Capstone Project

Explore Neighborhoods in Downtown Toronto

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Contents

Abstract

The aim of this research is to explore the restaurants, landmarks, and other neighborhoods in downtown Toronto, and find the proper location for people who are going to open their new restaurants or business. Geographical and other data used in this report are pulled from Wiki web page, Cognitive Class website, and Foursquare API. Python is used for the whole project including plotting map and charts, and doing the segmentation and clustering.

According to the current data and the final result, the area between St.Patrick and Queen is a good place for people who is planning to open a new restaurant. Yonge Street and Dundas also can be considered is the new business belongs to sweets or beverage category.

1 Introduction

1.1 Problem

Creating an area map and adding neighbours as marks on it is helpful to see the distribution of the local business and/or other buildings, and segmenting and classifying those neighborhoods are useful for analysing local business as well. The project aims to analyse a proper location for opening a new restaurant in downtown Toronto area.

1.2 Interest

The target audience of this report will be people who are planning to open a new business in downtown Toronto area, who would like to know more information about the local businesses (distribution, total likes by their customers, etc.) and be benefited from the competitive environment.

2 Data Acquisition and Cleaning

2.1 Data Sources

- Postal Code, borough, and neighborhoods information scraped from Wikipedia
- Latitude and longitude for each postal code in the given csv file from Cognitive Class.ai
- Foursquare API is utilized to pull the venue name, ID, location, category, and count of likes information on restaurants and business in Toronto, ON

2.2 Data Cleaning

A tabular data with title ”List of postal codes of Canada: M - Wikipedia” was scraped from the Wikipedia web page first using BeautifulSoup4 library in Python, and then changed to Pandas DataFrame format using Pandas library. The tabular data contained Postal Code, Borough, and Neighborhood information about Toronto downtown area.

The data-frame contained many ”Not assigned” values in the Borough and Neighborhoods columns, and duplicated postal codes in the Postal Code column. The rows with ”Not assigned” values in the Borough column were dropped, and rows which have the same postal code are combined (their borough was the same, so only the values in the Neighborhood column were combined and separated by a comma).

2.3 Geographic Data

The latitude and longitude values of Toronto and each postal code in the table were required in order to create an area map of Toronto and add those locations as marks on the map. One method is to use Geocoder package to obtain the latitude and longitude for each postal code. However, the problem with this package is you have to be persistent sometimes in order to get the geographical coordinates of a given postal code. So to save time and computational cost, a csv file with corresponding coordinates for the postal codes in Toronto is used for this project. The coordinate of Toronto was obtained using Nominatim from the geopy library.

3 Data Exploration and Preparation for Clustering

3.1 Foursquare API Usage

To use the Foursquare API, you need to create a personal account first. Then access Foursquare API using your personal account information (your Foursquare ID and Foursquare Secret). Remember that the regular account has a daily call quota which will be reset each day at midnight UTC.

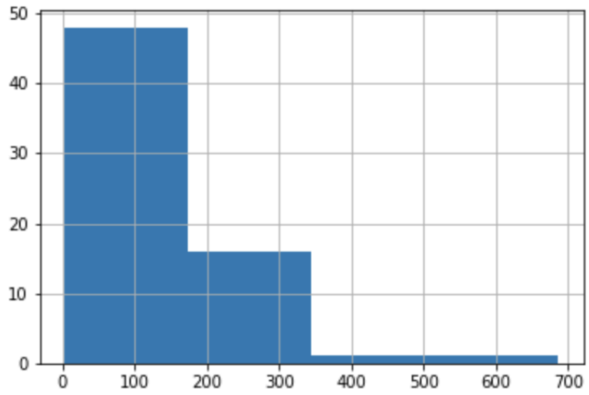
A url was generated by using personal account information, latitude and longitude values, and setting up the limit (limit of number of venues returned by Foursquare API) and radius. Then the actual data was pulled from the url and transformed to data-frame using 'json normalize' from Pandas library. The data-frame had Name, ID, Categories, Lat, and Lng these columns. Using the IDs, a new link was set up to pull the likes for each ID from the API, which would be added to the corresponding row in the data-frame.

3.2 Re-categorization

The data-frame had variety of categories including different cuisines of the world, and different stores/ business categories. However, some ambiguous categories were found after obtained the unique categories from the data-frame, and the neighborhoods with this current category were manually re-categorized. For instance, "The Keg Steakhouse + Bar - York Street" had the current category "Restaurant", which was then manually changed to "Steakhouse".

