Final Report - KMeans Clustering to compare Manhattan and Toronto

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Introduction

Background

Toronto is the most popular and most populated city in Canada, located in the Canadian province of Ontario. It has a population of 2,731,571, which is 1,026,877, approximately 60% higher than Montreal (the Canadian city with the second-highest population). On the other hand, with a population of approximately 8,175,133 people, New York City is the most populated city in the USA. There are five boroughs of New York: The Bronx, Brooklyn, Manhattan, Queens, and Staten Island. Of the five boroughs, Manhattan is the most popular of the 5 boroughs and serves as the financial capital of the USA. Each year, hundreds of thousands of people migrate to Canada yearly, and the United States of America (USA) is one of the top 5 origins of these immigrants[1]. Most of these immigrants settle in the province of Ontario.[2] The Ontarian city in which most immigrants settle in Toronto. Immigrants migrating from the USA and settling in Toronto may be doing so for a variety of reasons such as work, schooling, and family reunification.

Problem

Many immigrants in Canada are looking for neighborhoods similar to their old Neighbourhood when looking for a home. For example, a family with kids migrating from one neighbourhood to another may want to ensure there are similarly good parks and playgrounds in the new Neighbourhood. Also, a young person migrating for a job opportunity may want to enjoy bars and clubs in the new city as they did in the old city. It would be helpful if we can identify neighborhoods in Toronto that are like an immigrant's Neighbourhood of origin. This information would assist real estate agents in targeting immigrants moving from a given region. Ultimately, real estate agents would be better able to recommend them homes for rent/sale in neighborhoods that suit them based on their previous Neighbourhood. In this report, we consider the Neighbourhoods of Manhattan to Toronto.

To make this determination, we may use locational data related to venues found in each neighbourhood. The datasets should include the Neighbourhoods of each city along with their respective latitudinal and longitudinal coordinates. The goal is to assess and determine neighborhoods located in Toronto that are like those found in Manhattan based on the available venues within the areas by modeling clusters of neighbourhoods to identify similarities.

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[1] https://www.canada.ca/en/immigration-refugees-citizenship/corporate/publications-manuals/annual-report-parliament-immigration-2018/permanent-residents-admitted.html
[2] https://www.canada.ca/en/immigration-refugees-citizenship/corporate/publications-manuals/annual-report-parliament-immigration-2018/report.html

Interest

This information would be of interest to real estate agents looking to market the sale of homes to individuals settling into Toronto after migrating from Manhattan. Knowing neighbourhoods in Toronto that at similar to specific neighbourhoods in Manhattan can help real estate agents better serve their clients (in this case, the immigrant).

Also note that, although we analyze Manhattan and Toronto data in this report, the analysis can also be replicated in other cities.

Data Sourcing and Processing

Data sources

We source the data of this report from multiple locations. Locational data of Toronto boroughs and cities were scraped from Wikipedia[3]; however, the coordinate data need for the analysis is not included. Coursera provided this coordinate data. Locational data of New York boroughs and cities are available on the New York University website.[4] This data is then used to retrieve venue data from Foursquare API. The data receive that is received from Foursquare is a list of all recorded venues in each respective Neighbourhood of Toronto and Manhattan[5].

Data cleaning

As mentioned above, the data used was downloaded from a combination of websites. This data was then combined into two dataframes for Toronto neighbourhoods and New York neighbourhoods. In both dataframes, the fields are Neighbourhood, Borough, Latitude, and Longitude. The following changes were made in the Toronto dataframe:

- Their zip code grouped neighbourhoods. If two records have the same zip code, those records were combined.
- "Not Assigned" Neighbourhoods were dropped from the dataset.
- Records with "Note Assigned" Boroughs were given the name of their Neighbourhood (s) within it.

The New York and Toronto dataframe was then combined. This new data represents all boroughs of Toronto and Manhattan; however, it also contained data on other boroughs of the city of Toronto and New York. We are concerned with the proper boroughs of Toronto and not its neighbouring municipalities like Mississauga and Scarborough. As it pertains to the New York City data, we are interested in Manhattan for this report. The following boroughs were dropped leaving only the boroughs of Manhattan, East Toronto, Central Toronto, Downtown Toronto, and West Toronto. Table 1. shows those boroughs which were dropped and those that were kept.

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[3] https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M

[4] https://geo.nyu.edu/catalog/nyu_2451_34572

[5] https://developer.foursquare.com/

Table 1.

City	Boroughs	Number of Neighbourhood
Kept		
New York	Manhattan	40
Toronto	East Toronto, Central Toronto, Downtown Toronto, West Toronto	38
Dropped		
New York	'Bronx', 'Brooklyn', 'Queens', 'Staten Island'	266
Toronto	'Scarborough', 'North York', 'East York', 'York', 'Mississauga', 'Etobicoke	41

Foursquare Data

Using the dataframe of Manhattan and Toronto neighbourhoods along with their respective coordinates, we can request data from Foursquare that is specific to those coordinates. The data that we're interested in relating to the types of venues located in and around a give neighbourhood's coordinate. From Foursquare, we retrieved the top one hundred venues that are in each neighbor within a radius of 500 meters of its respective coordinates.

