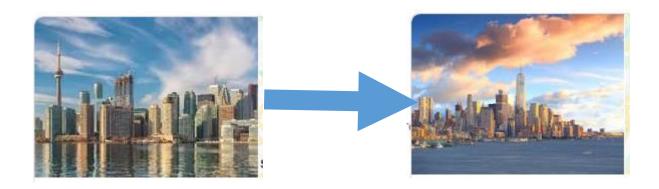
# Coursera Capstone Project – The Battle of Neighborhoods

IBM Data Science Professional Certificate

# Migrating from Toronto to New York

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#### Introduction

When you decide to live in a neighborhood, it is mainly because of quality of life. It depends on your personal choices. These choices are for amenities or venues that are in your neighborhood. These venues could be like gourmet restaurants, pharmacies, parks, schools and so on.

#### **Business Problem**

A friend of mine has been settled in Toronto, Canada for the last 25 years. She lives in Caledonia-Fairbanks neighborhood in York Borough (with postal code of M6E to be more specific). She loves her neighborhood based on above mentioned factors. Recently she received a very lucrative job offer from a

great company in city of New York with great career prospect. Because of location change she will have to move if she decides to accept the offer. Wouldn't it be great if she is able to decide the neighborhoods in New York that are exactly like her current neighborhood in Toronto? She can then pick a neighborhood that is exactly like her current neighborhood and also very close to her new workplace to move to. This exercise will also help her to make a decision whether to move based on what city of New York has to offer to her liking.

### Target Audience of this Project

This project is particularly useful for anyone moving from Toronto to New York City. It can also be used by recruiting agencies to motivate, guide and / or assist employees moving across these cities. The same technique can be applied for move between any two cities by leveraging similar data from those cities.

#### Data

To go about solving this problem, we need

- List of neighborhoods in these two cities
- Geographical coordinates of latitude and longitude information of these neighborhoods and
- Information about venues (categories like restaurant, park, hospital etc.) around these neighborhoods

For list of neighborhoods we will either get readymade data like <a href="https://ibm.box.com/shared/static/fbpwbovar7lf8p5sgddm06cgipa2rxpe.json">https://ibm.box.com/shared/static/fbpwbovar7lf8p5sgddm06cgipa2rxpe.json</a> for New York City or extract it from Wikipedia pages like <a href="https://en.wikipedia.org/wiki/List\_of\_postal\_codes\_of\_Canada: M">https://en.wikipedia.org/wiki/List\_of\_postal\_codes\_of\_Canada: M</a> for Toronto. Here is some sample data for Toronto:

	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,

We will get the geographical coordinates of these neighborhoods using python's geocoder package. Here is some sample data for Toronto:

Postal Code	Latitude	Longitude
<b>0</b> M1B	43.806686	-79.194353

	<b>Postal Code</b>	Latitude	Longitude
1	M1C	43.784535	-79.160497
2	M1E	43.763573	-79.188711
3	M1G	43.770992	-79.216917
4	M1H	43.773136	-79.239476

We will use Foursquare API (<a href="https://developer.foursquare.com/">https://developer.foursquare.com/</a>) to get information about venues around these neighborhoods. It has data of over 105 million places. It provides many categories of the venue data. Here is some sample data for Toronto:

	Neighborhood	Neighborh ood Latitude	Neighborh ood Longitude	Venue	Venue Latitud e	Venue Longitu de	Venue Categor y
0	Rouge,Malvern,	43.806686	-79.194353	Wendy's	43.8074 48	- 79.1990 56	Fast Food Restaura nt
1	Rouge,Malvern,	43.806686	-79.194353	Interprovin cial Group	43.8056 30	- 79.2003 78	Print Shop
2	Highland Creek,Rouge Hill,Port Union,	43.784535	-79.160497	Royal Canadian Legion	43.7825 33	- 79.1630 85	Bar
3	Guildwood,Morningside ,West Hill,	43.763573	-79.188711	G & G Electronics	43.7653 09	- 79.1915 37	Electron ics Store
4	Guildwood,Morningside ,West Hill,	43.763573	-79.188711	Marina Spa	43.7660 00	- 79.1910 00	Spa

We will leverage category of venues to identify similar neighborhoods.