Because this project aimed to find a good location for opening a new restaurant, two sub-data-frames needed to be created. One is obviously only contained restaurants data, and the other data-frame only contained data related to tourism, for instance, shopping malls and landmarks. Ideally, these neighbourhoods would affect the customer flow of their surrounding restaurants.

The next step was visualizing the total likes for each data-frame based on a histogram using matplotlib library, and computing the 25th percentile, 50th percentile, and 75th percentile using numpy library to find the categories for total likes.

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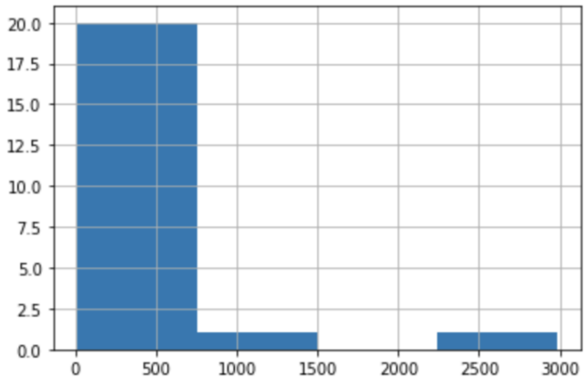
29.0
58.5
195.5
```

(a) Histogram and percentiles for restaurant data