Further Processing

The resulting dataframe holds 5036 rows of venues (Manhattan: 3326; Toronto: 1710). Each row provides the Neighbourhood, Neighbourhood Latitude, Neighbourhood Longitude, Venue, Venue Latitude, Venue Longitude, and the Venue Category. Taking the data in the Neighbourhood and Venue Category fields, we perform one-hot encoding. This will transform the categorical data in the Venue Category field into quantitative values between 0 and 1 for each Neighbourhood. The value is a function of the frequency at which a venue in each category occurs in the Neighbourhoods. Now there is a dataframe listing the neighbourhoods of Manhattan and Toronto along with values representing the kinds of venues that can be found in the areas. This dataframe is used to form the clusters.

Features

At this point, there are 78 samples (number of neighbourhoods) and 379 features (number of venue categories) in the data. These features are the terms in which neighbourhoods are described and are compared. Table 2. is an example of an element of the sample. This Neighbourhood is found in Manhattan called "Clinton." Each number in the column represents the proportion of venues retrieved from Foursquare found in Clinton in that venue category. For example, by reviewing the 'Theater' field, it is understood that 10% of the venues in Clinton retrieved from Foursquare are theaters. Conversely, it is also understood that 0% are yoga studios.

The goal here is to compare features of all the neighbourhoods – grouping together those neighbourhoods with a similar distribution of venues.

Table 2.

	Theater	Gym / Fitness Center	American Restaurant	Spa	Italian Restaurant	Wine Shop	Hotel	Steakhouse	New American Restaurant	French Restaurant	...	Fish Market	Fish & Chips Shop	Filipino Restaurant	Field	Festival	Fast Food Restaurant	Farmers Market	Falafel Restaurant	Exhibit	Yoga Studio
Neighbourhood																					
Clinton	0.1	0.05	0.04	0.04	0.04	0.03	0.03	0.02	0.02	0.02	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Methodology

Data Exploration

Landscape

As stated above, the data that we are sampling relates to neighbourhoods in the Manhattan and Toronto boroughs. Review Figures 1 and 2 below to see the distribution of neighbourhoods across the two landscapes.

Figure 1.

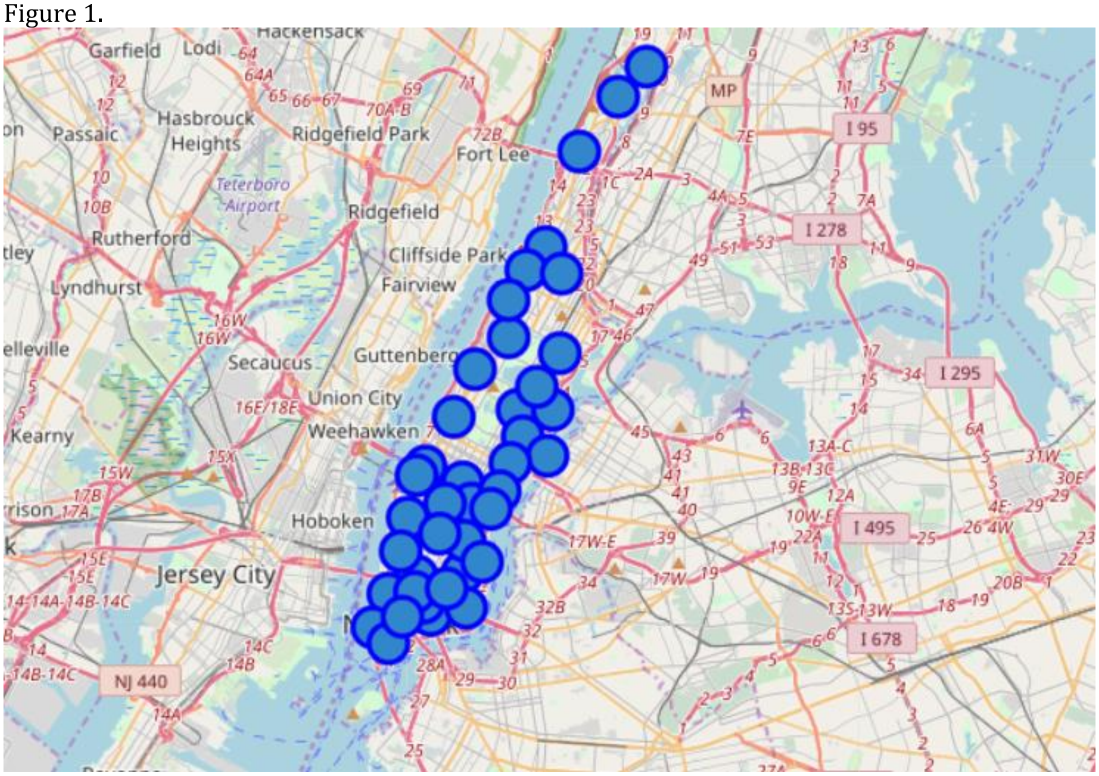
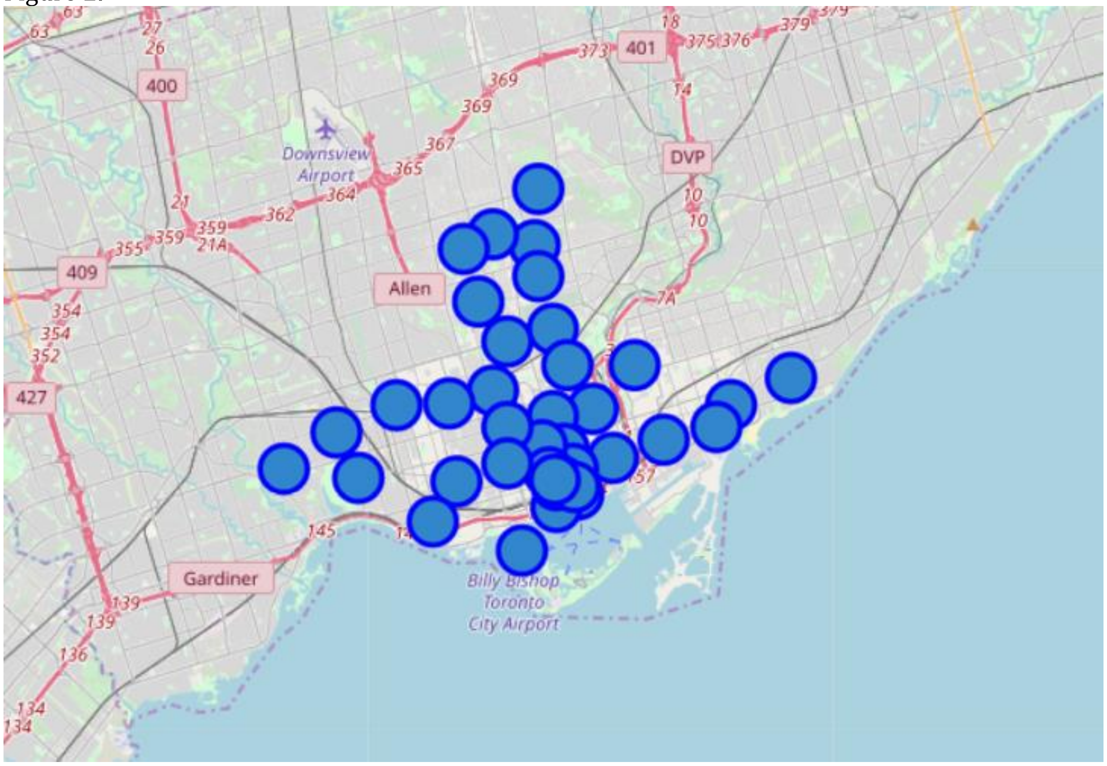


