17/12/2020

The Battle of Neighbourhood

Part Two

Jane Barrio

Introduction: Business Problem

Nowadays, with the rapid growth of the population density around the world, numerous collaborators have the possibility and the tendency to inaugurate new restaurants in different areas around the world which are safe and secure. This particular project has the objective to provide adequate information for stakeholders who have the aim to find the optimal location or area for their new restaurant.

Toronto is the fourth largest cities in the North America, which has a diverse population with multi-culture and patrimonial aspects. Within these years, many people are immigrated to Toronto because of its multi-racial and multi-cultural condition. Many businessmen recognise that Toronto is a potential location where stakeholders will have the possibility to establish their new restaurants. For the reason that Toronto undisputedly provide the opportunity to settle down different types of restaurants such as Chinese, Thai, European and American one. This specific location is considered to be a good decision as it has a great population density, people of different ages and the population have a good standard of living.

However, Toronto has recently been subjected to a record number of shooting in 2019 and it has been found that the situation is even worst in 2020. Its crime rate has been oscillating between 2.1 and 3.8. and this has a real impact on the standard of living of the citizens as well as on the economic aspect of the city. Numerous regions in Toronto who suffer from violence, have the tendency to be deserted from the citizens but also from the traders and restaurants. Toronto recorded an approximately violent year in 2019 against restaurants and sales keepers.

Before the inauguration of a new restaurant, many stakeholders have the need to adopt an important approach in the aim to find the optimal location which will improve them to be more performant, productive, competent and to make more profits. As a result, safety is considered to be a strategic factor for the decision making process of various stakeholders.

Stakeholders will undisputedly appreciate the possibilities to find out the safest borough in Toronto and in the different neighbourhoods

The objective of this project is to figure out if Toronto is a safe and an ideal location for the opening of new restaurant and to avoid a time consuming of moving from one place to another in the objective to find the proper place which will fit to the stakeholders.

Data Collection

The Toronto crime rate per neighbourhood is obtained from the waggle dataset and it gives an adequate view of the situation in Toronto areas.

For this particular project, we have collected some information on the crime rate from 2014 to 2019 in Toronto

Based on our problem, some factors should be taken into account in order to take the good decision are listed below:

1. Figure out the safest borough based on Toronto Crime Rate.
2. Discover the optimal common venues and select the appropriate neighbourhood within the borough.

We will treat the geographical data about Toronto in order to plot the corresponding neighbourhoods which are considered as safe and secure for the opening of a new restaurant.

In this project, extraction of data are made from the following data sources:

1. Toronto Crime rate (https://www.kaggle.com/alincijov/toronto-crime-rate-per-neighbourhood)
2. Venue Data in every neighbourhood will be obtained using Foursquare API
3. Geocoder Package are used to provide Geographical Location data (https://cocl.us/Geospatial_data)

The following codes listed below are used in order to install all the libraries required to perform our data collection, data cleaning and representation of the map of Toronto.

- Pandas and Numpy
- Google Geocoding APIs
- Foursquare APIs
- Folium library, including choropleth map, heatmap in map view
- K-Means Clustering Algorithm

```
import pandas as pd # library for data analsysis
import numpy as np # library to handle data in a vectorized manner
import random # library for random number generation

!conda install -c conda-forge geopy --yes
from geopy.geocoders import Nominatim # conversion an address into latitude and longitude values

# libraries for displaying images
from IPython.display import Image
from IPython.core.display import HTML


from IPython.display import display_html
import pandas as pd
import numpy as np


import requests # library to handle requests
# tranforming json file into a pandas dataframe library
from pandas.io.json import json_normalize

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors

# import k-means from clustering stage
from sklearn.cluster import KMeans


!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you haven't completed the Foursquare API lab
import folium # map rendering library

print('Libraries imported.')
```

Fig 1 represents the different python libraries used during this project.

Dataset 1: Wikipedia is used to provide Toronto Neighborhoods

WIKIPEDIA
The Free Encyclopedia

Main page
Contents
Featured content
Current events
Random article
Donate to Wikipedia
Wikipedia store

Interaction
Help
About Wikipedia
Community portal
Recent changes
Contact page

Tools
What links here
Related changes
Upload file
Special pages
Permanent link
Page information
Wikidata item
Cite this page

Print/export
Create a book
Download as PDF
Printable version

Article Talk Read

List of postal codes of Canada: M

From Wikipedia, the free encyclopedia

This is a list of postal codes in Canada where the first letter is M. Postal codes beginning with M are located within the city of Toronto in the province of Ontario. Only the first three characters are listed
Canada Post provides a free postal code look-up tool on its website,[1] via its applications for such smartphones as the iPhone and BlackBerry,[2] and sells hard-copy directories and CD-ROMs. Many
match addresses and postal codes. Hard-copy directories can also be consulted in all post offices, and some libraries.

