood wins over other.

Data

According to this problem, I will need to acquire data about the city of Toronto, specifically the boroughs and neighborhoods of the city. Geospatial data of the city, its boroughs and all the neighborhoods. Following this it also requires to gather data about each neighborhoods such as what are the top venues and most common venues, which categories these venues belong to.

To obtain the best datasets to achieve our aim, I will use **Foursquare API** (*) as my prime data gathering source.

** Foursquare API has a database of more than 105 million places, especially their places API which provides the ability to perform location search, location sharing and details about a business. Photos, tips and reviews jolted by Foursquare users can also be used in many productive ways to add value to the results*.

** Please note: Due to limitations (on API call Quota) the number of places per neighborhood parameter would reasonably be set to 100 and the radius parameter would be set to 700.*

Methodology

➢ Data Collection

This project depends on publicly available data, mainly from Wikipedia [1-5]. I will use **Web Scraping** with **Beautiful Soup** to retrieve data from different Web pages. Acquired data will then be cleaned and sorted according to the requirements.

```
#importing all libraries

import numpy as np
import pandas as pd
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
import json
from pandas.io.json import json_normalize
from geopy.geocoders import Nominatim
from bs4 import BeautifulSoup
import lxml.html as lh
import requests
import matplotlib.cm as cm
import matplotlib.colors as colors
from sklearn.cluster import KMeans
!conda install -c conda-forge folium=0.5.0 --yes
import folium
print('Folium installed')
print('Libraries imported.')
```

```
#Scraping Wikipedia

url = 'https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M'
r = requests.get(url)

soup = BeautifulSoup(r.content, 'html.parser')
table = soup.find('table')
trows = table.find_all('tr')
rows = []
for tr in trows:
    i = tr.find_all('td')
    if i:
        rows.append(i)
lst = []
for row in rows:
    postalcode = row[0].text.rstrip()
    borough = row[1].text.rstrip()
    neighborhood = row[2].text.rstrip()
    if borough != 'Not assigned':
        if neighborhood == 'Not assigned':
            neighborhood = borough
        lst.append([postalcode, borough, neighborhood])

cols = ['PostalCode', 'Borough', 'Neighborhood']
df = pd.DataFrame(lst, columns=cols)
print(df.shape)
```

```
(211, 3)
```

check – (.head) the scraped data:

	PostalCode	Borough	Neighborhood
0	M3A	North York	Parkwoods
1	M4A	North York	Victoria Village
2	M5A	Downtown Toronto	Harbourfront
3	M5A	Downtown Toronto	Regent Park
4	M6A	North York	Lawrence Heights

➢ Data Wrangle

I encountered that in the first data frame (df) there are several boroughs sharing the same postal code but recorded in separate rows. So I would group those by postal code to reduce the size of the data frame.

```
#Cleaning data

#groupby PostalCode, keep the first Borough and join() Neighborhoods
df = df.groupby('PostalCode').agg(
    {
        'Borough':'first',
        'Neighborhood': ', '.join,}
    ).reset_index()

df.shape
```

```
(103, 3)
```

The size now looks fine. Let's run a test to see if we have the dataset how we wanted it to be.

```
df.head()
```

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

Yes! that's fine.

