The Battle of Neighborhoods.

Identify the perfect place in the city of Toronto to open a café.

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1. Introduction

1.1 Background

According to Wikipedia, Toronto is Canada's largest city, the administrative center of Ontario. It has a population of 2,731,571 (2016). Toronto is part of the Golden Fory, a densely populated region around the western part of Lake Ontario with a population of about 7 million people. About one third of Canada's total population lives within a 500 km radius of Toronto. About a sixth of all Canadian jobs are within the city limits. The city of Toronto is also known as the "economic engine" of Canada, considered one of the leading metropolises in the world and has a lot of weight both in the region and at the state and international level. In The Economist'sannual global quality of liferanking, which measures overall quality of life, Toronto ranks fourth in the world among 140 participating cities.

1.2 Problem

But where is the best place to open your own café?
Using Foursquare location data and regional clustering, location information to determine which area in Toronto might be the "best" to open
The cafe aims to predict the most appropriate place to open a new cafe in Toronto, Canada.

1.3 Interest

Obviously, new entrepreneurs are very interested in accurately predicting the optimal location when deciding to buy, or rent a property when deciding to open a new café, to gain competitive advantages and business values.

2. Collecting and cleaning up data

2.1 Data sources

The data that will be required will be a combination of CSV files that have been produced for analysis from multiple sources that will provide a list of areas in Toronto (via Wikipedia), the geographic location of the districts (via the Geocoder Package) and location data related to the cafe (via Foursquare).

2.2 Cleaning up the data

First, we need to extract data from data sources:
Source 1: *Toronto Areas via Wikipedia (https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M)*

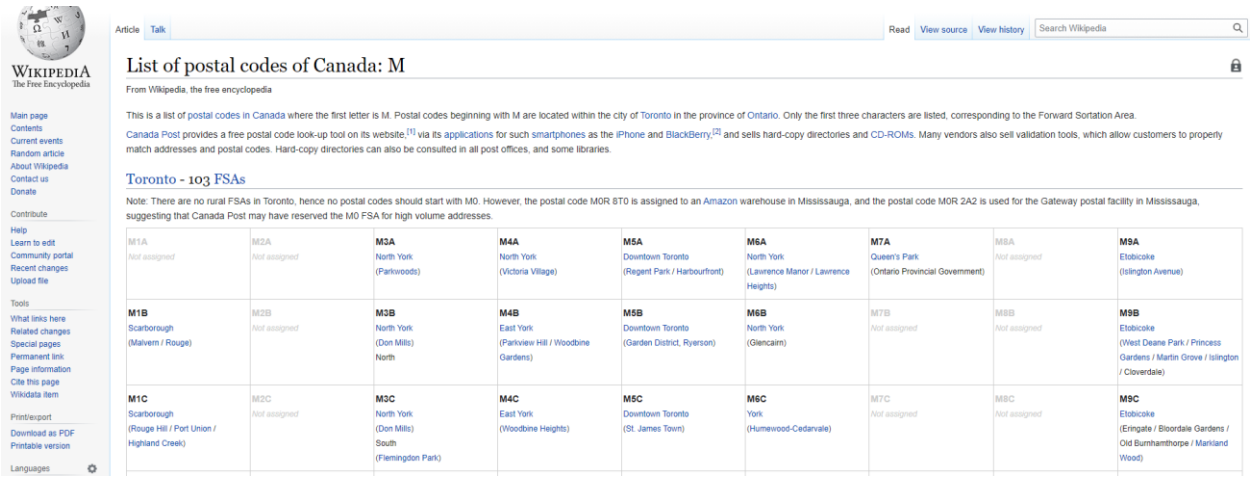


Figure 1: Wikipedia Page showing List of Neighborhoods in Toronto with respective Postal Codes

The Wikipedia website, as shown above, provides almost all information about neighborhoods. Including the postcode, the district and the name of the districts present in Toronto. Because the data is not in a format suitable for analysis, the data was cleaned from this site (shown in Figure 2).