```
26.5
114.5
317.5
```

(b) Histogram and percentiles for tourism data

From the outputs above, for restaurants data-frame, the 25th percentile was 29, the 50th percentile was 58, and the 75th percentile was 195. Then we set 4 categories: poor, below average, above average, and great; corresponding to the number of likes below 29, between 29 and 58, between 58 and 195, and above 195, respectively; and for tourism data-frame, the 25th percentile was 26, the 50th percentile was 114, and the 75th percentile was 317. Then we set 4 categories for it as well: poor, below average, above average, and great; corresponding to the number of likes below 26, between 26 and 114, between 114 and 317, and above 317, respectively. Then added the new total likes category to the data-frames as a new column.

The current categories we pulled from API were too detailed and messy, which was not beneficial for applying one-hot encoding and doing segmentation in the later steps, so we needed to created new categories and re-categorize all the data from the two data-frames. First, showed the unique existing categories, then created new lists of categories and added the existing categories to their corresponding lists, and added the new categories to the data-frames. Here I did these steps manually since the amount of data was not huge.

3.3 One-Hot Encoding

3.3.1 About One-Hot Encoding

One-hot encoding is used on categorical data (variables contain label values instead of numeric values). Those categories may have relationship to each other, and some algorithms can directly work on them (e.g. decision tree), however, for other algorithms we need to convert those categorical values to numerical values. For instance, we have a category named ”animals” which contains three variables: ”dog”, ”cat”, and ”bird”. In this case, we can assign integer values to these three variables: ”dog” can be 0, ”cat” can be 1, and ”bird” can be 2.

3.3.2 Application in the Project

In this project, the categorical variables that we needed to analyse were ”categories” and ”total likes categories”. After applying one-hot encoding to the two data-frames, we got new tables which looked like:

	Name	other_tour	shopping	above avg	below avg	great	poor
0	Downtown Toronto	1	0	1	0	0	0
1	Nathan Phillips Square	1	0	0	0	1	0
6	LUSH	0	1	0	0	0	1
7	Textile Museum of Canada	1	0	0	0	0	1
8	CF Toronto Eaton Centre	0	1	0	0	1	0

Figure 2: One-hot encoding table for tourism data

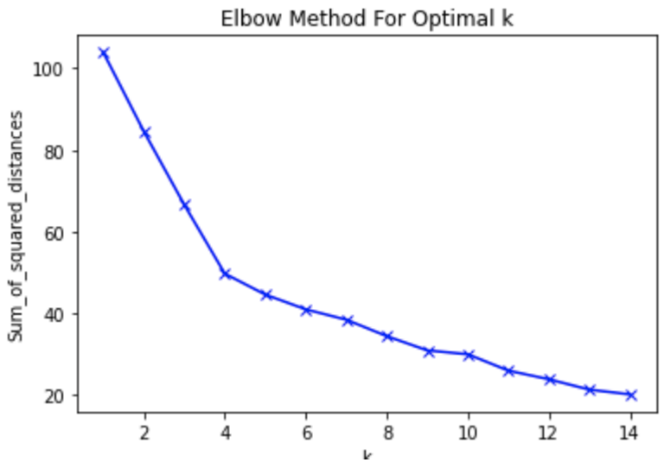
Only the first five rows were showed

4 K-Means Clustering

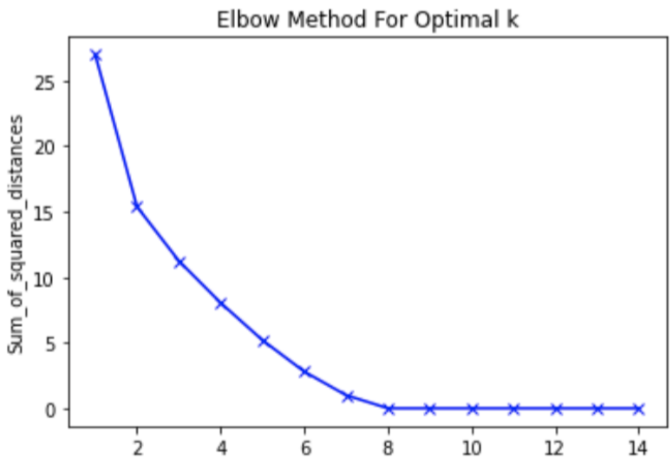
K-means clustering method could be applied after the one-hot encoding process. In the restaurants data-frame, there were many cuisine categories and four total likes categories, which means k could be four; and in the tourism data-frame, besides the four total likes categories, there were only two categories - ”shopping” and ”other tour”, so k for tourism data-frame could be four or eight.

4.1 Optimal K

I chose to find the optimal k for each data-frame using elbow method. KMeans from sklearn library was used to find the sum of squared distance of each member, and matplotlib library was used to plot the distances.



(a) Elbow method for restaurant data



(b) Elbow method for tourism data

4.2 Creating Labels

After analysing the plots, 4 was chosen to be the optimal k for the restaurants data-frame, and 8 was chosen to be the optimal k for the tourism data-frame. In the plot for tourism data, there was a slightly increasing trend when the number of distinct clusters was greater than 8, which was possibly due to duplicate points.