Toronto - 103 FSAs [edit]

Note: There are no rural FSAs in Toronto, hence no postal codes should start with M0, however, the postal code M0R 8T0 is assigned to an Amazon warehouse in Mississauga, suggesting that Canac

Postal Code	Borough	Neighborhood
M1A	Not assigned	
M2A	Not assigned	
M3A	North York	Parkwoods
M4A	North York	Victoria Village
M5A	Downtown Toronto	Regent Park, Harbourfront
M6A	North York	Lawrence Manor, Lawrence Heights
M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government
M8A	Not assigned	
M9A	Etobicoke	Islington Avenue
M1B	Scarborough	Malvern, Rouge
M2B	Not assigned	
M3B	North York	Don Mills
M4B	East York	Parkview Hill, Woodbine Gardens

Dataset 2 : The following dataset which is Toronto Crime rate (https://www.kaggle.com/alincijov/toronto-crime-rate-per-neighbourhood) is analysing.

Toronto Neighbourhoods Boundary File includes 2014-2019 Crime Data by Neighbourhood. Counts are available for Assault, Auto Theft, Break and Enter, Robbery, Theft Over and Homicide. Data also includes four year averages and crime rates per 100,000 people by neighbourhood based on 2016 Census Population.

From the dataset Toronto Crime Rate, we have modified and cleaned the dataset in the aim to have an average crime rate from 2014 to 2019 with the different types of crime.

OBJECTID	Neighbourhood	Hood_ID	Population	Assault_AVG	Assault_CHG	Assault_Rate_2019	AutoTheft_AVG	AutoTheft_CHG	AutoTheft_Rate_2019	BreakandEnter_AVG	...	Homicide_CHG	Homicide_Rate_2019
1	Yonge-St.Clair	97	12528	31.0	0.09	295.3	4.3	0.00	47.9	23.3	...	0.0	0.0
2	York University Heights	27	27593	333.2	0.04	1340.9	106.3	0.57	521.9	113.2	...	-1.0	0.0
3	Lansing-Westgate	38	16164	70.7	-0.04	445.4	23.7	1.00	198.0	38.8	...	-1.0	0.0
4	Yorkdale-Glen Park	31	14804	160.2	0.19	1411.8	55.5	-0.03	412.1	63.3	...	-0.5	6.8
5	Stonegate-Queensway	16	25051	83.2	-0.06	327.3	28.7	0.10	135.7	52.8	...	0.0	0.0

Dataset 3: Geocoder Package are used to provide Geographical Location data (https://cocl.us/Geospatial_data)

	Postal Code	Latitude	Longitude
0	M1B	43.806686	-79.194353
1	M1C	43.784535	-79.160497
2	M1E	43.763573	-79.188711
3	M1G	43.770992	-79.216917
4	M1H	43.773136	-79.239476

Dataset 4: Foursquare is employed to get Venue Data about different neighbourhood selected

	Neighbourhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Category
0	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	Jawny Bakers	Gastropub
1	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	Toronto Climbing Academy	Rock Climbing Spot
2	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	East York Gymnastics	Gym / Fitness Center
3	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	Muddy York Brewing Co.	Brewery
4	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	Peek Freans Cookie Outlet	Bakery
...	...	...	...	...	...
244	East Toronto, Broadview North (Old East York)	43.685347	-79.338106	Raj Kapuri Paan & Snacks	Indian Restaurant
245	East Toronto, Broadview North (Old East York)	43.685347	-79.338106	Pape Flower Market	Flower Shop
246	East Toronto, Broadview North (Old East York)	43.685347	-79.338106	Phyllo Cafe	Pastry Shop
247	East Toronto, Broadview North (Old East York)	43.685347	-79.338106	Pie in the Sky Studios	Performing Arts Venue
248	East Toronto, Broadview North (Old East York)	43.685347	-79.338106	Wine Rack	Wine Shop

249 rows × 5 columns

Methodology

3.1 Data Cleaning

we have gathered the dataset of the list of Postal code of Canada and we have proceed some data cleaning in the objective to have a good and adequate dataset to perform the analysis of data.

First of all, all boroughs which are not assigned, are removed from the dataset. Then we grouped the neighbourhood with the same postal as it is possible. Therefore, we proceeded with the same procedure with neighbourhood which are not assigned. We neglected them from the dataset.

