Capstone Project - The battle of Neighborhood

Introduction/Business Problem

The aim of this report is to study and analyze the neighborhoods of Toronto city and group them into similar clusters and, to analyze those clusters to gather meaningful information. That information can be used to find out neighborhoods that are same as your current neighborhood or at least similar. This information provided by this report would be valuable for people who are interested in relocating to different part of the city and are looking to find new neighborhoods that are very similar to their existing neighborhood.

2. Problem Description:

Now let me explain the context of this Capstone project through a scenario. Say you live on the west side of the city of Toronto in Canada. You love your neighborhood, mainly because of all the great amenities and other types of venues that exist in the neighborhood, such as gourmet fast food joints, pharmacies, parks, graduate schools and so on. Now say you receive a job offer from a great company on the other side of the city with great career prospects. However, given the far distance from your current place you unfortunately must move if you decide to accept the offer.

Wouldn't it be great if you are able to determine neighborhoods on the other side of the city that are the same as your current neighborhood, and if not perhaps similar neighborhoods that are at least closer to your new job?

2.1 Data Description:

To consider the objective stated above, we can list the below data sources used for the analysis.

a) Toronto Neighborhood Data:

The following Wikipedia page was scraped to pull out the necessary information: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M

The information obtained i.e. the table of postal codes, borough and neighborhood was transformed into a pandas data frame for further analysis.

b) Coordinate data for each Neighborhood in Toronto:

The following csv file was used to get the latitude and longitude for the Neighborhood http://cocl.us/Geospatial_data

3.0 Methodology

a. Scrape the Wikipedia page to get data and convert into Pandas dataframe

To start with our analysis, we used the **Beautiful Soup** package to transform the Wikipedia data into a pandas dataframe.

Kindly see figure below;

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

We also got the coordinate data for all neighborhoods in Toronto using the csv file and converted into a pandas dataframe.

	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

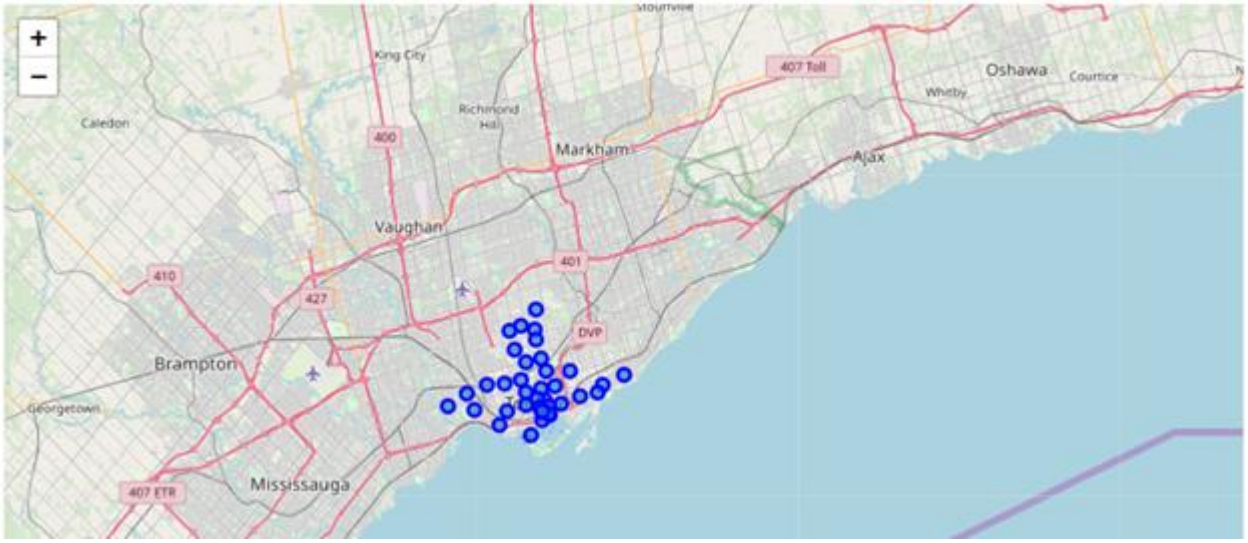
The dataframe's were merged i.e. adding the coordinate dataframe to the original dataframe.