With the optimal ks, we were able to build k-means clustering model for each data-frame which could properly fit the corresponding one-hot encoding table. Because in the one-hot coding tables, the first column was the names of neighborhoods, it should be dropped first before building the model. Then added the labels generated by the model to the data-frames.

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
0	Downtown Toronto	5227bb01498e17bf485e6202	Neighborhood	43.653232	-79.385296	316	above avg	other_tour	4
1	Nathan Phillips Square	4ad4c05ef964a520a6f620e3	Plaza	43.652270	-79.383516	692	great	other_tour	5
6	LUSH	4bd0b30d41b9ef3b8fa0fae5	Cosmetics Shop	43.653557	-79.380400	22	poor	shopping	6
7	Textile Museum of Canada	4ad4c05ef964a520e2f620e3	Art Museum	43.654396	-79.386500	25	poor	other_tour	0
8	CF Toronto Eaton Centre	4ad77a12f964a520260b21e3	Shopping Mall	43.654447	-79.380952	2986	great	shopping	2

Figure 4: Tourism data-frame after adding the labels
Only the first five rows were showed

5 Tables and Geographical Data

5.1 Map

With all the data we got, we were able to plot a map of Toronto downtown area using folium library, and add all the neighborhoods as marks on it.

For the restaurants data, cluster 0 represented 'poor' likes, cluster 1 represented 'great', cluster 2 represented 'below average', and cluster 3 represented 'above average' category; gray, red, green, and orange circle marks, filled with the same colors inside the circle, were used for the clusters respectively. For the tourism data, cluster 0 represented 'poor' and 'other tour', cluster 1 represented 'below average' and 'shopping', cluster 2 represented 'great' and 'shopping', cluster 3 represented 'below average' and 'other tour', cluster 4 represented 'above average' and 'other tour', cluster 5 represented 'great' and 'other tour', cluster 6 represented 'poor' and 'shopping', and cluster 7 represented 'above average' and 'shopping' categories; gray, green, red, purple, yellow, orange, dark blue, pink circle marks, filled without any color inside the circle, were used for the clusters respectively.

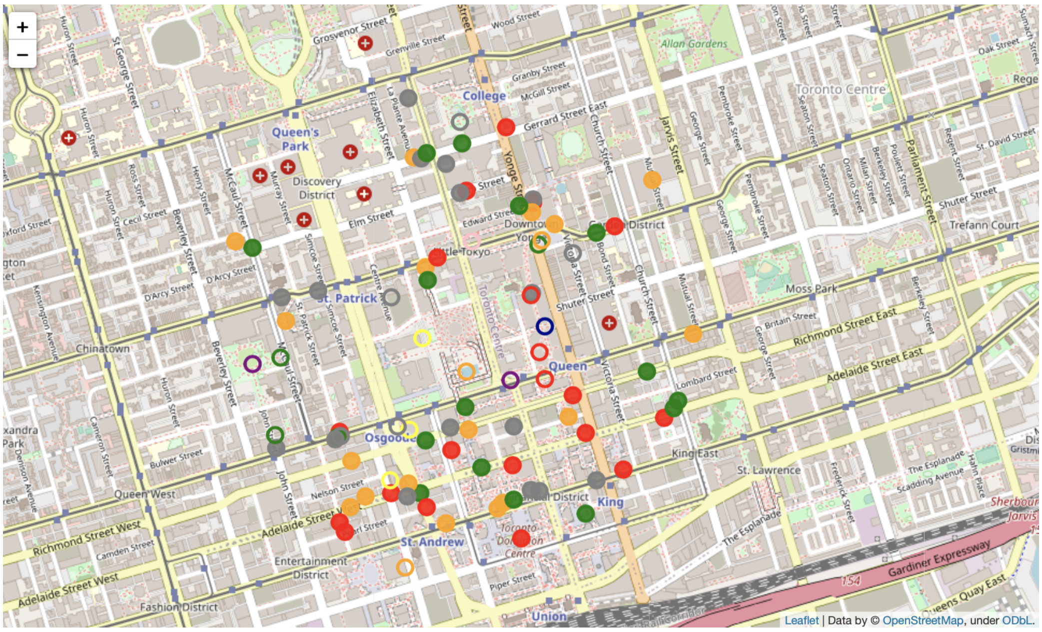


Figure 5: Map of downtown Toronto with neighborhoods

Only the first five rows were showed

5.2 Tables Based On Different Clusters

Grouped the data by different clusters to get more detailed information for analysing.

5.2.1 Restaurants

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
11	Crepe Delicious	4e5d8181a8092f63968617ee	Fast Food Restaurant	43.654536	-79.380889	8	poor	fast food	0
19	John & Sons Oyster House	50ecb1fae4b0beb13294f0aa	Seafood Restaurant	43.650656	-79.381613	21	poor	euro italian food	0
22	Bulldog On The Block	5a3a846af62e0960e9364d11	Coffee Shop	43.650652	-79.384141	9	poor	sweet and beverage	0
27	The Elm Tree Restaurant	539c6f13498e06f4cc765165	Modern European Restaurant	43.657397	-79.383761	28	poor	euro italian food	0
44	Cafe Plenty	4f513029e4b07c3382c9fdb9	Café	43.654571	-79.389450	19	poor	sweet and beverage	0
46	The Library Specialty Coffee	5a6b737b35f98359eed11974	Coffee Shop	43.654413	-79.390902	27	poor	sweet and beverage	0
53	Pilot Coffee Roasters	59cd51c71b0ea516e9e7b3aa	Coffee Shop	43.648835	-79.380936	24	poor	sweet and beverage	0
55	Brick Street Bakery	4dcbf219d22d7ffe9d39197e	Bakery	43.648815	-79.380605	16	poor	sweet and beverage	0
61	Panago	4ad4cba2f964a520d1fb20e3	Pizza Place	43.658258	-79.384313	11	poor	fast food	0
62	Tokyo Smoke	5a55078bda5ede6ed9d73a62	Coffee Shop	43.657230	-79.380870	5	poor	sweet and beverage	0