#### You can refer to notebook

https://github.com/sameermahajan/Coursera\_Capstone/blob/master/Neighborhoods%20in%20Toront o.ipynb for details on how it can be done for Toronto.

## Methodology

This project applies various data science techniques like

• Web scraping to gather data from Wikipedia page

- Working with APIs (Foursquare)
- Data cleaning
- Data wrangling
- Machine learning (k means clustering)
- Map visualization (folium)

to arrive at the solution.

First we get the list of neighborhoods in Toronto from Wikipedia page of <a href="https://en.wikipedia.org/wiki/List">https://en.wikipedia.org/wiki/List</a> of postal codes of Canada: M. We perform web scraping from this page to get the data. We get the geographical coordinates of these neighborhoods using geocoder python package. After gathering this data we plot a map of these neighborhoods using folium package. This map performs a simple validation of correctness of our data.

We then use Foursquare APIs to get top 100 venues within 500 meter radius of these neighborhoods. We check how many venues are returned for each neighborhood as a validation of this data. We take the mean of the frequency of occurrence of each venue by category to provide it as a feature to k means Clustering.

We perform k means clustering to categorize the neighborhoods into clusters of different characteristics based on categories of nearby venues.

We plot a graph of count of most common venue categories in each cluster to identify the type of the cluster.

We perform similar analysis for neighborhoods in New York.

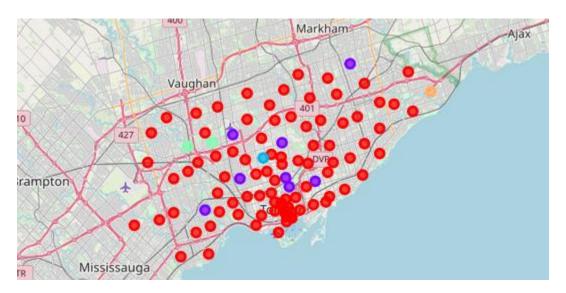
We compare the results of analysis of Toronto neighborhoods with that of New York.

We identify neighborhood cluster in New York that matches with neighborhood cluster in Toronto from where the user is moving. We recommend neighborhood from this identified cluster to the user based on its proximity to her new work place.

#### Results

The results of k means clustering of Toronto neighborhoods indicate that there are five clusters namely

- Cluster 0: Quite a few neighborhoods fall under this category. It has quite a few diverse venues like coffee shops, Cafes, Grocery Stores, Pizza Places, Parks etc.
- Cluster 1: 8 neighborhoods fall under this category. It has mostly Parks.
- Cluster 2: Only 1 neighborhood falls under this category. It has Garden.
- Cluster 3: Only 2 neighborhoods fall under this category. It has Food Truck and Baseball Field.
- Cluster 4: Only 1 neighborhood falls under this category. It has Bar.

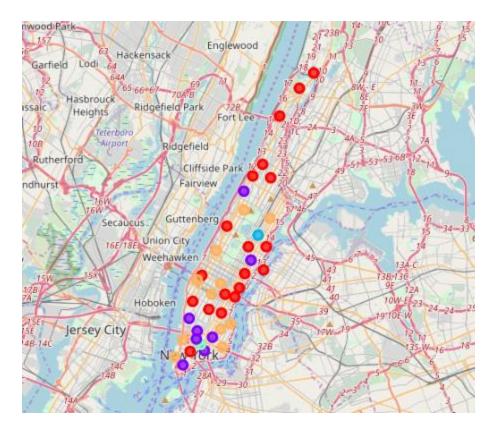


Our neighborhood of interest namely Caledonia-Fairbanks falls in cluster 1 with top 10 venue categories as:

Park	Market	Women's Store	Dumpling Restaurant	Drugstore	Donut Shop	Doner Restaurant	European	Dance Studio	Distribution Center
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The results of k means clustering of New York City neighborhoods indicate that there are five clusters namely

- Cluster 0: It consists of single neighborhood with Italian restaurant.
- Cluster 1: It consists of diverse venues like Coffee Shops, Italian Restaurants, cafes, fitness centers, theater etc..
- Cluster 2: It consists of venues like Parks, Italian restaurants, Cafés, Pizza Place, Theater, American Restaurant, Gym.
- Cluster 3: It consists of venues like Mexican and Korean Restaurant, Plaza, Hotel and Bar.
- Cluster 4: It consists of single neighborhood with Pizza Place.