This procedure is shown below:

```
# Dropping the rows where Borough is 'Not assigned'
df = df[df.Borough != 'Not assigned']

# Combining the neighbourhoods with same Postalcode
df = df.groupby(['Postal Code','Borough'], sort=False).agg(', '.join)
df.reset_index(inplace=True)

# Replacing the name of the neighbourhoods which are 'Not assigned' with names of Borough
df['Neighbourhood'] = np.where(df['Neighbourhood'] == 'Not assigned',df['Borough'], df['Neighbourhood'])

df.shape
df.head()
```

	Postal Code	Borough	Neighbourhood
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	Downtown Toronto	Queen's Park, Ontario Provincial Government

3.1.1 Adding geographical coordinates to the neighbourhoods

After the cleaning of the collected data, we have to get the geographical coordinates of the neighbourhood in the objective to proceed with the analysis. Geographical coordinates of Toronto are extracted and we merged them into the dataset containing neighbourhood.

```
latitude_longitude.rename(columns={'Postal Code':'Postal Code'},inplace=True)
df = pd.merge(df,latitude_longitude,on='Postal Code')
df
```

	Postal Code	Borough	Neighbourhood	Latitude	Longitude
0	M3A	North York	Parkwoods	43.753259	-79.329656
1	M4A	North York	Victoria Village	43.725882	-79.315572
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494
...	...	...	...	...	...
98	M8X	Etobicoke	The Kingsway, Montgomery Road, Old Mill North	43.653654	-79.506944
99	M4Y	Downtown Toronto	Church and Wellesley	43.665860	-79.383160
100	M7Y	East Toronto	Business reply mail Processing Centre, South C...	43.662744	-79.321558
101	M8Y	Etobicoke	Old Mill South, King's Mill Park, Sunnylea, Hu...	43.636258	-79.498509
102	M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999

Fig 2 represents the geographical coordinates of Toronto

3.1.2 Extraction of Toronto Crime Rate

In this project, we have the aim to help stakeholders to have an adequate and an efficient decision making process regarding the optimal place to establish their new restaurant in a safe environment.

We have extracted the Toronto Crime Rate (https://www.kaggle.com/alincijov/toronto-crime-rate-per-neighbourhood). This dataset give useful and important statistical data about different types of crime which happened in different neighbourhoods of Toronto from the period of 2014 to 2019. For our analysis, we have used the crime rate of 2019 as we want to have a more recent and precise idea of the situation.

	Postal Code	Borough	Neighbourhood	Latitude	Longitude	Hood_ID	Population	Assault_Rate_2019	AutoTheft_Rate_2019	BreakandEnter_Rate_2019	Homicide_Rate_2019	Robbery_Rate_2019
0	M4A	North York	Victoria Village	43.725882	-79.315572	43	17510	753.9	102.8	342.7	5.7	80.0
1	M6C	York	Humewood-Cedarvale	43.693781	-79.428191	106	14365	320.2	111.4	181.0	0.0	69.6
2	M4E	East Toronto	The Beaches	43.676357	-79.293031	63	21567	375.6	92.7	264.3	0.0	74.2
3	M1G	Scarborough	Woburn	43.770992	-79.216917	137	53485	798.4	112.2	187.0	0.0	125.3
4	M2H	North York	Hillcrest Village	43.803762	-79.363452	48	16934	407.5	159.4	212.6	5.9	94.5
5	M4H	East York	Thorncliffe Park	43.705369	-79.349372	55	21108	544.8	61.6	127.9	0.0	61.6
6	M1J	Scarborough	Scarborough Village	43.744734	-79.239476	139	16724	1046.4	107.6	239.2	0.0	167.4
7	M2K	North York	Bayview Village	43.786947	-79.385975	52	21396	308.5	172.9	172.9	0.0	65.4
8	M9L	North York	Humber Summit	43.756303	-79.565963	21	12416	950.4	1087.3	459.1	24.2	225.5
9	M9N	York	Weston	43.706876	-79.518188	113	17992	1089.4	272.3	322.4	11.1	144.5

Fig 3 represents the Crime rate in each neighbourhood.

4.0 Exploratory Data Analysis:

4.1 Folium Library

Python provides useful libraries such as Folium which gives us the ability to obtain an interactive map using geographical coordinates data together with the Toronto Crime Rate.