Figure 2.



Top Venues: Coffee Shop and Cafés

Caffeine is a very popular drug most often consumed using coffee beans. In Table 3. we see that 'Coffee Shop' is the most frequently observed venue category overall with 'Café' as the second most common. However, by parsing the data, we can see that the most common venue type in Manhattan is 'Italian Restaurant' with 'Café' as a close second. Coffee beverages are also sold at cafés, which further supports the notion that coffee is popular in both Manhattan and Toronto.

Although both coffee shops and cafés are known for selling coffee, for this report, they are represented as separate venue categories. This separation is intentional because although the terms are sometimes informally used interchangeably, the menu of a coffee shop is usually limited to coffee beverages, pastries, and small meals, cafés typical sell fuller meals for lunch and dinner. For this reason, it was decided to leave the type categories separate.

Table 3.

City	Most Common Venue Category	%	2nd Most Common Venue Category	%
Manhattan	Italian Restaurant	3.8	Café	3.7
Toronto	Coffee Shop	8.6	Café	5.5
Overall	Coffee Shop	5.4	Café	3.5

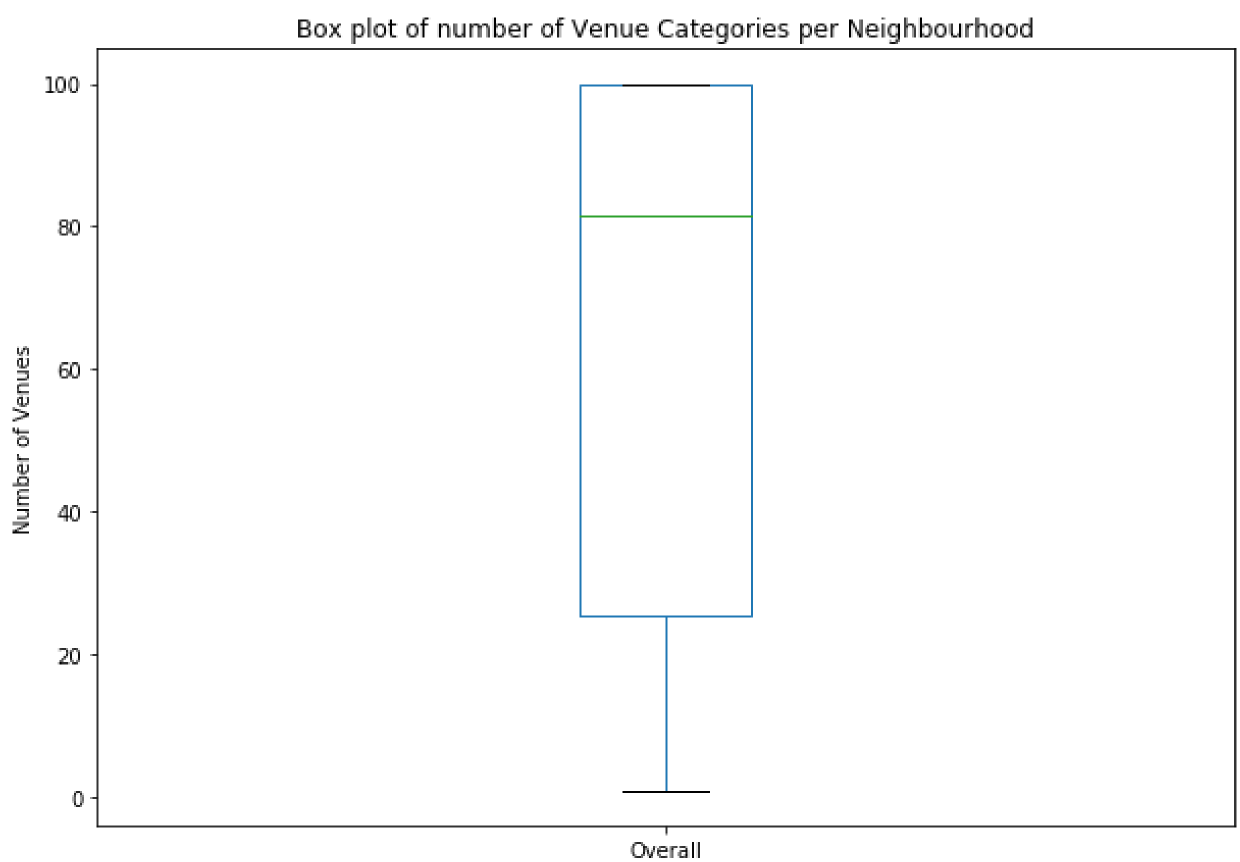
Distribution of Venues per Neighbourhood