	Postal Code	Borough	Neighborhood
0	M3A	North York	Parkwoods
1	M4A	North York	Victoria Village
2	M5A	Downtown Toronto	Regent Park, Harbourfront
3	M6A	North York	Lawrence Manor, Lawrence Heights
4	M7A	Queen's Park	Ontario Provincial Government
5	M9A	Etobicoke	Islington Avenue
6	M1B	Scarborough	Malvern, Rouge
7	M3B	North York	Don Mills North
8	M4B	East York	Parkview Hill, Woodbine Gardens
9	M5B	Downtown Toronto	Garden District, Ryerson
10	M6B	North York	Glencairn
11	M9B	Etobicoke	West Deane Park, Princess Gardens, Martin Grov...
12	M1C	Scarborough	Rouge Hill, Port Union, Highland Creek
13	M3C	North York	Don Mills South
14	M4C	East York	Woodbine Heights

Figure 2: Data that was scraped from Wikipedia site and put into Pandas data frame

3. Geographical Location data.

Second source of data provided (https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DS0701EN-SkillsNetwork/labs_v1/Geospatial_Coordinates.csv) us with geographical coordinates of areas with appropriate postcodes. Because the CSV file, attaching it to the Pandas data frame was easy (shown in Figure 3).

	Postal Code	Borough	Neighborhood	Latitude	Longitude
0	M1B	Scarborough	Malvern, Rouge	43.806686	-79.194353
1	M1C	Scarborough	Rouge Hill, Port Union, Highland Creek	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
5	M1J	Scarborough	Scarborough Village	43.744734	-79.239476
6	M1K	Scarborough	Kennedy Park, Ionview, East Birchmount Park	43.727929	-79.262029
7	M1L	Scarborough	Golden Mile, Clairlea, Oakridge	43.711112	-79.284577
8	M1M	Scarborough	Cliffside, Cliffcrest, Scarborough Village West	43.716316	-79.239476
9	M1N	Scarborough	Birch Cliff, Cliffside West	43.692657	-79.264848
10	M1P	Scarborough	Dorset Park, Wexford Heights, Scarborough Town...	43.757410	-79.273304
11	M1R	Scarborough	Wexford, Maryvale	43.750072	-79.295849

Figure 3: Conversion of file into Pandas data frame

Location data using Foursquare

The location, name and category of various sites in Toronto was collected using the Foursquare explore API.

To get the data, you needed to create an account where it provided a "Secret Key" as well as a "Customer ID" that would allow me to retrieve any data.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Malvern, Rouge	43.806686	-79.194353	Wendy's	43.807448	-79.199056	Fast Food Restaurant
1	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497	Royal Canadian Legion	43.782533	-79.163085	Bar
2	Guildwood, Morningside, West Hill	43.763573	-79.188711	RBC Royal Bank	43.766790	-79.191151	Bank
3	Guildwood, Morningside, West Hill	43.763573	-79.188711	G & G Electronics	43.765309	-79.191537	Electronics Store
4	Guildwood, Morningside, West Hill	43.763573	-79.188711	Sail Sushi	43.765951	-79.191275	Restaurant
5	Guildwood, Morningside, West Hill	43.763573	-79.188711	Big Bite Burrito	43.766299	-79.190720	Mexican Restaurant
6	Guildwood, Morningside, West Hill	43.763573	-79.188711	Enterprise Rent-A-Car	43.764076	-79.193406	Rental Car Location
7	Guildwood, Morningside, West Hill	43.763573	-79.188711	Krispy Kreme Doughnuts	43.767169	-79.189660	Donut Shop
8	Guildwood, Morningside, West Hill	43.763573	-79.188711	Woburn Medical Centre	43.766631	-79.192286	Medical Center
9	Guildwood, Morningside, West Hill	43.763573	-79.188711	Lawrence Ave E & Kingston Rd	43.767704	-79.189490	Intersection
10	Guildwood, Morningside, West Hill	43.763573	-79.188711	Eggsmart	43.767800	-79.190466	Breakfast Spot
11	Woburn	43.770992	-79.216917	Starbucks	43.770037	-79.221156	Coffee Shop

