

Capstone Project: The Battle of Neighbourhoods

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1 Introduction

1.1 Background

Toronto, Canada's largest city with 2,731,571 population in 2016, is the capital of Ontario Province, the most populous city in Canada, and the fourth largest populous city in North America. This city is a world leader in such areas as business, finance, technology, entertainment and culture. Its large population of immigrants from all over the globe has also made Toronto one of the most multicultural cities in the world. Toronto encompasses a geographical area formerly administered by many separate municipalities. These municipalities have each developed a distinct history and identity over the years, and their names remain in common use among Torontonians. Former municipalities include East York, Etobicoke, Forest Hill, Mimico, North York, Parkdale, Scarborough, Swansea, Weston and York. Throughout the city there exist hundreds of small neighbourhoods and some larger neighbourhoods covering a few square kilometres which made Toronto a city of neighbourhoods.

1.2 Problem Definition

In this project, we want to explore the neighborhoods in Toronto and group them into similar and dissimilar clusters. There can be many factors to consider some regions similar, including the facilities, events, restaurants, parks, schools, etc. in each neighborhood.

1.3 Interest

This study can be interesting for those who want to live temporary or for a long period in Toronto including new residents, tourists, and people who want to change their neighborhood. Imagine that someone wants to live a new neighborhood (whether they are tourists or Toronto residents), it is important for them to know their new neighborhood and compare it to their previous or desired districts. Hence, this project will help them to know every area in Toronto and choose their new and favorite neighborhood.

2 Data Acquisition and Cleaning

2.1 Data Sources

The following Wikipedia page is used to get information about neighborhoods in Toronto: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M. This defines the scope of this project, which is the city of Toronto in Canada.

Also, we use the following CSV file to extract the geographical coordinates of different postal codes (neighborhoods): http://cocl.us/Geospatial_data. This is required to get the venue data and plot the map.

Finally, we request the venue data for each neighborhood from the Foursquare API. This data is used to execute clustering on the neighborhoods.

2.2 Data Cleaning

We combine the data downloaded from multiple sources into one table. After transforming the data into the Pandas data frame, we ignore the rows with ‘Not assigned’ label in the Borough column. Then we merge the neighborhoods with the same postal code. Finally, if a neighborhood has ‘Not assigned’ name, we consider the name of their borough as their neighborhood’s name.

2.3 Feature Selection

After all the merging and cleaning data that we mentioned above, we consider postal code, borough, neighborhood’s name, latitude, and longitude of each neighborhood as shown in the following table (there are 103 rows and five columns). Note that in the methodology section, we will discuss how to consider and insert different events for each neighborhood as a new data frame.

| | Postalcode | Borough | Neighbourhood | 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 |

3 Methodology

3.1 Preparing the Primary Data

First, we use the BeautifulSoup package to read the data about Toronto neighborhoods on the Wikipedia page, and then we transform it into the Pandas data frame as below.

| | Postalcode | Borough | Neighbourhood |
|---|------------|------------------|------------------|
| 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 | Harbourfront |