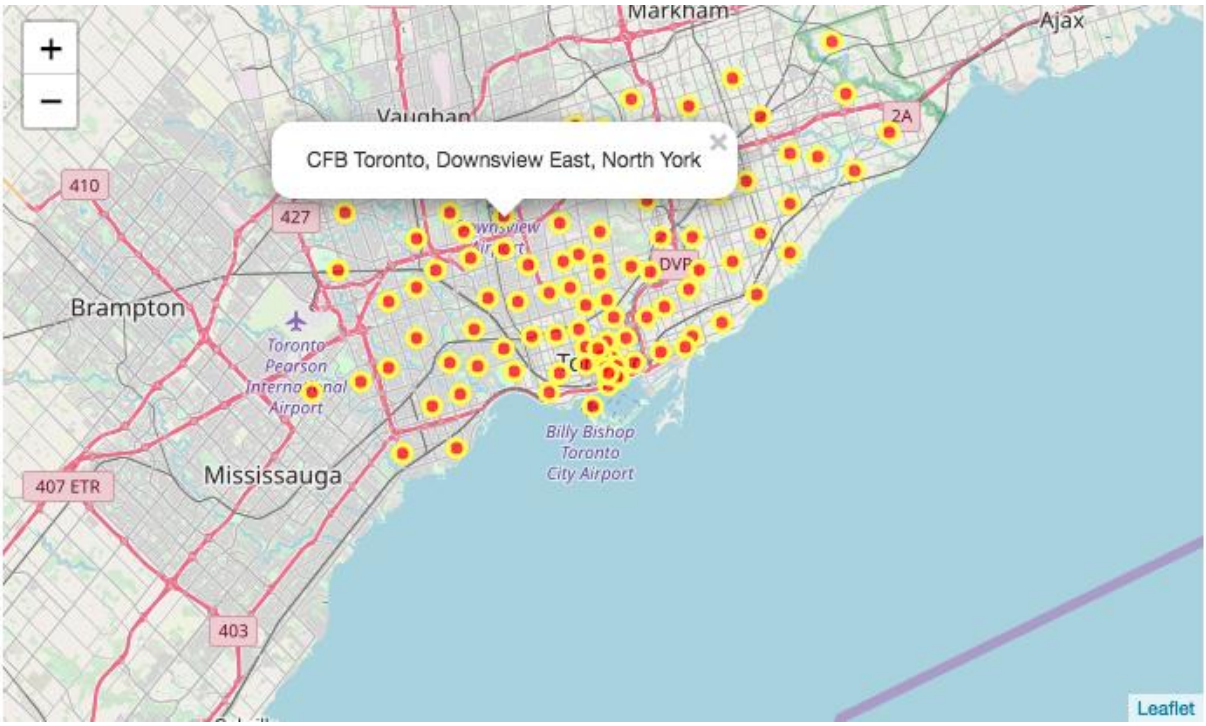
Another requirement of the dataset is to obtain the geospatial data for each neighborhood. I have collected geospatial data various sources [1-4]. I initially put all the collected data into .csv file and then read (dfgeo) in python and converted into pandas data frame (df2).

```
#Clean and sort
#read the csv and put it into pandas data frame
dfgeo = pd.read_csv("Geospatial.csv")
dfgeo.rename(columns={'Postal Code': 'PostalCode'}, inplace=True)
df2 = pd.merge(df, dfgeo, on="PostalCode", how='left')
df2.head()
```

	PostalCode	Borough	Neighborhood	Latitude	Longitude	Population
0	M1B	Scarborough	Rouge, Malvern	43.806686	-79.194353	66108
1	M1C	Scarborough	Highland Creek, Rouge Hill, Port Union	43.784535	-79.160497	35626
2	M1E	Scarborough	Guildwood, Morningside, West Hill	43.763573	-79.188711	46943
3	M1G	Scarborough	Woburn	43.770992	-79.216917	29690
4	M1H	Scarborough	Cedarbrae	43.773136	-79.239476	24383

The city of Toronto has 11 Boroughs and 103 Neighborhoods.

After finding the geographical coordinate of Toronto, I used **Folium** (python visualization library) to visualize the neighborhoods and the cluster distribution of the city of Toronto over an interactive leaflet map.



Then I used **Foursquare** to collect the venue data of each neighborhood. As mentioned earlier I have set the limit for API calls for venue parameter to 100 and the radius parameter to 700.

	name	categories	lat	lng
0	Downtown Toronto	Neighborhood	43.653232	-79.385296
1	Textile Museum of Canada	Art Museum	43.654396	-79.386500
2	Sansotei Ramen 三草亭	Ramen Restaurant	43.655157	-79.386501
3	Japango	Sushi Restaurant	43.655268	-79.385165
4	Tsujiri	Tea Room	43.655374	-79.385354

Then I created a function to have the same process repeated for all 103 neighborhoods of Toronto. After processing the dataset I found that there are 319 unique venue categories exist in Toronto. However the size of the dataset is quite large and I reduced it from (3461, 319) to (102, 319) by "one hot encoding" and ".groupby()" method.