Figure 4: Venue data pulled from Foursquare explore API

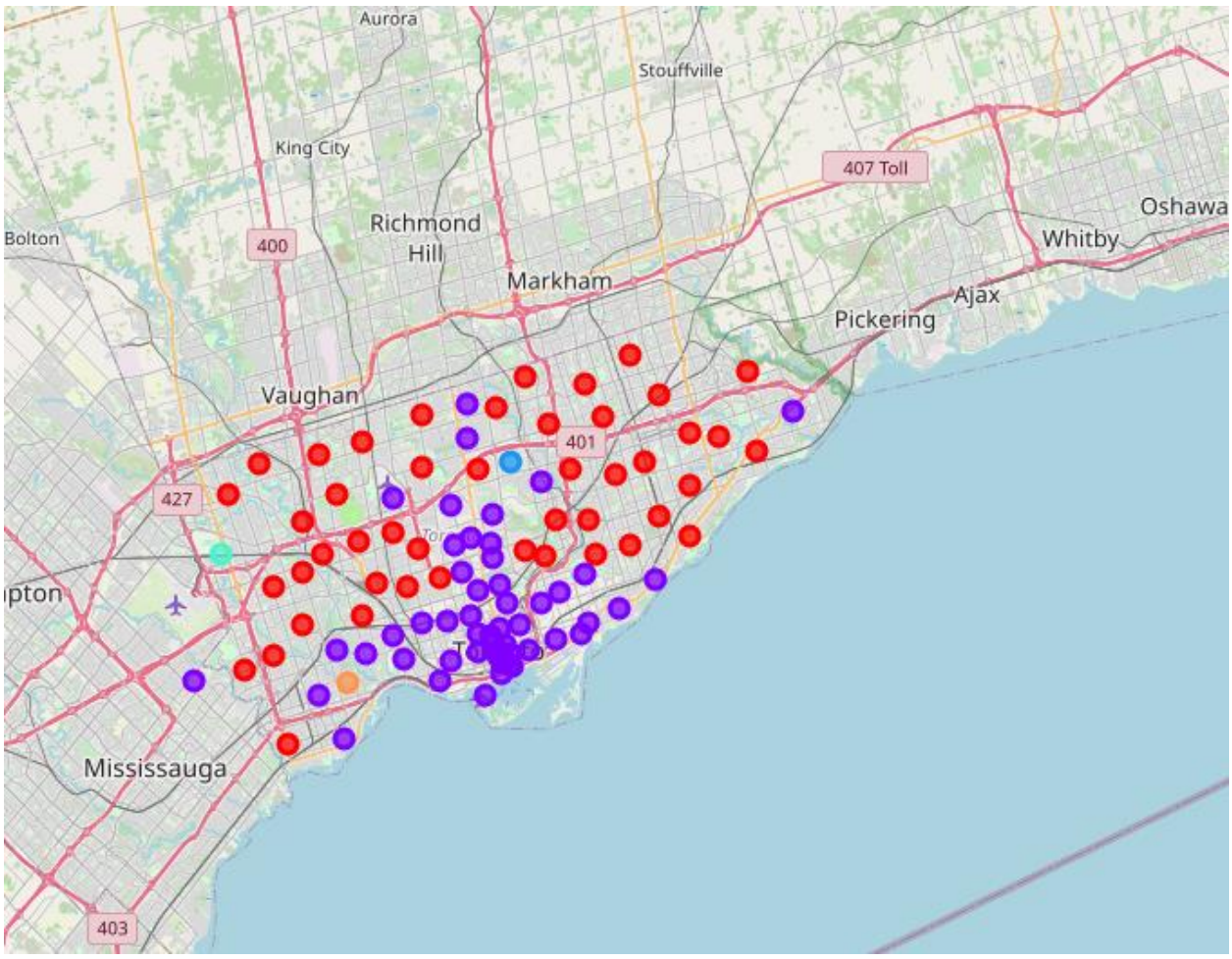
On Figure 4 (above) you can see that the neighborhoods are grouped around the neighborhood, so clustering data is further simplified.

Once all the data has been collected and placed in the data frame, the analysis process must be cleaned and merged.

After, the venue data pulled from the Foursquare API was merged with the table above providing us with the local venue within a 500-meter radius shown below.

	name	categories	lat	lng
0	Dairy Queen	Ice Cream Shop	43.710378	-79.290701
1	Warden Ave & St. Clair Ave E	Intersection	43.712057	-79.281005
2	TTC Bus #68 Warden	Bus Line	43.711778	-79.279714
3	Warden Station Bus Loop	Bus Station	43.711241	-79.279576
4	TTC Bus 102 Markham Road	Bus Line	43.711381	-79.279588

Now after cleansing the data, the next step was to analyze it. We then created a map using folium and color coded each Neighborhood depending on what Borough it was located in.