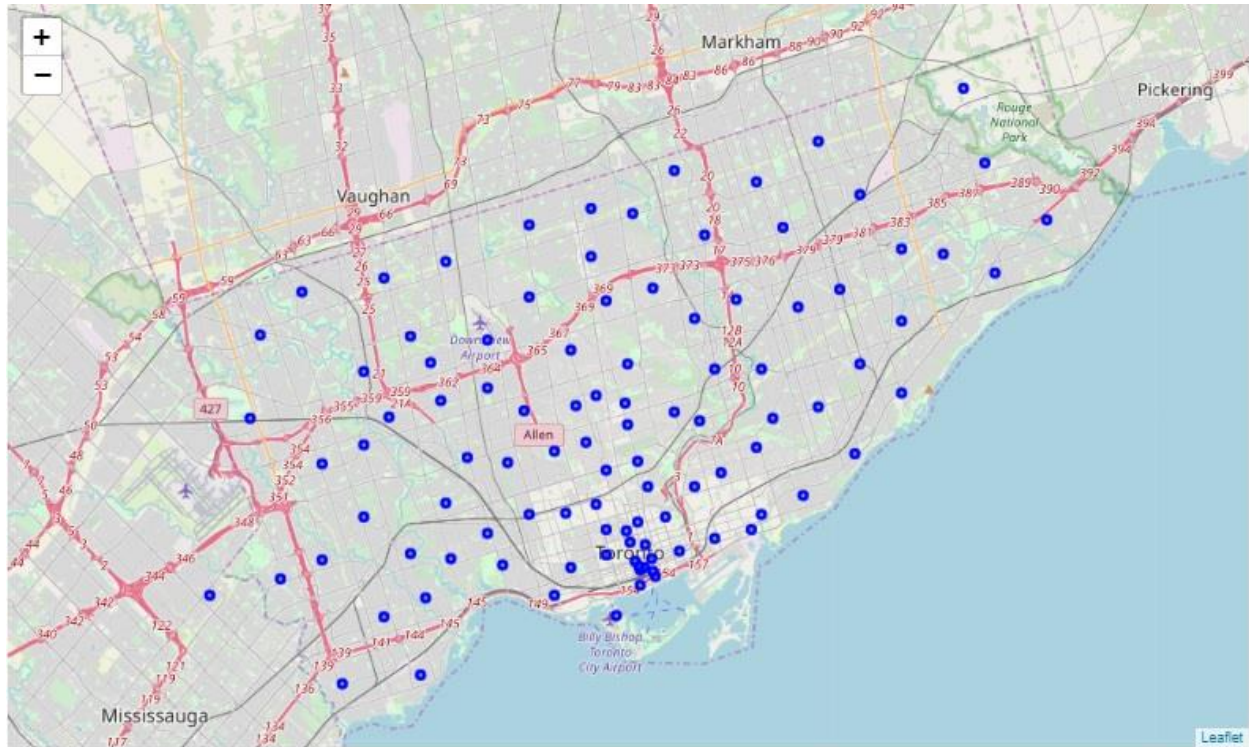
Second, we use the CSV file to extract the geographical coordinates of different neighborhoods.

Finally, after doing some data cleaning mentioned in section 2.2, we combine the data as follows.

| | Postalcode | Borough | Neighbourhood | Latitude | Longitude |
|---|------------|-------------|--|-----------|------------|
| 0 | M1B | Scarborough | Rouge, Malvern | 43.806686 | -79.194353 |
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3.2 Showing the Toronto Neighborhoods on the Map

By using the latitude and longitude of each neighborhood, and the Python folium library, we generate the following map to visualize the data (Toronto neighborhoods).



3.3 Using Foursquare API to Explore each Neighborhood

By using the Foursquare API, we explore the neighborhoods to find out what venues exist in each neighborhood. We get the top 50 venues of each neighborhood within the radius of 600 meters of their geographical coordinates. Eventually, we create a new data frame as follows to display the ten most common venues of each neighborhood.

| | 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 | 8th Most Common Venue | 9th Most Common Venue | 10th Most Common Venue |
|---|----------------|---|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|------------------------|
| 0 | 0 | Adelaide, King, Richmond | Coffee Shop | Café | Steakhouse | Bar | Restaurant | Burger Joint | Bakery | Asian Restaurant | Thai Restaurant | Cosmetics Shop |
| 1 | 0 | Berczy Park | Coffee Shop | Cocktail Bar | Beer Bar | Farmers Market | Bakery | Seafood Restaurant | Steakhouse | Cheese Shop | Café | Greek Restaurant |
| 2 | 0 | Brockton, Exhibition Place, Parkdale Village | Breakfast Spot | Café | Nightclub | Coffee Shop | Yoga Studio | Pet Store | Stadium | Burrito Place | Restaurant | Climbing Gym |
| 3 | 0 | Business Reply Mail Processing Centre 969 Eastern | Skate Park | Auto Workshop | Brewery | Smoke Shop | Spa | Restaurant | Farmers Market | Fast Food Restaurant | Burrito Place | Recording Studio |
| 4 | 0 | CN Tower, Bathurst Quay, Island airport, Harbo... | Airport Service | Airport Lounge | Airport Terminal | Coffee Shop | Harbor / Marina | Rental Car Location | Sculpture Garden | Bar | Boat or Ferry | Airport |