These two cities are similar in terms of their neighborhoods. We can map these neighborhood clusters as:

Toronto	<b>New York City</b>
Cluster 0	Cluster 1
Cluster 1	Cluster 2
Cluster 2	Cluster 0
Cluster 3	Cluster 3
Cluster 4	Cluster 4

As you can easily see the closest type of neighborhoods for my Toronto based friend in New York city is cluster 2 You can also verify the similarity looking at the neighborhoods and their top 10 common venue categories as below:

	Boro ugh	Neighb orhoo d	Latit ude	Long itude	Clu ste r Lab els	1st Most Com mon Venu e	2nd Most Com mon Venu e	3rd Most Com mon Venu e	4th Most Com mon Venu e	5th Most Com mon Venu e	6th Most Comm on Venue	7th Most Com mon Venu e	8th Most Com mon Venu e	9th Most Com mon Venu e	10th Most Com mon Venu e
0	Man hatta n	Marble Hill	40.8 7655 1	- 73.9 1066 0	2	Gym	Amer ican Resta urant	Sand wich Place	Coffe e Shop	Yoga Studi o	Deli / Bodega	Suppl emen t Shop	Steak hous e	Shop ping Mall	Seafo od Resta urant
2	Man hatta n	Washi ngton Height s	40.8 5190 3	- 73.9 3690 0	2	Café	Bake ry	Groc ery Store	Mobi le Phon e Shop	Suppl emen t Shop	Sandwi ch Place	Mexic an Resta urant	Coffe e Shop	Liquo r Store	Spani sh Resta urant
8	Man hatta n	Upper East Side	40.7 7563 9	- 73.9 6050 8	2	Italia n Resta urant	Exhib it	Art Galle ry	Bake ry	Coffe e Shop	Gym / Fitness Center	Juice Bar	Hotel	Fren ch Resta urant	Pizza Place
9	Man hatta n	Yorkvill e	40.7 7593 0	- 73.9 4711 8	2	Italia n Resta urant	Coffe e Shop	Gym	Bar	Deli / Bode ga	Pizza Place	Sushi Resta urant	Japan ese Resta urant	Mexi can Resta urant	Diner
1	Man hatta n	Roosev elt Island	40.7 6216 0	- 73.9 4916 8	2	Park	Coffe e Shop	Deli / Bode ga		Sceni c Looko ut	Gym	Dry Clean er	Base ball Field	Liquo r Store	Outd oors & Recre ation
1 4	Man hatta n	Clinton	40.7 5910 1	- 73.9 9611 9	2	Thea ter	Italia n Resta urant		Amer ican Resta urant	Coffe e Shop	Spa	Sand wich Place	Hotel	Wine Shop	Cockt ail Bar
2	Man hatta n	Lower East Side	40.7 1780 7	- 73.9	2	Café	Coffe e Shop	Pizza Place	Art Galle ry	Cockt ail Bar	Japane se	Baker y	Rame n	Chin ese	Night club