In addition, I looked at the neighborhoods with the top 10 most common venue and their frequencies.

```
-----Adelaide, King, Richmond-----
                venue  freq
0         Coffee Shop  0.07
1                Café  0.06
2          Steakhouse  0.04
3    Sushi Restaurant  0.04
4  American Restaurant  0.04
5           Gastropub  0.03
6          Restaurant  0.03
7                 Bar  0.03
8      Thai Restaurant  0.03
9             Theater  0.03


-----Agincourt-----
                venue  freq
0  Shanghai Restaurant   0.1
1           Pool Hall   0.1
2      Badminton Court   0.1
3       Breakfast Spot   0.1
4          Coffee Shop   0.1
5       Sandwich Place   0.1
6       Clothing Store   0.1
7      Motorcycle Shop   0.1
8               Lounge   0.1
9         Skating Rink   0.1


-----Agincourt North, L'Amoreaux East, Milliken, Steeles Ea
```

I then put the collected data into pandas data frame and merged with the df2.

;talCode	Borough	Neighborhood	Latitude	Longitude	Population	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
M1B	Scarborough	Rouge, Malvern	43.806686	-79.194353	66108	4.0	Fast Food Restaurant	Coffee Shop	Spa	Bus Station	Hobby Shop	Construction & Landscaping	Women's Store	Donut Shop
M1C	Scarborough	Highland Creek, Rouge Hill, Port Union	43.784535	-79.160497	35626	4.0	Breakfast Spot	Bar	Burger Joint	Dumpling Restaurant	Discount Store	Dive Bar	Dog Run	Doner Restaurant
M1E	Scarborough	Guildwood, Morningside, West Hill	43.763573	-79.188711	46943	0.0	Pizza Place	Fast Food Restaurant	Grocery Store	Breakfast Spot	Moving Target	Electronics Store	Fried Chicken Joint	Rental Car Location
M1G	Scarborough	Woburn	43.770992	-79.216917	29690	1.0	Park	Coffee Shop	Convenience Store	Business Service	Event Space	Ethiopian Restaurant	Dessert Shop	Dim Sum Restaurant
M1H	Scarborough	Cedarbrae	43.773136	-79.239476	24383	4.0	Coffee Shop	Indian Restaurant	Bakery	Thai Restaurant	Gym / Fitness Center	Fried Chicken Joint	Flower Shop	Chinese Restaurant

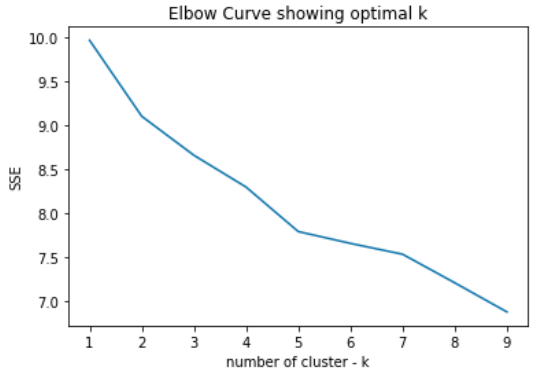
Before I proceeded to the next steps, I have done a small test on a single neighborhood as a part of the data exploration and to check the workability of our resources. (*see the supporting notebook*). The results look fine and I am ready to step forward.