	PostalCode	Borough	Neighborhood	Latitude	Longitude
0	M1B	Scarborough	Rouge, Malvern	43.806686	-79.194353
1	M1C	Scarborough	Highland Creek, Rouge Hill, Port Union	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

b. Generating a map of Toronto and plotting the Neighborhood data on it
We first filter the data to find boroughs containing the word "Toronto",

	PostalCode	Borough	Neighborhood	Latitude	Longitude
37	M4E	East Toronto	The Beaches	43.676357	-79.293031
41	M4K	East Toronto	The Danforth West, Riverdale	43.679557	-79.352188
42	M4L	East Toronto	The Beaches West, India Bazaar	43.668999	-79.315572
43	M4M	East Toronto	Studio District	43.659526	-79.340923
44	M4N	Central Toronto	Lawrence Park	43.728020	-79.388790

We then use the python **folium** library to visualize geographic details of Toronto and its boroughs. I created a map of Toronto with boroughs superimposed on top using the latitude and longitude values to get the visual as below:



C. Utilizing Foursquare API to explore the neighborhoods

Next, start utilizing the Foursquare API to explore the neighborhoods and segment them. We set the LIMIT parameter to **100**, which would limit the number of venues returned by the Foursquare API and the radius of 50 meter. Below is the first five (5) list of Nearby Venues for the various Towns (Borough) i.e. McCowan Park, Price Chopper

	Borough	Borough Latitude	Borough Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Scarborough	43.744734	-79.239476	McCowan Park	43.745089	-79.239336	Playground
1	Scarborough	43.799525	-79.318389	Price Chopper	43.799445	-79.318563	Grocery Store
2	North York	43.803762	-79.363452	New York Fries	43.803664	-79.363905	Fast Food Restaurant
3	Central Toronto	43.704324	-79.388790	Jules Cafe Patisserie	43.704138	-79.388413	Dessert Shop
4	Central Toronto	43.704324	-79.388790	Thobors Boulangerie Patisserie Café	43.704514	-79.388616	Café

d. Analyze each neighborhood

Using One Hot Encoding, the data frame was standardized and the data was grouped by neighborhoods, we created a new data frame consisting of the top 10 venues in each neighborhood.

	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	8th Most Common Venue	9th Most Common Venue
0	Central Toronto	Supermarket	Liquor Store	Furniture / Home Store	Dessert Shop	Park	Italian Restaurant	Coffee Shop	Seafood Restaurant	Bowling Alley
1	Downtown Toronto	Coffee Shop	Café	Performing Arts Venue	Gym	Deli / Bodega	Sushi Restaurant	Art Gallery	Concert Hall	Bakery
2	East Toronto	Trail	Yoga Studio	Diner	Coffee Shop	College Gym	Concert Hall	Cosmetics Shop	Dance Studio	Deli / Bodega
3	East York	Coffee Shop	Sporting Goods Shop	Sandwich Place	Housing Development	Indian Restaurant	College Gym	Concert Hall	Cosmetics Shop	Dance Studio
4	Etobicoke	Dance Studio	Coffee Shop	Pizza Place	Diner	College Gym	Concert Hall	Cosmetics Shop	Deli / Bodega	Dessert Shop

From the results there were some common venue categories in the neighborhoods. So there is a need to segment these similarities for easy identification.

e. K-means Algorithm

K-means is vastly used for clustering and useful when you need to discover insights of unlabeled data.

K-means uses Euclidean distance hence doesn't work well with categorical variables The unsupervised K-means algorithm was used to cluster the neighborhoods. K-Means algorithm is one of the most common method for clustering and discovering insights.

We use a k-cluster value of 5 to split the neighborhoods into 5 different clusters based on the similarity of the venues.

4.0 Results:

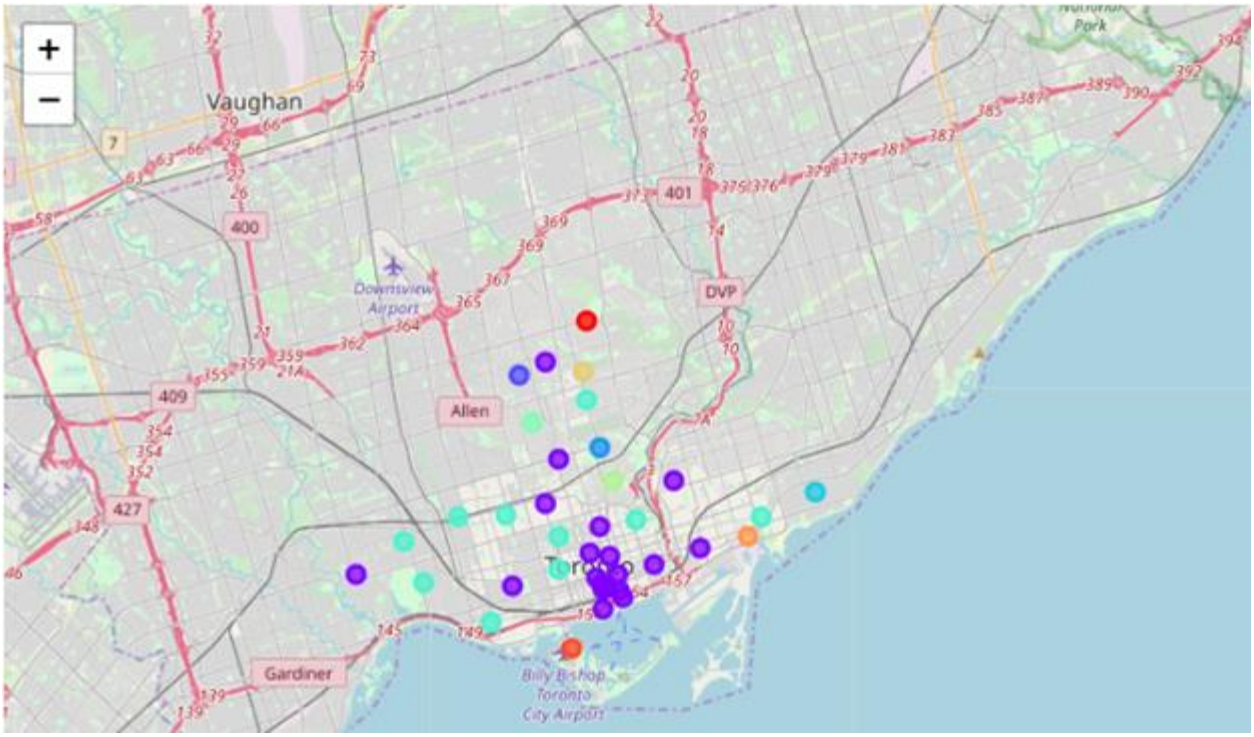
a. Adding the Cluster Labels to the Venue Data