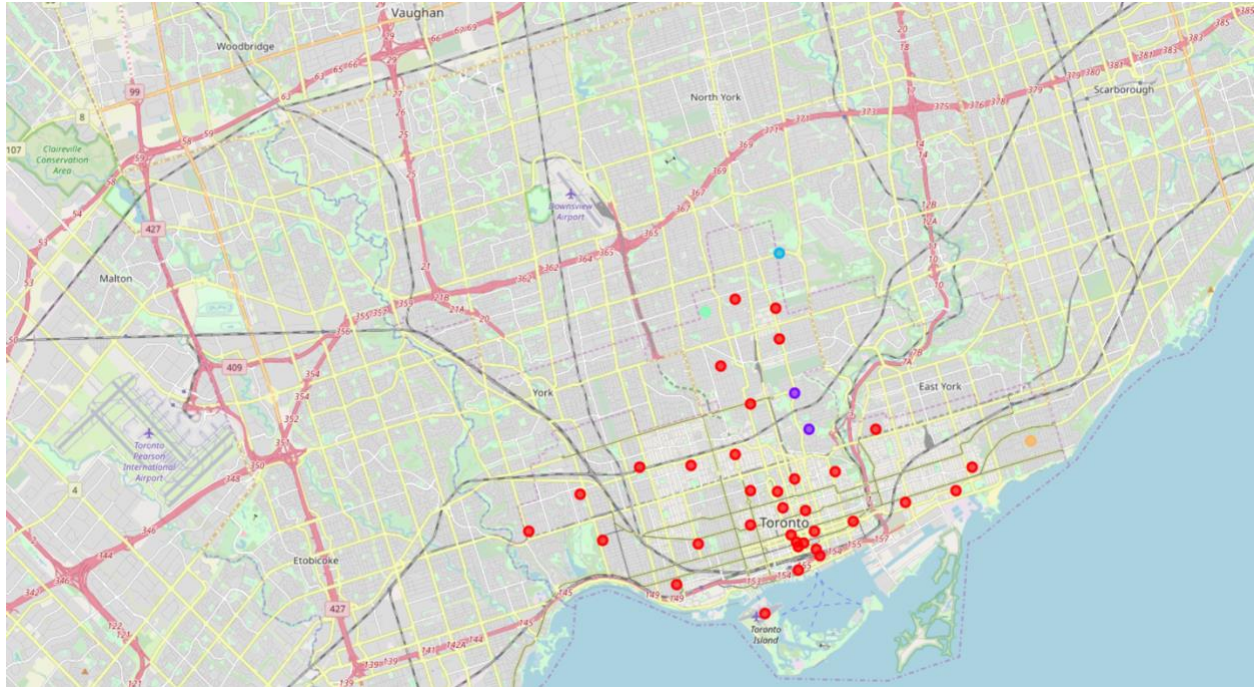
3.4 K-Means Clustering Algorithm

There are some common venues among neighborhoods. So, the K-means algorithm is a suitable way to group neighborhoods into different categories in which each category shows similar neighborhoods.

K-means algorithm is a popular unsupervised machine learning algorithm, which is used for clustering data. Note that we categorize neighborhoods into 6 clusters.

4 Results

The following map visualizes the cluster of each neighborhood in Toronto by using the Folium package and Matplotlib library.



5 Discussion

Now, we know about the most common venues in each neighborhood. Also, we categorized similar neighborhoods into 5 clusters. This helps those who want to live in a new place to choose the neighborhood which is similar to their previous or desired neighborhood.

We can analyze the clusters and see similar neighborhoods in each cluster. For example, the below table shows a part of the neighborhoods in cluster 1.