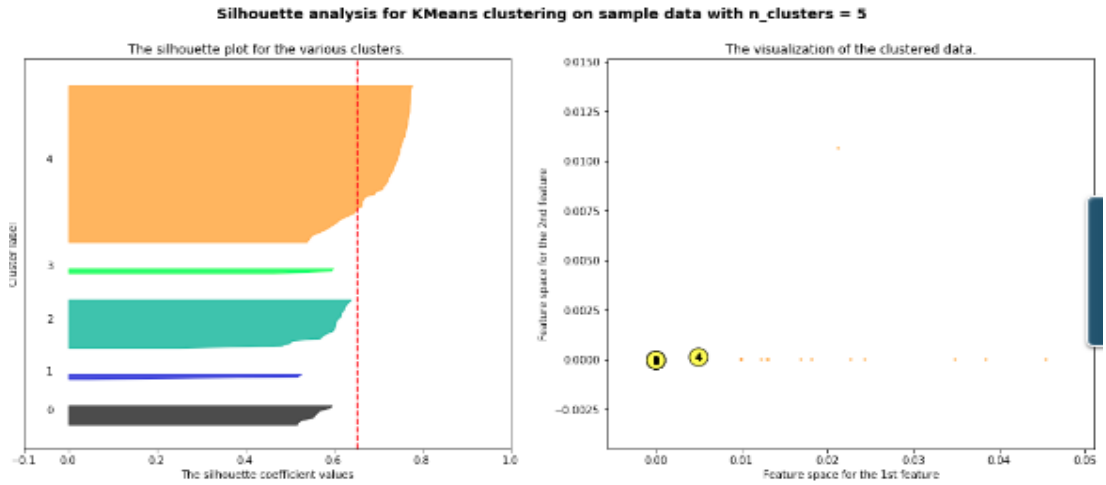
➢ Clustering

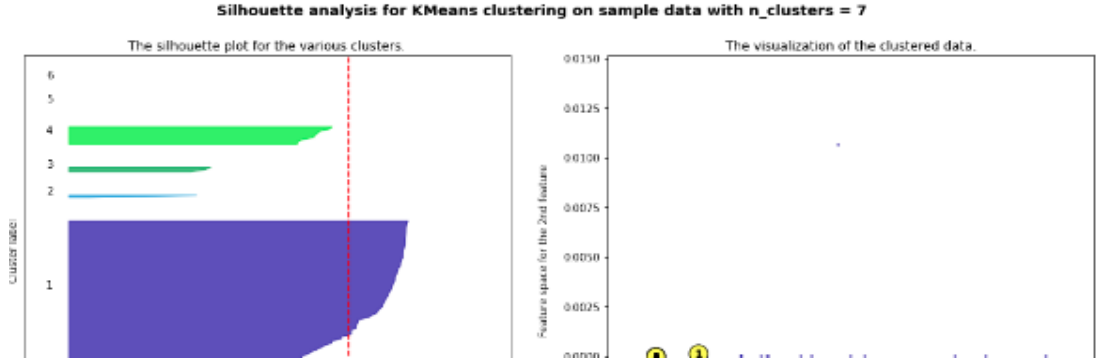
In order to carry out the extensive comparative analysis of randomly chosen neighborhoods, I have used K-means clustering; an unsupervised machine learning algorithm; to form the clusters of different categories of places residing in and around the neighborhoods.

However determining the optimal number of clusters in a data set is a fundamental issue in partitioning clustering, such as K-means clustering in our case, which requires the user to specify the number of clusters k to be generated. There are many methods to determine the optimal number. These methods include **direct methods** and **statistical testing methods**.

In this project, I have considered the direct methods. I used **Elbow method** and **Average Silhouette method** to calculate the optimal number of k.





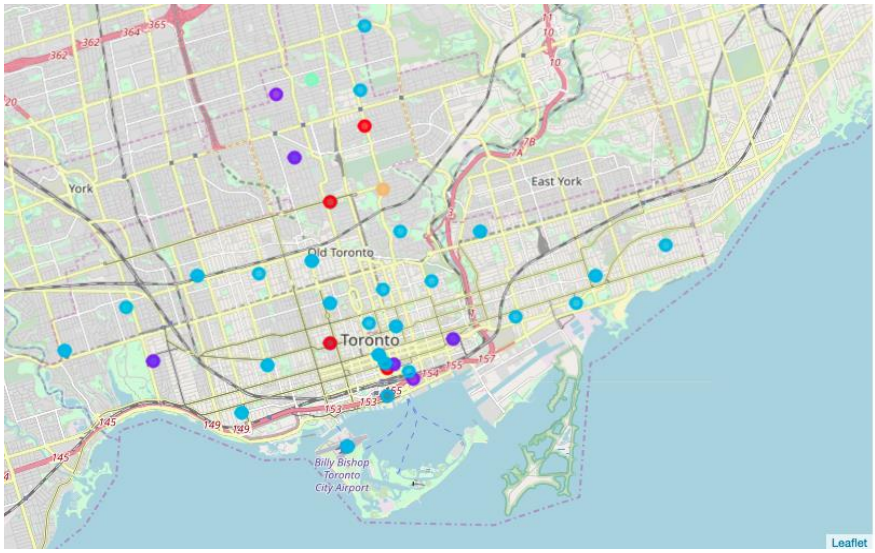


I set k = 5 and added the cluster labels to each group of neighborhoods accordingly.

```
new_toronto=toronto_merged.set_index("Neighborhood",drop=True)
new_toronto.head(10)
```