63	Hakata Ikkousha Ramen	5c9aaa3f66f3cd002c95bd58	Ramen Restaurant	43.650299	-79.388753	14	poor	asia food	0
67	Somethin' 2 Talk About	4b744336f964a520d8d02de3	Middle Eastern Restaurant	43.658395	-79.385338	6	poor	middle east food	0
79	Omg! Oh My Gyro!	595d4380c876c841c08f1959	Souvlaki Shop	43.650064	-79.391104	17	poor	middle east food	0
88	Pi Co.	5a5a59c5a423620ec1dafd41	Pizza Place	43.648651	-79.385874	13	poor	fast food	0
89	Café Plenty	53c524bd498efaeebf73b291	Café	43.649118	-79.378313	20	poor	sweet and beverage	0
99	NEO COFFEE BAR	5db70a0c306d6b000861ac9f	Coffee Shop	43.660130	-79.385830	3	poor	sweet and beverage	0

Cluster 0 - ’poor’

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
4	Chatime 日出茶太	4e2284b11fc7c0ef9857d143	Bubble Tea Shop	43.655542	-79.384684	198	great	sweet and beverage	1
14	Richmond Station	506db1a9e4b0a3f3b31412f0	American Restaurant	43.651569	-79.379266	248	great	american food	1
21	The Keg Steakhouse + Bar - York Street	4ad69511f964a520e40721e3	Steakhouse	43.649987	-79.384103	269	great	american food	1
23	The Queen and Beaver Public House	4ab2b0b9f964a520e56b20e3	Gastropub	43.657472	-79.383524	232	great	bars	1
30	Dineen Coffee	514627d1e4b0dba1b85e9ba8	Café	43.650497	-79.378765	450	great	sweet and beverage	1
38	Soho House Toronto	50322b6ae4b09116a296568c	Speakeasy	43.648734	-79.386541	219	great	bars	1
39	Five Guys	5064c3dde4b07c5a18986283	Burger Joint	43.657117	-79.380853	230	great	fast food	1
52	Cactus Club Cafe	55fc571f498ec35023360858	American Restaurant	43.649552	-79.381671	204	great	american food	1
54	Banh Mi Boys	51755dc7498ece19b7261641	Sandwich Place	43.659292	-79.381949	311	great	breakfast	1
56	The Rex Hotel Jazz & Blues Bar	4b68aed1f964a520de862be3	Jazz Club	43.650505	-79.388577	204	great	bars	1
64	Pai	529612de11d2ab526191ccc9	Thai Restaurant	43.647923	-79.388579	687	great	thai vietnamese food	1
70	Canoe	4ad4c05df964a52059f620e3	American Restaurant	43.647452	-79.381320	286	great	american food	1
73	Hokkaido Ramen Santouka らーめん山頭火	509e9ef6e4b0ab175389a6c5	Ramen Restaurant	43.656435	-79.377586	305	great	asia food	1
74	Byblos Toronto	5321f4d9e4b07946702e6e08	Mediterranean Restaurant	43.647615	-79.388381	247	great	euro italian food	1
77	Pizzeria Libretto	5462ac56498e128ccafe8fea	Pizza Place	43.648334	-79.385111	209	great	fast food	1
90	Terroni	4b49183ff964a520a46526e3	Italian Restaurant	43.650927	-79.375602	280	great	euro italian food	1
97	Beerbistro	4b5ca7d8f964a5207c3c29e3	Gastropub	43.649419	-79.377237	325	great	bars	1

Cluster 1 - ’great’

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
5	Poke Guys	57bcd3b7498e652a678d0378	Poke Place	43.654895	-79.385052	32	below avg	american food	2
13	M Square Coffee Co	54132b3b498ee9ca9332e189	Coffee Shop	43.651218	-79.383555	32	below avg	sweet and beverage	2
18	Rosalinda	5aff06ca6e4650002cc6286b	Vegetarian / Vegan Restaurant	43.650252	-79.385156	29	below avg	vegan gluten free	2
36	Hy's Steakhouse	4bd8cde92e6f0f47dcb20808	Steakhouse	43.649505	-79.382919	43	below avg	american food	2
37	Hailed Coffee	5a81ae339deb7d369fa7f146	Coffee Shop	43.658833	-79.383684	41	below avg	sweet and beverage	2
42	Burrito Boyz	55a9bbf9498e00ffd7f4c71f	Burrito Place	43.656265	-79.378343	29	below avg	mex southam food	2
49	The Black Canary Espresso Bar	506a2591e4b0961239b8c825	Café	43.657029	-79.381385	44	below avg	sweet and beverage	2
51	Cafe Landwer	5b6c842bc36588002c80a934	Café	43.648753	-79.385367	42	below avg	sweet and beverage	2
57	HotBlack Coffee	59f784dd28122f14f9d5d63d	Coffee Shop	43.650364	-79.388669	40	below avg	sweet and beverage	2
78	Mos Mos Coffee	52138db911d22803b334c641	Café	43.648159	-79.378745	54	below avg	sweet and beverage	2