The below table and box plot represent the distribution of the number of Venue Categories per Neighbourhood. A box plot is a useful tool when trying to identify outliers in a distribution of data. Here we can note the following: Based on the 3rd quartile being equal to the maximum value, we can state that 75% of the sampled neighbourhoods have maximum about of venues in the dataset (100). There are some neighbourhoods with only one venue recorded in the data set. Most importantly, there are no outliers in the data set. An outlier here is defined as a value, and that is greater than the third quartile or less than the first quartile by 1.5 times the interquartile range (IQR). The IQR of the data below is 74.5 (the difference between the third and first quartile. As we can see, no values are fitting that description.

Table 4.

Statistic	Value
Count	78.0
Maximum Value	100.0
3rd Quartile	100.0
Median	81.5
1st Quartile	25.5
Minimum Value	1.0

Figure 3



Clustering Analysis

There are different kinds of methods used for clustering data. Some of these types are partitioning, hierarchical, and density-based clustering. The concept and objective are the same for these different types; however, the steps taken to achieve those objectives are different. Because of these differences, there are pros and cons to using either approach. For instance, a partitioning method of clustering called k-means requires the user to decide the number of clusters to group the data subjectively. On the other hand, the hierarchical approach does not require the user to choose the number of clusters. However, KMeans is generally considered more efficient than the hierarchical approach. In this report, we use the KMeans clustering method because it's efficient. To avoid the inherent bias in specifying the K number of clusters subjectively, we utilize the 'elbow method' to find the optimal number of 'k' clusters. The YellowBrick extension of the Scikit-Learn API is employed for this purpose.

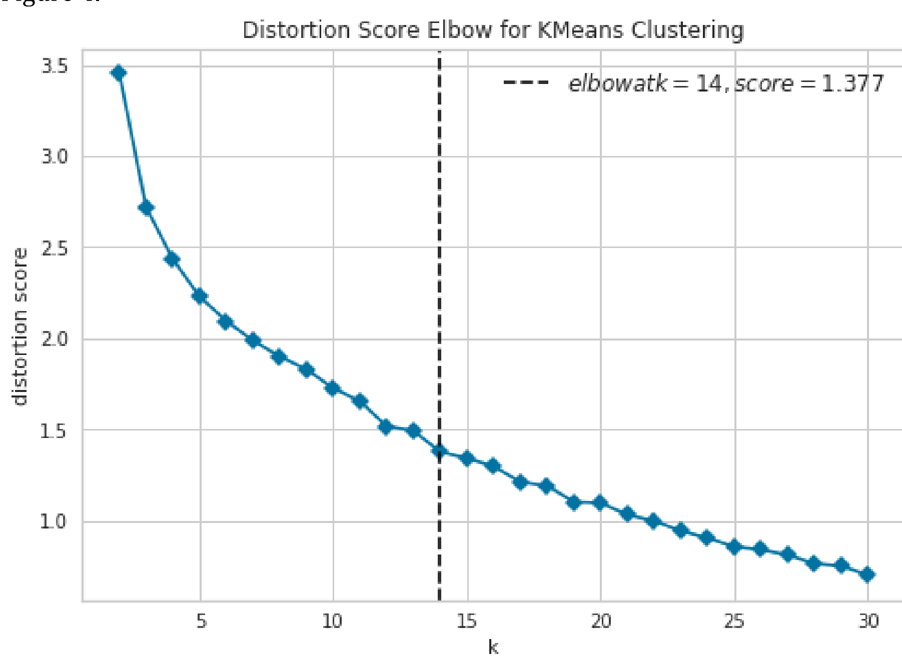
Optimal K Clusters

One method to choose the optimal number of clusters is the elbow method. The objective of the elbow method is to decrease the distance of elements within a given cluster. The steps of the elbow method are to first run the KMeans algorithm multiple times with varying about of clusters/centroids/ k. Then the distortion score is calculated, which is a measurement of the sum-squared-distance from each point to its respective centroid. As k approaches the sample size, the level of distortion decreases. This relationship between k and distortion isn't a bad thing; however, we do not want that many centroids. Thus, the last step is to select the point on the graph at which the marginal improvement begins to decline significantly (the elbow). Thankfully, the KElbowVisualizer of YellowBrick extension finds this point automatedly.