Neighborhood	PostalCode	Borough	Latitude	Longitude	Population	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
Rouge, Malvern	M1B	Scarborough	43.806686	-79.194353	66108	4	Fast Food Restaurant	Coffee Shop	Spa	Bus Station	Hobby Shop	Construction & Landscaping	Women's Store
Highland Creek, Rouge Hill, Port Union	M1C	Scarborough	43.784535	-79.160497	35626	4	Breakfast Spot	Bar	Burger Joint	Dumpling Restaurant	Discount Store	Dive Bar	Dog Run
Guildwood, Morningside, West Hill	M1E	Scarborough	43.763573	-79.188711	46943	0	Pizza Place	Fast Food Restaurant	Grocery Store	Breakfast Spot	Moving Target	Electronics Store	Fried Chicken Joint
Woburn	M1G	Scarborough	43.770992	-79.216917	29690	1	Park	Coffee Shop	Convenience Store	Business Service	Event Space	Ethiopian Restaurant	Dessert Shop
Cedarbrae	M1H	Scarborough	43.773136	-79.239476	24383	4	Coffee Shop	Indian Restaurant	Bakery	Thai Restaurant	Gym / Fitness	Fried Chicken Joint	Flower Shop

Visualization: I have visualized this dataset (new_toronto), neighborhoods along with cluster labels by using Folium (as mentioned before).



Analysis

In this section the clusters from each of the chosen neighborhoods would be analyzed individually, collectively and comparatively to derive the conclusions.

To begin with analysis, I have examined all the clusters. Individual outcomes are as follows:

```
#Examine
#Cluster 1

df3=toronto_merged.loc[toronto_merged['Cluster Labels'] == 0, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
df3
```

	Borough	Population	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
2	Scarborough	46943	0	Pizza Place	Fast Food Restaurant	Grocery Store	Breakfast Spot	Moving Target	Electronics Store	Fried Chicken Joint	Rental Car Location	Thrift / Vintage Store	Greek Restaurant
5	Scarborough	36699	0	Fast Food Restaurant	Women's Store	Convenience Store	Coffee Shop	Pizza Place	Dim Sum Restaurant	Diner	Discount Store	Dive Bar	Dog Run
8	Scarborough	22913	0	Furniture / Home Store	Chinese Restaurant	Wings Joint	Burger Joint	Dim Sum Restaurant	Diner	Discount Store	Dive Bar	Dog Run	Doner Restaurant
11	Scarborough	29858	0	Pizza Place	Burger Joint	Coffee Shop	Middle Eastern Restaurant	Seafood Restaurant	Bakery	Korean Restaurant	Fish Market	Intersection	Convenience Store
13	Scarborough	34588	0	Pharmacy	Shopping Mall	Pizza Place	Chinese Restaurant	Italian Restaurant	Sandwich Place	Bus Stop	Thai Restaurant	Fried Chicken Joint	Seafood Restaurant
14	Scarborough	54680	0	Chinese Restaurant	Pharmacy	BBQ Joint	Pizza Place	Park	Noodle House	Caribbean Restaurant	Shop & Service	Fast Food Restaurant	Bakery
15	Scarborough	48471	0	Fast Food Restaurant	Grocery Store	Chinese Restaurant	Pharmacy	Indian Restaurant	Burger Joint	Cosmetics Shop	American Restaurant	Other Great Outdoors	Sandwich Place

```
#Cluster 2

df4=toronto_merged.loc[toronto_merged['Cluster Labels'] == 1, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
df4
```