80	Tim Hortons	557231e3498e540f05f3083c	Coffee Shop	43.658570	-79.385123	41	below avg	sweet and beverage	2
82	Hawthorne Food and Drink	505c7c30e4b071a17ec2678f	Gastropub	43.652270	-79.376318	31	below avg	bars	2
87	Gyu-Kaku Japanese BBQ	574ad72238fa943556d93b8e	Japanese Restaurant	43.651422	-79.375047	42	below avg	asia food	2
92	Versus Coffee	57963897498e6873394a559d	Coffee Shop	43.651213	-79.375236	34	below avg	sweet and beverage	2
94	Kupfert & Kim (First Canadian Place)	50e44770e4b0e03a48c0d8a8	Gluten-free Restaurant	43.648547	-79.381624	47	below avg	vegan gluten free	2
98	Jimmy's Coffee	57fe5f64498e08c9fc55cb87	Café	43.655827	-79.392042	32	below avg	sweet and beverage	2

Cluster 2 - ’below average’

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
2	Japango	4ae7b27df964a52068ad21e3	Sushi Restaurant	43.655268	-79.385165	161	above avg	asia food	3
25	Blaze Pizza	5615b6c4498e3c32c67ad78f	Pizza Place	43.656518	-79.380015	76	above avg	fast food	3
31	Assembly Chef's Hall	5a32970da42362290203a9d6	Food Court	43.650579	-79.383412	67	above avg	fast food	3
35	JaBistro	509bb871e4b09c7ac93f6642	Sushi Restaurant	43.649687	-79.388090	188	above avg	asia food	3
40	Jimmy's Coffee	537d4d6d498ec171ba22e7fe	Coffee Shop	43.658421	-79.385613	162	above avg	sweet and beverage	3
43	Karine's	4c90c810ae96a093599f9d46	Breakfast Spot	43.653699	-79.390743	60	above avg	breakfast	3
45	The Chase	5214e7c111d2a83379eae21f	New American Restaurant	43.650952	-79.379422	141	above avg	american food	3
60	Bosk at Shangri-La	50468014e4b01c18bb731df8	Asian Restaurant	43.649023	-79.385826	69	above avg	asia food	3
66	Maman	559a8f5a498e31f945041245	Café	43.648309	-79.382253	84	above avg	sweet and beverage	3
69	Chipotle Mexican Grill	4adc9148f964a520512d21e3	Mexican Restaurant	43.656860	-79.380910	171	above avg	mex southam food	3
72	King Taps	59603f86112c6c70931c9401	Gastropub	43.648476	-79.382058	59	above avg	bars	3
81	GEORGE Restaurant	4af618daf964a520220122e3	Vegetarian / Vegan Restaurant	43.653346	-79.374445	77	above avg	vegan gluten free	3
83	Sam James Coffee Bar (SJCB)	4fccaa8fe4b05a98df3d9417	Café	43.647881	-79.384332	71	above avg	sweet and beverage	3
85	Page One Cafe	56d4d1b3cd1035fe77e1492c	Café	43.657772	-79.376073	68	above avg	sweet and beverage	3
86	Vegetarian Haven	4aeb711ef964a52017c221e3	Vegetarian / Vegan Restaurant	43.656016	-79.392758	58	above avg	vegan gluten free	3
91	The Burger's Priest	5578720f498ee3b165b1f32b	Fast Food Restaurant	43.648643	-79.387539	135	above avg	fast food	3
95	Copacabana Grilled Brazilian	52ec621e498ec68fa15ee922	Brazilian Restaurant	43.648333	-79.388151	149	above avg	mex southam food	3

Cluster 3 - ’above average’

5.2.2 Tourism

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
7	Textile Museum of Canada	4ad4c05ef964a520e2f620e3	Art Museum	43.654396	-79.386500	25	poor	other_tour	0
28	Friendly Stranger - Cannabis Culture Shop	4b7ed424f964a5208a0230e3	Smoke Shop	43.650387	-79.388523	17	poor	other_tour	0
29	Canadian Opera Company	4ad4c062f964a520baf720e3	Opera House	43.650660	-79.386242	21	poor	other_tour	0
41	Jazz Bistro	514cc159e4b0e4f73af4eced	Music Venue	43.655678	-79.379276	24	poor	other_tour	0
75	College Park Area	4c8facf91664b1f79c90aa2f	Park	43.659453	-79.383785	9	poor	other_tour	0

Cluster 0 - 'poor' and 'other tour'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
12	UNIQLO ユニクロ	57eda381498ebe0e6ef40972	Clothing Store	43.655910	-79.380641	114	below avg	shopping	1
26	Silver Snail Comics	4ad4c062f964a5200bf820e3	Comic Shop	43.657031	-79.381403	115	below avg	shopping	1