Results

In the graph below, we can see that the KMeans algorithm was executed 30 times, and the elbow is located where k=14. Therefore, we proceed with 14 as the optimal number of clusters to model the data.

Figure 4.

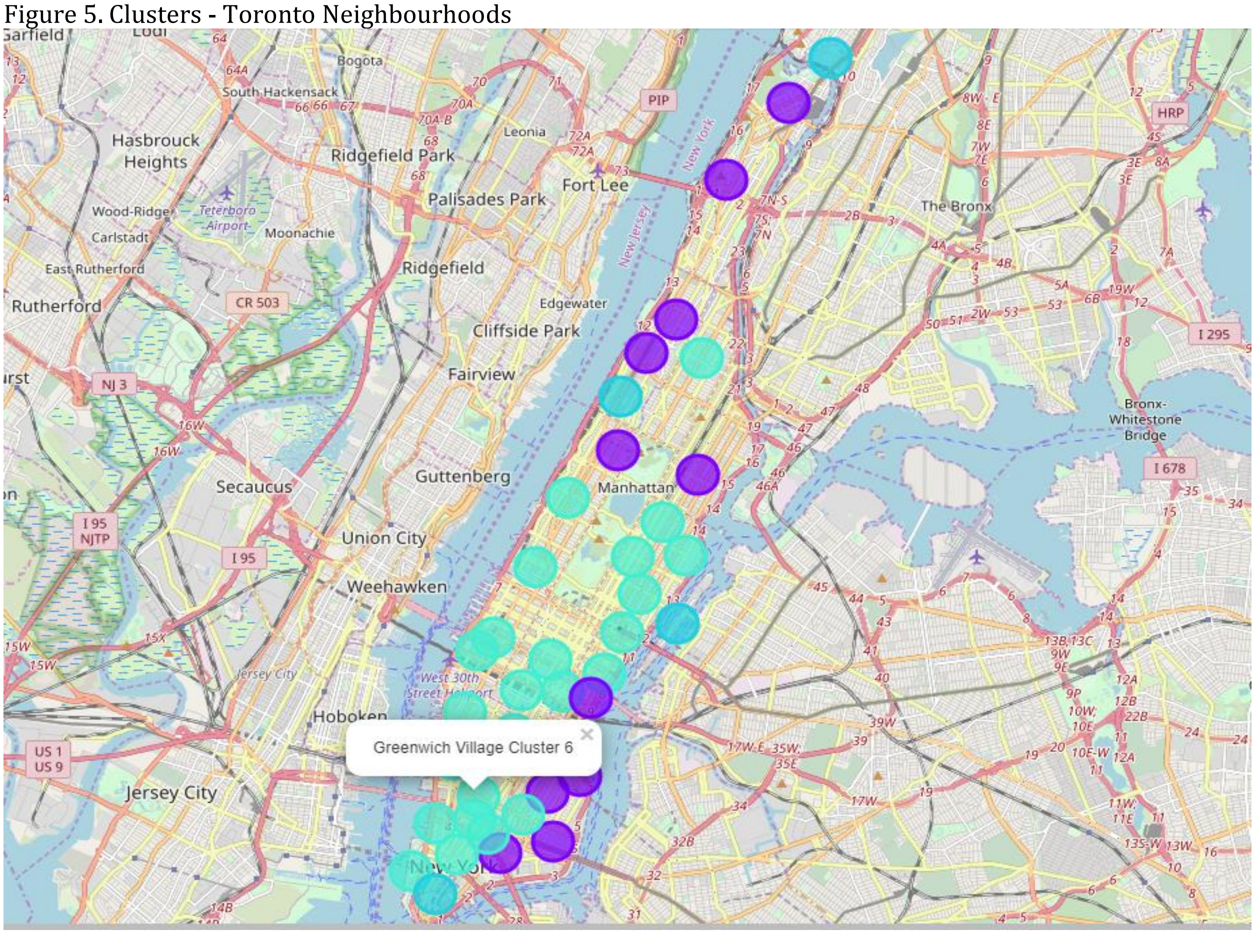


KMeans clustering

Using the KMeans approach with 14 centroids, the clusters depicted on the maps in Figures 5 & 6 were generated. Note the following:

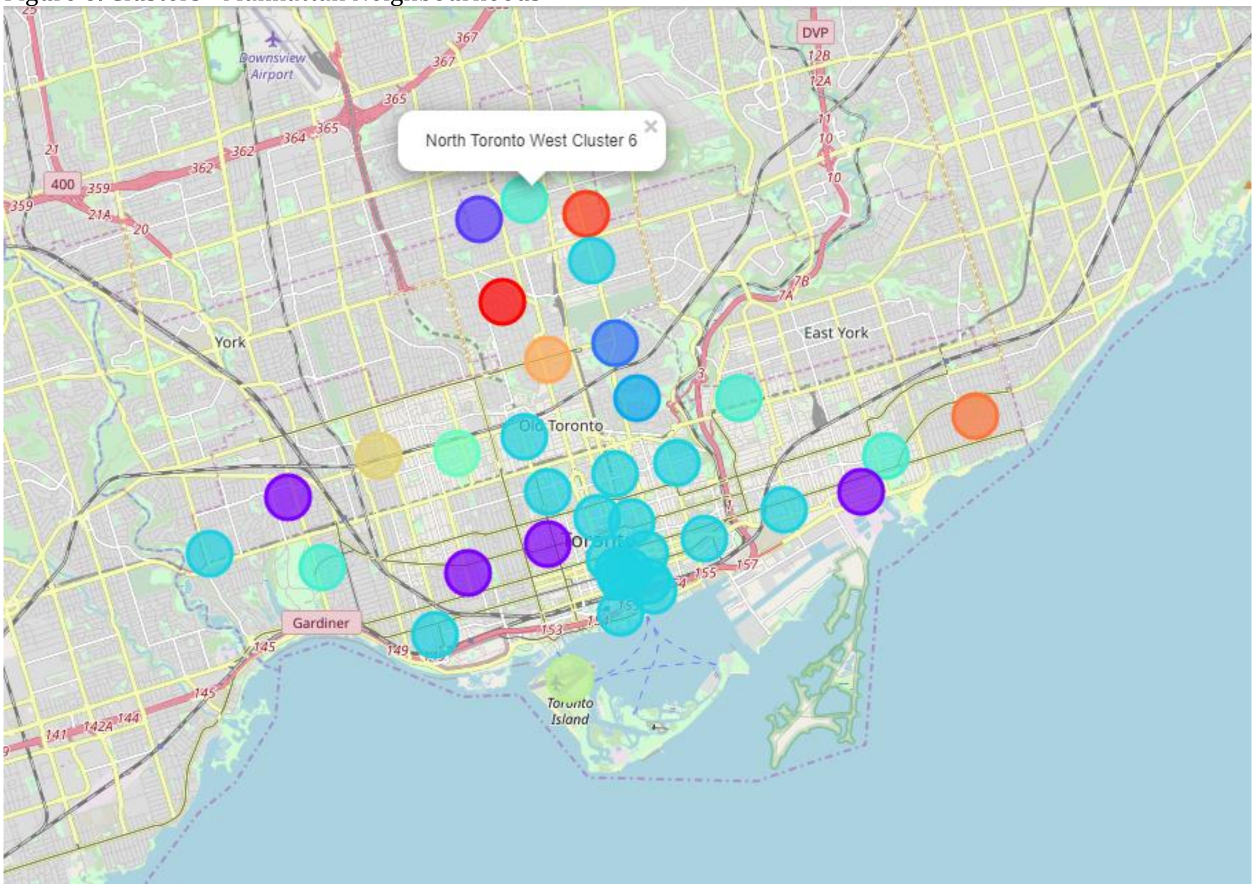
- The colors indicate neighbourhoods in the same cluster. For example, two neighbourhoods colored purple are a part of the same cluster.
- Neighbourhoods on two different maps are still a part of the same cluster if they are the same color. For example, Greenwich Village in Manhattan is of the same cluster as North Toronto West in Toronto.
- Table 5 below shows a sample of 4 neighbourhoods in cluster 1 and the top 5 venues categories of each Neighbourhood.

Figure 5. Clusters - Toronto Neighbourhoods



[73]:

Figure 6. Clusters - Manhattan Neighbourhoods



[74]:

Table 5.

Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
Manhattan	Chinatown	40.715618	-73.994279	1	Chinese Restaurant	Cocktail Bar	Bakery	American Restaurant	Optical Shop
Manhattan	Washington Heights	40.851903	-73.936900	1	Café	Mobile Phone Shop	Bakery	Mexican Restaurant	Grocery Store
Manhattan	Inwood	40.867684	-73.921210	1	Café	Mexican Restaurant	Deli / Bodega	Pizza Place	Lounge
Manhattan	Hamilton Heights	40.823604	-73.949688	1	Café	Mexican Restaurant	Pizza Place	Coffee Shop	Deli / Bodega
Manhattan	Marble Hill	40.876551	-73.910660	5	Sandwich Place	Coffee Shop	Miscellaneous Shop	Steakhouse	Supplement Shop

Discussion

Recommendation

We now go back to the initial question, "Which neighbourhoods in Toronto are similar to those neighbourhoods of potential immigrants from Manhattan?" Table 6 lists the 14 clusters and the total number of neighbourhoods in each cluster based on their origin (Manhattan or Toronto). Note that only Cluster 1, 5, and 6 hold neighbourhoods from both Manhattan and Toronto. The remaining clusters are made up of only Toronto neighbourhoods. Those clusters are not useful to us. Moving forward, we shall only focus on elements included in those clusters. With that said, Tables 7, 8, and 9 display the neighbourhoods in clusters 1,5 and 6, respectively. These are Manhattan and Toronto neighbourhoods that are like each other. My recommendation is to market homes in neighbourhoods of Toronto to individuals migrating from neighbourhoods in Manhattan located within the same cluster. The logic is that those neighbourhoods would be more compatible with those migrants based on the idea that the venues in the neighbourhoods match their former neighbourhoods in Manhattan. For example, if a new immigrant is from Marble Hill, Manhattan, he or she would probably be keen on Toronto's Davisville or King/Adelaide/Richmond neighbourhoods considering that they're both in Cluster 5 and have similar venues. The same can be said about those moving from Chinatown in Manhattan, which is in Cluster 1 along with the Kensington/Grange Town/Chinatown. These clusters may be very useful in narrowing down neighbourhoods matching the perspective buyers.

Table 6.