	Boro ugh	Neighb orhoo d		Long itude	Clu ste r Lab els	1st Most Com mon Venu e	2nd Most Com mon Venu e	3rd Most Com mon Venu e	4th Most Com mon Venu e	5th Most Com mon Venu e	6th Most Comm on Venue	7th Most Com mon Venu e	8th Most Com mon Venu e	9th Most Com mon Venu e	10th Most Com mon Venu e
				8089 0							Restau rant			Resta urant	
2	Man hatta n	Tribeca	40.7 2152 2	- 74.0 1068 3	2	Park	Italia n Resta urant		Café	Spa	Boutiq ue	Wine Bar	Wine Shop	Coffe e Shop	Greek Resta urant
2	Man hatta n	Little Italy	40.7 1932 4	- 73.9 9730 5	2	Café	Bake ry	Bubb le Tea Shop	Sand wich Place	Salon / Barbe rshop	Medite rranea n Restau rant	Italia n Resta urant	Cockt ail Bar	Yoga Studi o	Wom en's Store
2	Man hatta n	Manha ttan Valley	40.7 9730 7	- 73.9 6428 6	2	Pizza Place	India n Resta urant	Bar	_	Thai Resta urant	Playgro und	Coffe e Shop	Mexi can Resta urant	Deli / Bode ga	Vietn ames e Resta urant
2	Man hatta n	Mornin gside Height s	40.8 0800 0	- 73.9 6389 6	2	Park	Book store	Amer ican Resta urant	e	Burge r Joint	Sandwi ch Place	Deli / Bode ga	Pub	Café	Seafo od Resta urant
2	Man hatta n	Battery Park City	40.7 1193 2	- 74.0 1686 9	2	Park	Coffe e Shop	Hotel	Wine Shop	Gym	Shoppi ng Mall	Wom en's Store	Mem orial Site	Food Cour t	Men' s Store
3	Man hatta n	Noho	40.7 2325 9	- 73.9 8843 4	2	Italia n Resta urant	ch Resta	Hotel	Cock tail Bar	Rock Club	Art Gallery	Sushi Resta urant	Groc ery Store	Gift Shop	Pizza Place

	Boro ugh	Neighb orhoo d	Latit ude	Long	II ah	Com	Com mon	3rd Most Com mon Venu e	Com mon	5th Most Com mon Venu e	6th Most Comm on Venue	7th Most Com mon Venu e	Com mon	9th Most Com mon Venu e	10th Most Com mon Venu e
3	hatta	Hudso n Yards	40.7 5665 8	- 74.0 0011 1	2	l.		Coffe e Shop	Hotel	Gym / Fitnes s Cente r	Café	Thai Resta urant	Burg er Joint	_	Resta urant

You can pick the actual neighborhood to move to base on its proximity to the new work place and / or venues in the neighborhood.



Based on top 10 venues we recommend Battery Park City. Comparing the top 10 venues in these two neighborhoods you can easily conclude that there are quite a few common venues like Parks, Women's Store, Market, and Restaurants making my friend's transition a smooth one!

#### **Discussions**

As you can see Toronto has around 100 neighborhoods with New York City having 40 neighborhoods. Toronto has 266 unique venue categories with different neighborhoods having different number of venues and some neighborhoods even reaching the limit of 100 for the number of venues. There are quite a few Coffee Shops, variety of restaurants, parks, stores etc. New York has 341 unique venue

categories. Most of the neighborhoods have reached the limit of 100 with the remaining having overall a very high count. There is a variety of Coffee Shops, various restaurants, fitness centers, parks, theater, hotel and plaza.

#### Limitations and Further Work

In this project we only consider the factor of frequency of occurrences of venues of certain category to categorize neighborhoods. It can be augmented by many other factors (e.g. other statistical measures like variance, various percentiles etc. of this number, cost of living, family factors, availability of housing, public transportation etc.). We are also relying on data from foursquare for our analysis. We are also using the free developer's account imposing some restrictions on the data that we obtain. The study can be enhanced further w.r.t. both these factors as well.

#### Conclusion

Toronto and New York City are similar in terms of their neighborhoods being large metropolitan cities of developed countries like Canada and New York, respectively both from North America on the east coast in nearby vicinity. A person hailing from Caledonia-Fairbanks is advised to pick Battery Park City for settling down while moving from Toronto to New York City. You can carry out similar analysis for any neighborhood in these cities or extend it for migration between any other cities / countries by gathering similar data for those two cities.