After using K-means algorithm for clustering of the data, the cluster labels were then added to easily identify when neighborhood belong to the different clusters. The below table depicts the clustered data along with the top 10 most common venues in that cluster.

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
The Beaches	43.676357	-79.293031	4	Trail	Health Food Store	Pub	Eastern European Restaurant	Discount Store	Dog Run	Doner Restaurant	Donut Shop
The Danforth West, Riverdale	43.679557	-79.352188	1	Greek Restaurant	Coffee Shop	Ice Cream Shop	Italian Restaurant	Furniture / Home Store	Pizza Place	Bookstore	Brewery
The Beaches West, India Bazaar	43.668999	-79.315572	5	Park	Gym	Pub	Liquor Store	Board Shop	Fast Food Restaurant	Burger Joint	Fish & Chips Shop
Studio District	43.659526	-79.340923	1	Café	Coffee Shop	Bakery	Italian Restaurant	American Restaurant	Yoga Studio	Comfort Food Restaurant	Seafood Restaurant
Lawrence Park	43.728020	-79.388790	0	Park	Swim School	Bus Line	Women's Store	Discount Store	Fast Food Restaurant	Farmers Market	Falafel Restaurant

b. Visualizing the resulting Clusters

We use the matplotlib and folium packages to visualize the clusters on a map of Toronto.



5.0 **Discussion:**

The goal of this analysis was carried out to find out similar neighborhoods for a person relocating within the city of Toronto.
As we analyze the results section, we can analyze the clusters and see similar neighborhoods in different parts of the city. For example, if we compare the different neighborhoods clustered in cluster 2.

	Borough	Cluster Labels	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
0	Scarborough	1.0	Central Toronto	Supermarket	Liquor Store	Furniture / Home Store	Dessert Shop	Park	Italian Restaurant	Coffee Shop
1	Scarborough	1.0	Downtown Toronto	Coffee Shop	Café	Performing Arts Venue	Gym	Deli / Bodega	Sushi Restaurant	Art Gallery
6	Scarborough	1.0	North York	Coffee Shop	Fried Chicken Joint	Theater	Bank	Fast Food Restaurant	Deli / Bodega	Italian Restaurant
7	Scarborough	1.0	Scarborough	Grocery Store	Electronics Store	Chinese Restaurant	Pharmacy	Sandwich Place	Cosmetics Shop	Bubble Tea Shop
8	Scarborough	1.0	West Toronto	Yoga Studio	Beer Store	Coffee Shop	Record Shop	Mac & Cheese Joint	Japanese Restaurant	Brewery

As seen in the table above, if a person wished to move from a suburb region in Downtown Toronto to Central Toronto. If a person's current location were in the Neighborhood of Studio District in Downtown Toronto, which has venues like cafes, Gym, Art Gallery and Sushi restaurants nearby, the person, would like to relocate to a neighborhood like North York which also has venues like Coffee Shops and Restaurants. This is just one example of how our data analysis can help people relocate from one part of the city to another.

6.0 Conclusion

In a world like ours driven by data, there are many real-life problems or scenarios where data can be used to find solutions to those problems. As seen in the example above, data was used to cluster neighborhoods in Toronto based on the most common venues in those neighborhoods hence someone that is searching for a neighborhood were there are shops, restaurants and gym places can use this data as a guide to relocate.

References:

· https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M
· CSV for Coordinate data: http://cocl.us/Geospatial_data
· Foursquare API