Clusters	# Manhattan Neighbourhoods	# Toronto Neighbourhoods
0	0	1
1	12	4
2	0	1
3	0	1
4	0	1
5	4	19
6	24	4
7	0	1
8	0	1
9	0	1
10	0	1
11	0	1
12	0	1
13	0	1

Table 7. Cluster 1

Cluster Labels	Borough	Neighbourhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
1	Manhattan	Chinatown	Chinese Restaurant	Cocktail Bar	Bakery	American Restaurant	Optical Shop
1	Manhattan	Washington Heights	Café	Mobile Phone Shop	Bakery	Mexican Restaurant	Grocery Store
1	Manhattan	Inwood	Café	Mexican Restaurant	Deli / Bodega	Pizza Place	Lounge
1	Manhattan	Hamilton Heights	Café	Mexican Restaurant	Pizza Place	Coffee Shop	Deli / Bodega
1	Manhattan	Manhattanville	Coffee Shop	Mexican Restaurant	Chinese Restaurant	Italian Restaurant	Park
1	Manhattan	East Harlem	Mexican Restaurant	Bakery	Deli / Bodega	Pizza Place	Latin American Restaurant
1	Manhattan	East Village	Bar	Wine Bar	Ice Cream Shop	Mexican Restaurant	Pizza Place
1	Manhattan	Lower East Side	Pizza Place	Café	Coffee Shop	Sandwich Place	Japanese Restaurant
1	Manhattan	Manhattan Valley	Indian Restaurant	Coffee Shop	Pizza Place	Szechuan Restaurant	Bar
1	Manhattan	Gramercy	Bar	Mexican Restaurant	Italian Restaurant	American Restaurant	Pizza Place
1	Manhattan	Tudor City	Park	Café	Mexican Restaurant	Greek Restaurant	Deli / Bodega
1	Manhattan	Stuyvesant Town	Bar	Park	Tennis Court	Fountain	Coffee Shop
1	Downtown Toronto	Kensington Market,Grange Park,Chinatown	Café	Vegetarian / Vegan Restaurant	Chinese Restaurant	Bar	Vietnamese Restaurant
1	West Toronto	Trinity,Little Portugal	Bar	Coffee Shop	Men's Store	Asian Restaurant	French Restaurant
1	West Toronto	High Park,The Junction South	Mexican Restaurant	Café	Thai Restaurant	Bookstore	Arts & Crafts Store
1	East Toronto	Business Reply Mail Processing Centre 969 Eastern	Light Rail Station	Comic Shop	Park	Brewery	Spa

Table 8. Cluster 5

Cluster Labels	Borough	Neighbourhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
5	Manhattan	Marble Hill	Sandwich Place	Coffee Shop	Miscellaneous Shop	Steakhouse	Supplement Shop
5	Manhattan	Roosevelt Island	Coffee Shop	Sandwich Place	Outdoors & Recreation	Greek Restaurant	Restaurant
5	Manhattan	Morningside Heights	Coffee Shop	Park	Bookstore	American Restaurant	Burger Joint
5	Manhattan	Financial District	Coffee Shop	Pizza Place	Wine Shop	Hotel	Gym
5	East Toronto	Studio District	Café	Coffee Shop	Bakery	Italian Restaurant	American Restaurant
5	Central Toronto	Davisville	Sandwich Place	Pizza Place	Dessert Shop	Italian Restaurant	Coffee Shop
5	Downtown Toronto	Cabbagetown,St. James Town	Restaurant	Café	Coffee Shop	Park	Italian Restaurant
5	Downtown Toronto	Church and Wellesley	Coffee Shop	Japanese Restaurant	Sushi Restaurant	Gay Bar	Restaurant
5	Downtown Toronto	Regent Park,Harbourfront	Coffee Shop	Café	Pub	Park	Bakery
5	Downtown Toronto	Ryerson,Garden District	Coffee Shop	Clothing Store	Cosmetics Shop	Café	Fast Food Restaurant
5	Downtown Toronto	St. James Town	Coffee Shop	Café	Restaurant	Italian Restaurant	Hotel
5	Downtown Toronto	Berczy Park	Coffee Shop	Cocktail Bar	Farmers Market	Bakery	Café
5	Downtown Toronto	Central Bay Street	Coffee Shop	Café	Italian Restaurant	Sandwich Place	Fried Chicken Joint
5	Downtown Toronto	King,Adelaide,Richmond	Coffee Shop	Café	Steakhouse	American Restaurant	Thai Restaurant
5	Downtown Toronto	Toronto Islands,Harbourfront East,Union Station	Coffee Shop	Hotel	Aquarium	Café	Scenic Lookout
5	Downtown Toronto	Toronto Dominion Centre,Design Exchange	Coffee Shop	Café	Hotel	Restaurant	Bar
5	Downtown Toronto	Commerce Court,Victoria Hotel	Coffee Shop	Café	Hotel	Restaurant	American Restaurant
5	Central Toronto	The Annex,Yorkville,North Midtown	Sandwich Place	Café	Pizza Place	Coffee Shop	Indian Restaurant
5	Downtown Toronto	University of Toronto,Harbord	Café	Bakery	Restaurant	Italian Restaurant	Japanese Restaurant
5	Downtown Toronto	Stn A PO Boxes 25 The Esplanade	Coffee Shop	Café	Restaurant	Italian Restaurant	Fast Food Restaurant
5	Downtown Toronto	Underground city,First Canadian Place	Coffee Shop	Café	Hotel	Steakhouse	Restaurant
5	West Toronto	Exhibition Place,Brockton,Parkdale Village	Breakfast Spot	Café	Coffee Shop	Restaurant	Stadium
5	West Toronto	Runnymede,Swansea	Café	Coffee Shop	Pizza Place	Restaurant	Sushi Restaurant