Next, we used the Foursquare API to get a list of all the Venues in Toronto which included Parks, Schools, Café Shops, Asian Restaurants etc. Getting this data was crucial to analyzing the number of Café all over Toronto. There was a total of 93 cafe in Toronto.

```
to_merged['Venue Category'].value_counts()['Café']
```

```
5]: 93
```

We then merged the Foursquare Venue data with the Neighborhood data which then gave us the nearest Venue for each of the Neighborhoods.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Malvern, Rouge	43.806686	-79.194353	Wendy's	43.807448	-79.199056	Fast Food Restaurant
1	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497	Royal Canadian Legion	43.782533	-79.163085	Bar
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9	Guildwood, Morningside, West Hill	43.763573	-79.188711	Lawrence Ave E & Kingston Rd	43.767704	-79.189490	Intersection
10	Guildwood, Morningside, West Hill	43.763573	-79.188711	Eggsmart	43.767800	-79.190466	Breakfast Spot

Then to analyze the data we performed a technique in which Categorical Data is transformed into Numerical Data for Machine Learning algorithms. This technique is called One hot encoding. For each of the neighborhoods, individual venues were turned into the frequency at how many of those Venues were located in each neighborhood.

	Neighborhood	Accessories Store	Adult Boutique	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antique Shop	Aquarium	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Ath & S
0	Malvern, Rouge	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1	Rouge Hill, Port Union, Highland Creek	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2	Guildwood, Morningside, West Hill	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
3	Guildwood, Morningside, West Hill	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
4	Guildwood, Morningside, West Hill	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

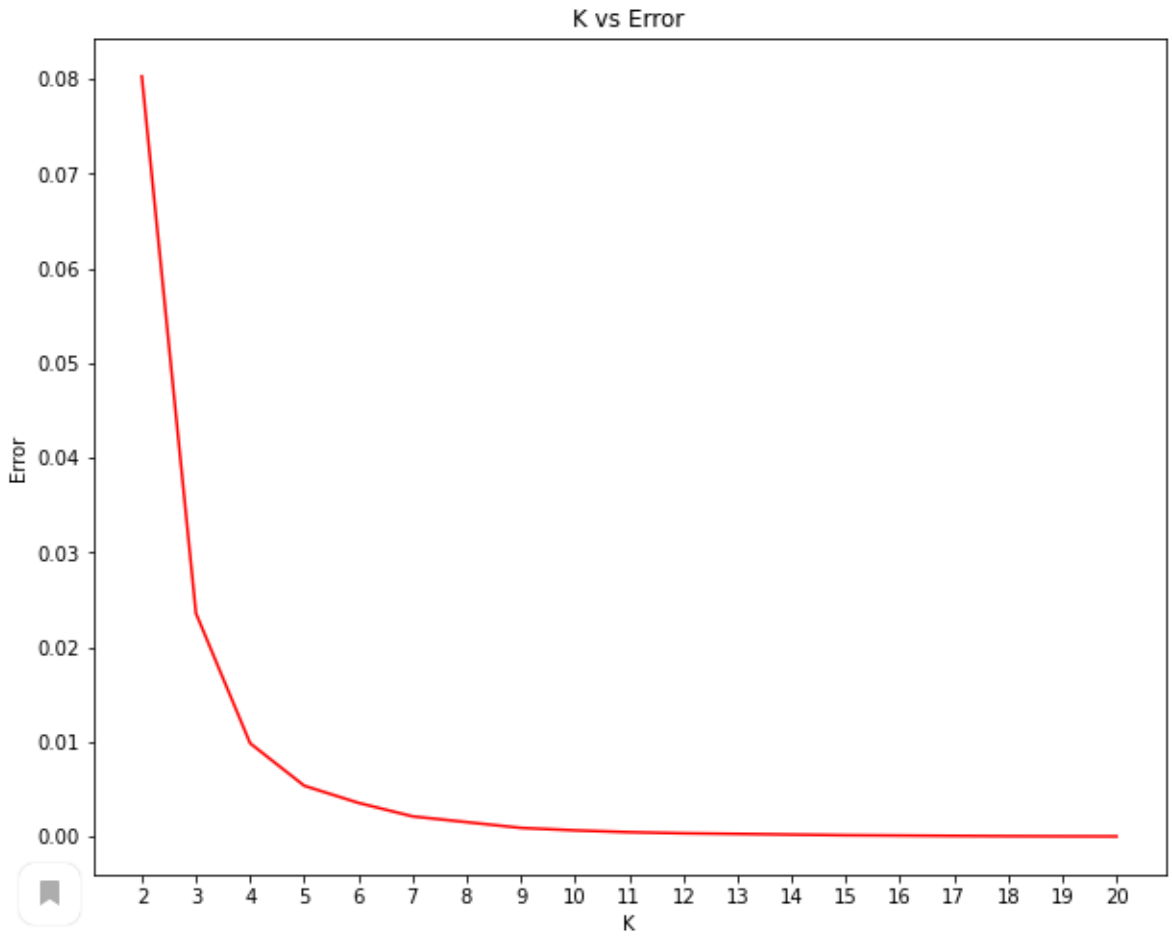
Then we grouped those rows by Neighborhood and by taking the Average of the frequency of occurrence of each Venue Category.