47	Aboveground Art Supplies	4adf3c01f964a5208f7821e3	Arts & Crafts Store	43.652646	-79.390925	35	below avg	shopping	1
71	Umbra Concept Store	4ae734bef964a5205ea921e3	Furniture / Home Store	43.650417	-79.391136	31	below avg	shopping	1

Cluster 1 - 'below avg' and 'shopping'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
8	CF Toronto Eaton Centre	4ad77a12f964a520260b21e3	Shopping Mall	43.654447	-79.380952	2986	great	shopping	2
24	Hudson's Bay	4adf85e1f964a5206e7b21e3	Department Store	43.652040	-79.380391	573	great	shopping	2
33	Apple Eaton Centre	4ad788c8f964a520e40b21e3	Electronics Store	43.652818	-79.380617	493	great	shopping	2

Cluster 2 - 'great' and 'shopping'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
10	Old City Hall	4ad4c05ef964a5208ef620e3	Monument / Landmark	43.652009	-79.381744	73	below avg	other_tour	3
93	Grange Park	4b54deadf964a520a3d027e3	Park	43.652488	-79.392053	45	below avg	other_tour	3

Cluster 3 - 'below avg' and 'other tour'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
0	Downtown Toronto	5227bb01498e17bf485e6202	Neighborhood	43.653232	-79.385296	316	above avg	other_tour	4
9	Four Seasons Centre for the Performing Arts	4ad4c062f964a520e5f720e3	Concert Hall	43.650592	-79.385806	222	above avg	other_tour	4
32	Shangri-La Toronto	4e31b74252b131dcebb08743	Hotel	43.649129	-79.386557	181	above avg	other_tour	4

Cluster 4 - 'above avg' and 'other tour'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
1	Nathan Phillips Square	4ad4c05ef964a520a6f620e3	Plaza	43.652270	-79.383516	692	great	other_tour	5
20	Yonge-Dundas Square	4ad8cd16f964a520c91421e3	Plaza	43.656054	-79.380495	823	great	other_tour	5
96	Roy Thomson Hall	4ad4c061f964a520b0f720e3	Concert Hall	43.646589	-79.385979	318	great	other_tour	5

Cluster 5 - 'great' and 'other tour'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
6	LUSH	4bd0b30d41b9ef3b8fa0fae5	Cosmetics Shop	43.653557	-79.3804	22	poor	shopping	6

Cluster 6 - 'poor' and 'shopping'

	name	id	categories	lat	lng	total likes	total likes_cat	categories_new	label
17	MUJI	5479da4f498e8569fb44985c	Miscellaneous Shop	43.656024	-79.383284	135	above avg	shopping	7

Cluster 7 - 'above avg' and 'shopping'

6 Conclusion

6.1 Summary of Main Contributions

Since we only pulled some data of restaurants/ neighborhoods located in Downtown Toronto, we will only analyse the neighborhoods in downtown area.

From the numerical and geographical data shown above, we can see that most of the restaurants are located on or nearby Yonge Street and the area between Osgoode and King. So it is not recommended to open a new restaurant in these areas due to the highly competitive environment.

However, among these restaurants, many of them with 'poor' likes are cafe/tea shop/bakery. If someone is very confident about starting a cafe/bubble-tea store business, there might still be a chance to win customers' heart.

In the area between St. Patrick and Queen, we can see that there are many shopping malls, parks, and some places for entertainment, which will attract tourists and local people and can be helpful for improving customer flow. Especially in the area which is closer to the Queen and Yonge Street, the shopping mall and landmarks here have competitively higher number of likes. Besides, there are only few restaurants located in this area, so it is a good place to open a new restaurant.

6.2 Future Work

For this project we only have about 100 neighborhoods to be analyzed. With the increasing number of samples for analysis in the future, the accuracy of the model will be increasing as well, and there will be more detailed information that can be offered.