| | Borough | 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 |
|----|------------------|----------------|-----------------------|-----------------------|-----------------------|-----------------------|------------------------|-----------------------|-----------------------|--------------------------|-----------------------|-----------------------------|
| 41 | East Toronto | 0 | Greek Restaurant | Coffee Shop | Italian Restaurant | Ice Cream Shop | Furniture / Home Store | Restaurant | Bubble Tea Shop | Grocery Store | Pub | Pizza Place |
| 42 | East Toronto | 0 | Park | Board Shop | Sushi Restaurant | Sandwich Place | Brewery | Liquor Store | Burger Joint | Italian Restaurant | Burrito Place | Fast Food Restaurant |
| 43 | East Toronto | 0 | Café | Coffee Shop | Gastropub | Bakery | Italian Restaurant | Brewery | American Restaurant | Yoga Studio | Bookstore | Sandwich Place |
| 45 | Central Toronto | 0 | Park | Department Store | Breakfast Spot | Sandwich Place | Food & Drink Shop | Hotel | Gym | Comic Shop | Dim Sum Restaurant | Eastern European Restaurant |
| 46 | Central Toronto | 0 | Clothing Store | Coffee Shop | Sporting Goods Shop | Salon / Barbershop | Restaurant | Rental Car Location | Café | Chinese Restaurant | Park | Mexican Restaurant |
| 47 | Central Toronto | 0 | Dessert Shop | Sandwich Place | Coffee Shop | Sushi Restaurant | Gym | Café | Italian Restaurant | Pizza Place | Brewery | Restaurant |
| 49 | Central Toronto | 0 | Coffee Shop | Pub | Pizza Place | Sushi Restaurant | Sports Bar | Fried Chicken Joint | Restaurant | American Restaurant | Supermarket | Liquor Store |
| 51 | Downtown Toronto | 0 | Restaurant | Coffee Shop | Italian Restaurant | Pizza Place | Bakery | Pub | Café | Butcher | Sandwich Place | Breakfast Spot |
| 52 | Downtown Toronto | 0 | Coffee Shop | Japanese Restaurant | Gay Bar | Sushi Restaurant | Restaurant | Fast Food Restaurant | Men's Store | Mediterranean Restaurant | Hotel | Gym |
| 53 | Downtown Toronto | 0 | Coffee Shop | Park | Bakery | Café | Pub | Breakfast Spot | Restaurant | Mexican Restaurant | Farmers Market | Event Space |
| 54 | Downtown Toronto | 0 | Coffee Shop | Clothing Store | Café | Japanese Restaurant | Cosmetics Shop | Electronics Store | Tea Room | Ice Cream Shop | Bubble Tea Shop | Pizza Place |
| 55 | Downtown Toronto | 0 | Coffee Shop | Café | Restaurant | Cocktail Bar | Cosmetics Shop | Italian Restaurant | Beer Bar | Clothing Store | American Restaurant | Hotel |
| 56 | Downtown Toronto | 0 | Coffee Shop | Cocktail Bar | Beer Bar | Farmers Market | Bakery | Seafood Restaurant | Steakhouse | Cheese Shop | Café | Greek Restaurant |
| 57 | Downtown Toronto | 0 | Coffee Shop | Sandwich Place | Café | Italian Restaurant | Ice Cream Shop | Juice Bar | Japanese Restaurant | Burger Joint | Salad Place | Chinese Restaurant |
| 58 | Downtown Toronto | 0 | Coffee Shop | Café | Steakhouse | Bar | Restaurant | Burger Joint | Bakery | Asian Restaurant | Thai Restaurant | Cosmetics Shop |
| 59 | Downtown Toronto | 0 | Coffee Shop | Aquarium | Italian Restaurant | Hotel | Café | Sporting Goods Shop | Restaurant | Fried Chicken Joint | Scenic Lookout | Brewery |
| 60 | Downtown Toronto | 0 | Coffee Shop | Café | Hotel | Restaurant | Steakhouse | Gastropub | Seafood Restaurant | Bar | Del / Bodega | Italian Restaurant |
| 61 | Downtown Toronto | 0 | Coffee Shop | Café | Hotel | Restaurant | Gym | Seafood Restaurant | Bakery | Italian Restaurant | Del / Bodega | Gastropub |

6 Conclusion and Future Directions

In this project, we explored the neighborhoods in Toronto through preparing data, categorize neighborhoods into six groups by performing K-means clustering algorithm (which is an unsupervised machine learning algorithm). Lastly, we developed recommendations to the people who want to live temporary or for a long period in Toronto including new residents, tourists, and people who want to change their neighborhood.

As new research, some can consider other algorithms to cluster neighborhoods and compare the results of different algorithms. Also, we can find a way to determine the optimal number of clusters (k) before performing the K-means algorithm.

7 References

- Wikipedia page: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M
- CSV file for geographical data: http://cocl.us/Geospatial_data
- Foursquare API