	Neighborhood	Accessories Store	Adult Boutique	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antique Shop	Aquarium	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Athletic & Sport
0	Agincourt	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	Alderwood, Long Branch	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	Bathurst Manor, Wilson Heights, Downsview North	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	Bayview Village	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	Bedford Park, Lawrence Manor East	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.045455	0.0	0.0	0.0	0.0	0.0	0.0	0.0

After, we created a new data frame which only stored the Neighborhood names as well as the mean frequency of Cafe in that Neighborhood. This allowed the data to be summarized based on each individual Neighborhood and made the data much simpler to analyze.

	Neighborhood	Café
0	Agincourt	0.000000
1	Alderwood, Long Branch	0.000000
2	Bathurst Manor, Wilson Heights, Downsview North	0.000000
3	Bayview Village	0.250000
4	Bedford Park, Lawrence Manor East	0.045455
5	Berczy Park	0.016949
6	Birch Cliff, Cliffside West	0.250000

To make the analysis more interesting, we wanted to cluster the neighborhoods based on the neighborhoods that had similar averages of Café in that Neighborhood. To do this we used K-Means clustering. To get our optimum K value that was neither overfitting or underfitting the model, we used the Elbow Point Technique. In this technique we ran a test with different number of K values and measured the accuracy and then chose the best K value. The best K value is chosen at the point in which the line has a sharpest turn. In our case we had the Elbow Point at K = 4. That means we will have a total of 4 clusters.