	Borough	Population	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
3	Scarborough	29690	1	Park	Coffee Shop	Convenience Store	Business Service	Event Space	Ethiopian Restaurant	Dessert Shop	Dim Sum Restaurant	Diner	Discount Store
21	North York	32320	1	Park	Coffee Shop	Bus Line	Trail	Women's Store	Donut Shop	Dim Sum Restaurant	Diner	Discount Store	Dive Bar
23	North York	7843	1	Park	Tennis Court	Intersection	Pet Store	Bank	Donut Shop	Dim Sum Restaurant	Diner	Discount Store	Dive Bar
25	North York	34615	1	Park	Fast Food Restaurant	Pet Store	Burger Joint	Food & Drink Shop	Women's Store	Donut Shop	Diner	Discount Store	Dive Bar
30	North York	5997	1	Sandwich Place	Coffee Shop	Airport	Park	Donut Shop	Dessert Shop	Dim Sum Restaurant	Diner	Discount Store	Dive Bar
36	East York	46866	1	Park	Pharmacy	Skating Rink	Asian Restaurant	Bus Stop	Bus Line	Curling Ice	Cosmetics Shop	Athletics & Sports	Video Store
44	Central Toronto	15330	1	Bus Line	Park	Business Service	Swim School	Women's Store	Donut Shop	Dim Sum Restaurant	Diner	Discount Store	Dive Bar
48	Central Toronto	10463	1	Park	Thai Restaurant	Gym / Fitness Center	Gym	Grocery Store	Playground	Bank	Women's Store	Dive Bar	Design Studio
50	Downtown Toronto	14561	1	Park	Playground	Gym / Fitness	Trail	Doner Restaurant	Design Studio	Dessert Shop	Dim Sum Restaurant	Diner	Discount Store

```
#Examine
#Cluster 3

df5=toronto_merged.loc[toronto_merged['Cluster Labels'] == 2, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
df5
```

	Borough	Population	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
20	North York	11717	2	Martial Arts Dojo	Cafeteria	Falafel Restaurant	Exhibit	Dessert Shop	Dim Sum Restaurant	Diner	Discount Store	Dive Bar	Dog Run

```
#Examine
#Cluster 4

df6=toronto_merged.loc[toronto_merged['Cluster Labels'] == 3, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
df6
```

	Borough	Population	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
96	North York	11950	3	Bakery	Pizza Place	Empanada Restaurant	Women's Store	Donut Shop	Dim Sum Restaurant	Diner	Discount Store	Dive Bar	Dog Run

```
#Examine
#Cluster 5

df7=toronto_merged.loc[toronto_merged['Cluster Labels'] == 4, toronto_merged.columns[[1] + list(range(5, toronto_merged.shape[1]))]]
df7
```

	Borough	Population	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	Scarborough	66108	4	Fast Food Restaurant	Coffee Shop	Spa	Bus Station	Hobby Shop	Construction & Landscaping	Women's Store	Donut Shop	Diner	Discount Store
1	Scarborough	35626	4	Breakfast Spot	Bar	Burger Joint	Dumpling Restaurant	Discount Store	Dive Bar	Dog Run	Doner Restaurant	Donut Shop	Drugstore
4	Scarborough	24383	4	Coffee Shop	Indian Restaurant	Bakery	Thai Restaurant	Gym / Fitness Center	Fried Chicken Joint	Flower Shop	Chinese Restaurant	Rental Car Location	Caribbean Restaurant
6	Scarborough	48434	4	Discount Store	Coffee Shop	Sandwich Place	Light Rail Station	Department Store	Convenience Store	Chinese Restaurant	Intersection	Grocery Store	Metro Station
7	Scarborough	35081	4	Intersection	Diner	Coffee Shop	Bus Line	Bakery	Bus Station	Fast Food Restaurant	Park	Metro Station	Soccer Field
9	Scarborough	22136	4	Skating Rink	Bank	Café	Diner	Discount Store	General Entertainment	Thai Restaurant	Park	College Stadium	Eastern European Restaurant
10	Scarborough	45571	4	Electronics Store	Indian Restaurant	Fast Food Restaurant	Wings Joint	Gym / Fitness Center	Vietnamese Restaurant	Coffee Shop	Pet Store	Bakery	Chinese Restaurant

From this I could observe that cluster 5 (with Cluster Label 4) has the highest number of neighborhood with the first most common venue "Fast Food Restaurant" and the second largest is cluster 2 (with Cluster Label 1) with the first most common venue "Park".

The project aims to compare randomly chosen neighborhoods and to do so I have created a table that contains all the data frames (df3,df4,df5,df6 and df7) according to the cluster labels.

```
#creating cluster table
cluster_t=pd.DataFrame({"Cluster1":df3["Borough"],
                        "Cluster2":df4["Borough"],
                        "Cluster3":df5["Borough"],
                        "Cluster4":df6["Borough"],
                        "Cluster5":df7["Borough"]
                        })
```

```
cluster_t = cluster_t.replace(np.nan, '', regex=True)
cluster_t
```

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
0					Scarborough
1					Scarborough
2	Scarborough				
3		Scarborough			
4					Scarborough
5	Scarborough				
6					Scarborough
7					Scarborough
8	Scarborough				
9					Scarborough

Results and Discussion

In this step I take 2 random neighborhood names as input and run the comparison.