Table 9. Cluster 6

Cluster Labels	Borough	Neighbourhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
6	Manhattan	Central Harlem	American Restaurant	French Restaurant	Chinese Restaurant	Art Gallery	Bar
6	Manhattan	Upper East Side	Exhibit	Italian Restaurant	Bakery	Art Gallery	Juice Bar
6	Manhattan	Yorkville	Italian Restaurant	Gym	Coffee Shop	Bar	Pizza Place
6	Manhattan	Lenox Hill	Coffee Shop	Italian Restaurant	Pizza Place	Sushi Restaurant	Cosmetics Shop
6	Manhattan	Upper West Side	Italian Restaurant	Coffee Shop	Wine Bar	Bar	Indian Restaurant
6	Manhattan	Lincoln Square	Theater	Italian Restaurant	Gym / Fitness Center	Café	Plaza
6	Manhattan	Clinton	Theater	Gym / Fitness Center	Italian Restaurant	Spa	American Restaurant
6	Manhattan	Midtown	Hotel	Steakhouse	Coffee Shop	Theater	Clothing Store
6	Manhattan	Murray Hill	Coffee Shop	Hotel	Sandwich Place	Japanese Restaurant	Italian Restaurant
6	Manhattan	Chelsea	Coffee Shop	Ice Cream Shop	Bakery	Italian Restaurant	Nightclub
6	Manhattan	Greenwich Village	Italian Restaurant	Clothing Store	Sushi Restaurant	Indian Restaurant	Café
6	Manhattan	Tribeca	American Restaurant	Park	Italian Restaurant	Spa	Café
6	Manhattan	Little Italy	Bakery	Café	Italian Restaurant	Clothing Store	Mediterranean Restaurant
6	Manhattan	Soho	Clothing Store	Boutique	Art Gallery	Women's Store	Shoe Store
6	Manhattan	West Village	Italian Restaurant	New American Restaurant	American Restaurant	Wine Bar	Park
6	Manhattan	Battery Park City	Park	Coffee Shop	Memorial Site	Gym	Hotel
6	Manhattan	Carnegie Hill	Pizza Place	Coffee Shop	Bar	Café	Yoga Studio
6	Manhattan	Noho	Italian Restaurant	Cocktail Bar	French Restaurant	Art Gallery	Mexican Restaurant
6	Manhattan	Civic Center	Gym / Fitness Center	Sandwich Place	Italian Restaurant	Hotel	French Restaurant
6	Manhattan	Midtown South	Korean Restaurant	Hotel	Hotel Bar	Japanese Restaurant	Cosmetics Shop
6	Manhattan	Sutton Place	Gym / Fitness Center	Indian Restaurant	Italian Restaurant	Furniture / Home Store	Gym
6	Manhattan	Turtle Bay	Italian Restaurant	Coffee Shop	Sushi Restaurant	Steakhouse	Wine Bar
6	Manhattan	Flatiron	Gym / Fitness Center	Yoga Studio	Gym	Japanese Restaurant	American Restaurant
6	Manhattan	Hudson Yards	American Restaurant	Gym / Fitness Center	Italian Restaurant	Café	Restaurant
6	East Toronto	The Danforth West,Riverdale	Greek Restaurant	Coffee Shop	Italian Restaurant	Ice Cream Shop	Furniture / Home Store
6	East Toronto	The Beaches West,India Bazaar	Movie Theater	Italian Restaurant	Sandwich Place	Park	Sushi Restaurant
6	Central Toronto	North Toronto West	Clothing Store	Sporting Goods Shop	Coffee Shop	Restaurant	Spa
6	West Toronto	Roncesvalles,Parkdale	Breakfast Spot	Gift Shop	Bookstore	Restaurant	Eastern European Restaurant

Limitation / Future Opportunity

There are a few limitations to this report; however, these limitations present an opportunity for further research in the area.

- The assumption here is that people migrating from Manhattan to Toronto would like to live in a neighbourhood like the one they are leaving. It can also be true that they want to live in a new neighbourhood, considering that they are moving to a new city.
    - Real estate agents may resolve this by first asking their clients whether they want to live in a neighbourhood like the ones they are leaving. If the answer is 'yes', then the results from this report would help narrow that search down.
    - Also, further survey research can be done to assess what factors most influence immigrants' preference regarding were to Toronto would like to live.
- Elements of the sample representing neighbourhoods in Toronto grouped neighbourhoods based on zip code. For example, Kensington Market, Grange Park, and Chinatown are all treated as one neighbourhood into the dataset; although, there may be some differences between Kensington Market and Chinatown.
    - Further research may be done to consider whether there's any material difference in the results of this report if neighbourhoods in Toronto are not grouped based on zip code.
- KMeans was used to create the clusters in the data.

- Further research could be done to consider whether there's any material difference in the results of this report if other clustering methods were used, such as hierarchical clustering and DBSCAN.

Conclusion

In this report, we analyzed the similarities between neighbourhoods in Manhattan and Toronto based on the types of venues found in those neighbourhoods. This was done using locational data provided Foursquare, which included the venue's categories and their coordinates. We identified 14 clusters in which neighbourhoods in Manhattan and Toronto can be grouped by using the KMeans approach. Manhattan neighbourhoods fit into three clusters, and within those clusters, there were neighbourhoods in Toronto that were also included. Those neighbourhoods in Toronto match the respective neighbourhoods in Manhattan. This information can be useful in helping real estate agents select the most suitable Neighbourhood for clients immigrating from Manhattan to Toronto.