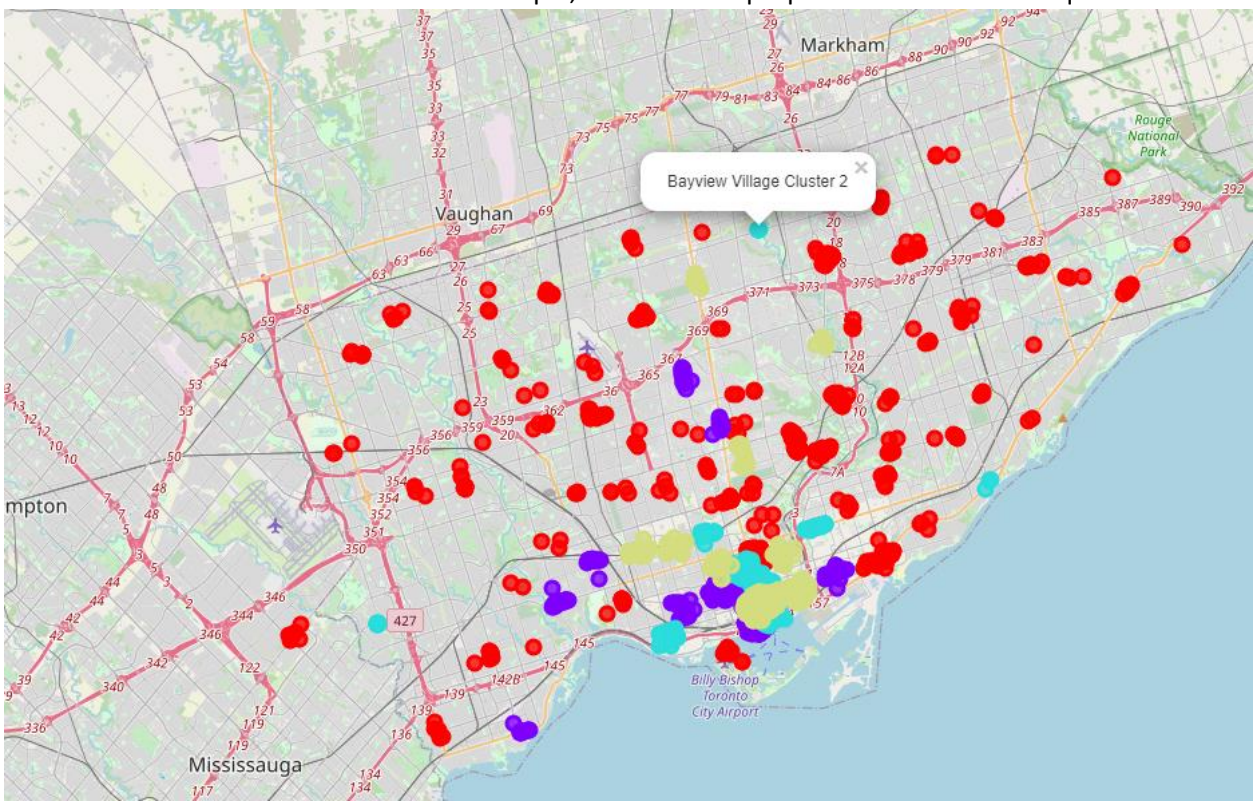


In K-Means clustering, objects that are similar based on a certain variable are put into the same cluster. Neighborhoods that had similar mean frequency of Italian Restaurants were divided into 4 clusters. Each of these clusters were labelled from 0 to 3 as the indexing of labels begin with 0 instead of 1.

	Neighborhood	Café	Cluster Labels
0	Agincourt	0.000000	0
1	Alderwood, Long Branch	0.000000	0
2	Bathurst Manor, Wilson Heights, Downsview North	0.000000	0
3	Bayview Village	0.250000	3
4	Bedford Park, Lawrence Manor East	0.045455	2
5	Berczy Park	0.016949	3
6	Birch Cliff, Cliffside West	0.250000	3
7	Brockton, Parkdale Village, Exhibition Place	0.136364	3
8	CN Tower, King and Spadina, Railway Lands, Har...	0.000000	0
9	Caledonia-Fairbanks	0.000000	0
10	Cedarbrae	0.000000	0
11	Central Bay Street	0.049180	2

	Neighborhood	Café	Cluster Labels	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Agincourt	0.0	0	43.794200	-79.262029	Panagio's Breakfast & Lunch	43.792370	-79.260203	Breakfast Spot
35	Forest Hill North & West	0.0	0	43.696948	-79.411307	Kay Gardner Beltline Trail	43.698446	-79.406873	Trail
35	Forest Hill North & West	0.0	0	43.696948	-79.411307	Forest Hill Road Park	43.697945	-79.406605	Park
35	Forest Hill North & West	0.0	0	43.696948	-79.411307	Nikko Sushi Japenese Restaurant	43.700443	-79.407957	Sushi Restaurant
35	Forest Hill North & West	0.0	0	43.696948	-79.411307	Oliver jewelry	43.700374	-79.407644	Jewelry Store

Then we created a map using the Folium package in Python and each neighborhood was colored based on the cluster label. For example, cluster 1 was purple and cluster 2 was aquamarine.



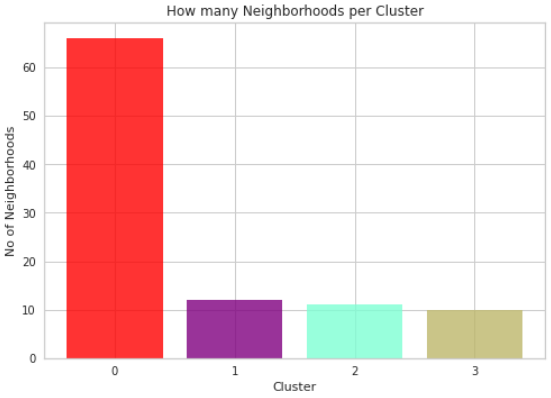
The map above shows the different clusters that had similar mean frequency of Café.