Compare the neighborhoods

```
Nbd1=input("Enter the Neighborhood: ")
```

```
Enter the Neighborhood:  Northwest
```

```
Nbd2=input("Enter the Neighborhood: ")
```

```
Enter the Neighborhood:  Weston
```

```
venue_comparison=new_toronto.loc[[Nbd1,Nbd2]].T
venue_comparison
```

Neighborhood	Northwest	Weston
PostalCode	M9W	M9N
Borough	Etobicoke	York
Latitude	43.7067	43.7069
Longitude	-79.5941	-79.5182
Population	40684	25074
Cluster Labels	0	4
1st Most Common Venue	Rental Car Location	Diner
2nd Most Common Venue	Home Service	Fried Chicken Joint
3rd Most Common Venue	Drugstore	Pharmacy
4th Most Common Venue	Hotel	Breakfast Spot
5th Most Common Venue	Donut Shop	Women's Store
6th Most Common Venue	Dessert Shop	Donut Shop
7th Most Common Venue	Dim Sum Restaurant	Dim Sum Restaurant
8th Most Common Venue	Diner	Discount Store
9th Most Common Venue	Discount Store	Dive Bar
10th Most Common Venue	Dive Bar	Dog Run

From the comparison between “Northwest” and “Weston” I could retrieve the geospatial data of the neighborhoods, population count, the top 10 most common venue categories.

This comparison model also works for more than 2 randomly chosen neighborhoods. I have tested with 3 random neighborhood names as follows:

```
Nbd1=input("Enter the Neighborhood: ")
```

```
Enter the Neighborhood:  Rosedale
```

```
Nbd2=input("Enter the Neighborhood: ")
```

```
Enter the Neighborhood:  Woburn
```

```
Nbd3=input("Enter the Neighborhood: ")
```

```
Enter the Neighborhood:  Humber Summit
```

```
venue_comparison=new_toronto.loc[[Nbd1,Nbd2,Nbd3]].T
venue_comparison
```

Neighborhood	Rosedale	Woburn	Humber Summit
PostalCode	M4W	M1G	M9L
Borough	Downtown Toronto	Scarborough	North York
Latitude	43.6796	43.771	43.7563
Longitude	-79.3775	-79.2169	-79.566
Population	14561	29690	11950
Cluster Labels	1	1	3
1st Most Common Venue	Park	Park	Bakery
2nd Most Common Venue	Playground	Coffee Shop	Pizza Place

From the comparison among “Rosedale”, “Woburn” and “Humber Summit” I could retrieve the postal code, name of the boroughs, geospatial data of the neighborhoods, population count, cluster labels and the top 10 most common venue categories.

This comparison model clearly shows the expected outcomes. I aimed to build up a model that can compare two or more randomly chosen neighborhoods of the city of Toronto. The comparison is carried out using K-means clustering algorithm to cluster the neighborhoods based on its venue categories. This model could be helpful for stakeholders to gain more insights about individual neighborhood or to compare chosen neighborhoods.

Conclusion

In this project, I have taken into account the need of an application or one platform that would help stakeholders to understand a country, state, city or its neighborhoods better. I have also mentioned that this would require a search algorithm that usually would return the requested features such as population rate, median housing price, school ratings, crime rates, weather conditions, recreational facilities etc. But I specifically focused only on the neighborhood analysis in means of simple comparison of geospatial data, population counts and the top most common venues based on venue categories. This leaves us to an open end to elaborate the search algorithms by adding more features in the future and nonetheless refining and improving the algorithm further.

References

1. *http://cocl.us/Geospatial_data*
2. *https://www.statcan.gc.ca*
3. *https://en.wikipedia.org/wiki/Demographics_of_Toronto_neighbourhoods*
4. *https://ipfs.io/ipfs/QmXoypizjW3WknFiJnKLwHCnL72vedxjQkDDP1mXWo6uco/wiki/Demographics_of_Toronto.html*
5. *https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M*
6. *Foursquare*