4. Analysis:

We have a total of 4 clusters (0,1,2,3). Before we analyze them one by one lets check the total amount of neighborhoods in each cluster and the average café in that cluster.

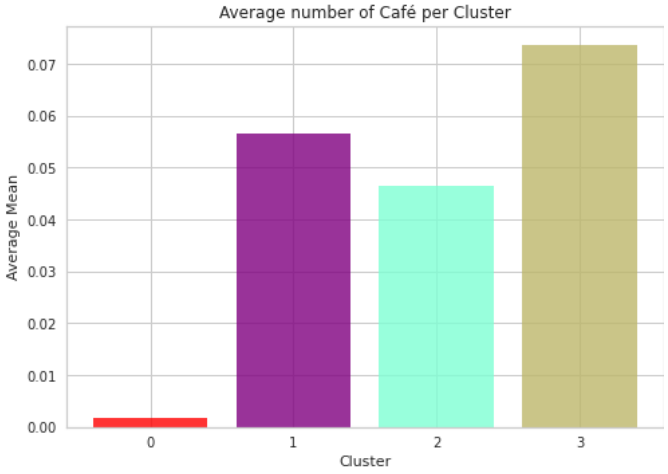
From the bar graph that was made using Matplotlib, we can compare the number of Neighborhoods per Cluster. We see that Cluster 1 has the least neighborhoods (1)

while cluster 0 has the most (66). Cluster 3 has 12 neighborhoods, cluster 1 - 11 and cluster 2 has only 10. Then we compared the average Café per cluster.




```
# How many neighborhoods in each cluster
cafe['Cluster Labels'].value_counts()
```

```
1]: 0    66
    3    12
    1    11
    2    10
```



Therefore, the ordering of the average Café in each cluster goes as follows:

1. Cluster 0 (≈0.012987) 2. Cluster 2 (≈0.031250) 3. Cluster 1 (≈0.049180) 4. Cluster 3 (≈0.063830)

Claster 0

There are only 1 cafes in this cluster and the lowest value.

	Borough	Neighborhood	Café	Cluster Labels
500	Downtown Toronto	Church and Wellesley	0.012987	0
512	Downtown Toronto	Church and Wellesley	0.012987	0
514	Downtown Toronto	Church and Wellesley	0.012987	0
515	Downtown Toronto	Church and Wellesley	0.012987	0
516	Downtown Toronto	Church and Wellesley	0.012987	0
517	Downtown Toronto	Church and Wellesley	0.012987	0
518	Downtown Toronto	Church and Wellesley	0.012987	0
519	Downtown Toronto	Church and Wellesley	0.012987	0
520	Downtown Toronto	Church and Wellesley	0.012987	0
521	Downtown Toronto	Church and Wellesley	0.012987	0
522	Downtown Toronto	Church and Wellesley	0.012987	0
523	Downtown Toronto	Church and Wellesley	0.012987	0

Claster 1

	Borough	Neighborhood	Café	Cluster Labels
0	Downtown Toronto	Central Bay Street	0.049180	1
1	Downtown Toronto	Central Bay Street	0.049180	1
2	Downtown Toronto	Central Bay Street	0.049180	1
3	Downtown Toronto	Central Bay Street	0.049180	1
4	Downtown Toronto	Central Bay Street	0.049180	1
5	Downtown Toronto	Central Bay Street	0.049180	1
6	Downtown Toronto	Central Bay Street	0.049180	1
7	Downtown Toronto	Central Bay Street	0.049180	1
8	Downtown Toronto	Central Bay Street	0.049180	1
9	Downtown Toronto	Central Bay Street	0.049180	1
10	Downtown Toronto	Central Bay Street	0.049180	1
11	Downtown Toronto	Central Bay Street	0.049180	1

```
df_cluster1['Venue Category'].value_counts(ascending=False)['Café']
```

```
29
```

Claster 2

	Borough	Neighborhood	Café	Cluster Labels
0	Queen's Park	Ontario Provincial Government	0.031250	2
1	Queen's Park	Ontario Provincial Government	0.031250	2
2	Queen's Park	Ontario Provincial Government	0.031250	2
3	Queen's Park	Ontario Provincial Government	0.031250	2
4	Queen's Park	Ontario Provincial Government	0.031250	2
5	Queen's Park	Ontario Provincial Government	0.031250	2
6	Queen's Park	Ontario Provincial Government	0.031250	2
7	Queen's Park	Ontario Provincial Government	0.031250	2
8	Queen's Park	Ontario Provincial Government	0.031250	2
9	Queen's Park	Ontario Provincial Government	0.031250	2
10	Queen's Park	Ontario Provincial Government	0.031250	2
11	Queen's Park	Ontario Provincial Government	0.031250	2

```
df_cluster2['Venue Category'].value_counts(ascending=False)['Café']
```

```
18
```

Claster 3

	Borough	Neighborhood	Café	Cluster Labels
0	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
1	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
2	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
3	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
4	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
5	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
6	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
7	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
8	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
9	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
10	Downtown Toronto	Regent Park, Harbourfront	0.063830	3
11	Downtown Toronto	Regent Park, Harbourfront	0.063830	3

```
_cluster3['Venue Category'].value_counts(ascending=False)['Café']
```

```
45
```

5. Discussion:

Most of the Café are in cluster 3, represented by "darkkhaki" clusters.

Areas located in the Downtown Toronto area, which have the highest average level of Café Regent Park, Harbourfront and St. James Town. In spite of what is in the cluster of 0 huge number of districts, café are almost non-existent. Looking To nearby establishments, the optimal place to host a new café is in the city centre Toronto, as there are many areas in the area, but virtually no café , that excludes any competition. Having 66 districts in the area without Italian restaurants provides a good opportunity for opening a new café . Some of the drawbacks of this analysis are that clustering based entirely on data from the Foursquare API. And only the geographical location of similar establishments is considered.
This sums up the initial conclusions for this project and recommends that the entrepreneur think about opening cafes in these places with little or no competition.

6. Conclusion:

Finally, to complete this project, we had the opportunity to solve a business problem, and it was solved in a way that a real data scientist would.

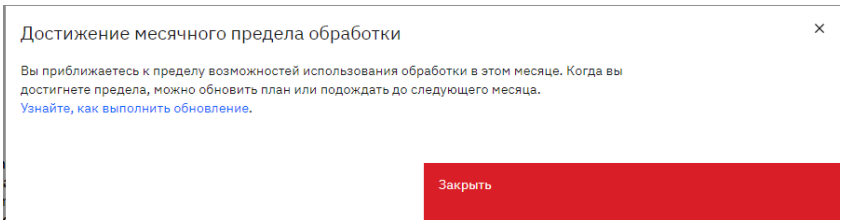
We've used multiple Python libraries to extract information, manage content, and break and visualize these datasets.
We used the Foursquare API to study the settings in the Toronto area, and we got a lot of data from Wikipedia that we collected using the Beautifulsoup Web Scraper Library.
We have also visualized the use of different graphs present in seaborn and matplotlib libraries.
Similarly, we used the AI strategy to anticipate the error, taking into account the information, and used Folium to map it.

Places that are there to improve or certain shortcomings give us the opportunity to further improve this project with the help of additional information and the distinctive machine of the Learning Strategy.
In addition, we can use this venture to investigate any situation, such as opening an alternative kitchen or opening a movie theater and so on.

In a more serious analysis, with sufficient resources, computing power and funding, additional analysis is needed in the final decision, taking into account, among other things:

- ✓ Popularity of the supposed place of opening of cafes among locals and tourists (the number of daily flow of people in this place)
- ✓ Transport logistics
- ✓ Cost of rent or cost of property purchase
- ✓ Local law (opportunity to sell alcoholic beverages)
- ✓ Income level of residents living in the area
- ✓ crime rate in the immediate vicinity,
- ✓ And many other factors.

But, something Watson Studio deprives me of those opportunities, and the payment for the course has come to an end☹.



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