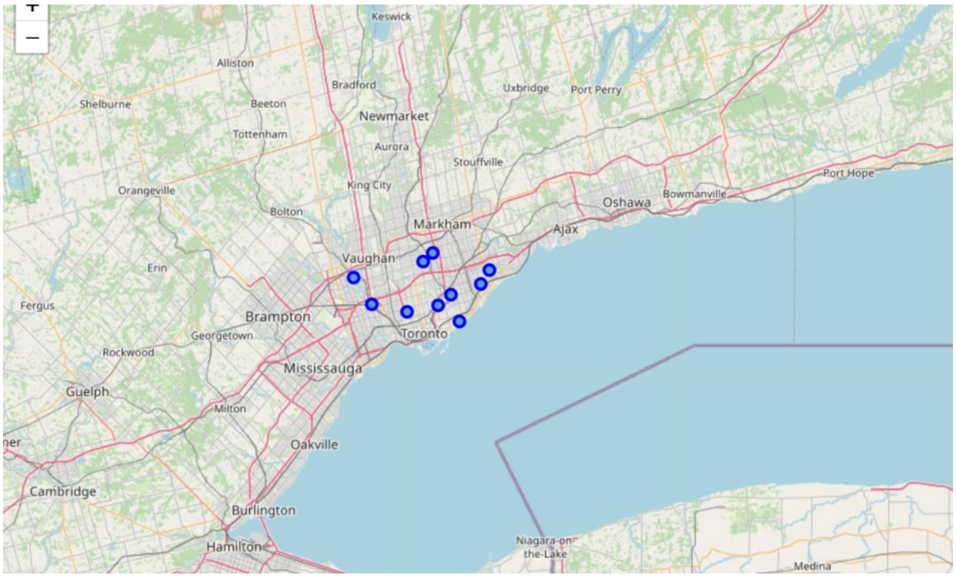
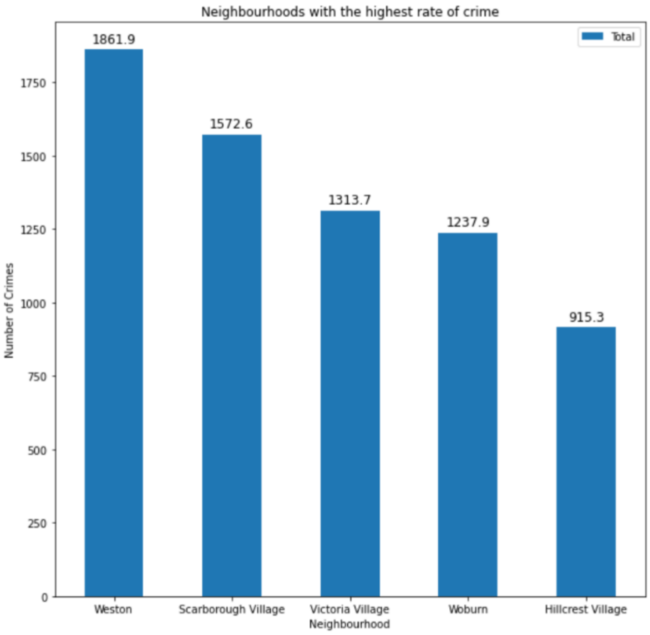


Fig 4 represents the Interactive map of Toronto.

4.2 Relationship between neighbourhoods and Crime Rate

After the obtention of the Toronto Crime Rate with the respective borough and neighbourhood, we calculated the total of crime rate per neighbourhood in order figure out the neighbourhood with the highest and the lowest crime rate.



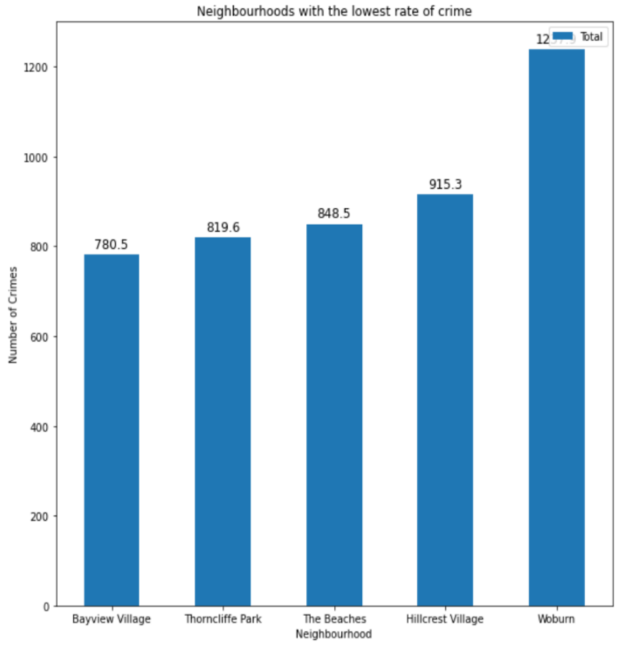


Fig 5 shows the neighbourhood with the highest rate fig 6 shows the neigbourhood with the lowest crime rate.

As our project is based on the inauguration of new restaurant in a safe place, we have analysed the neighbourhoods with the lowest crime rate. We can figure out that the Bayview Village and Thorncliffe Park have recorded low crime rate compared to the other neighbourhoods. We have concentrated our research on them. The type of crime which can have real impact on the establishment of new restaurant are assault crime and robbery crime. Based on this analysis, we will make analysis on the East York borough as it is considered to be a borough with the lowest crime rate.

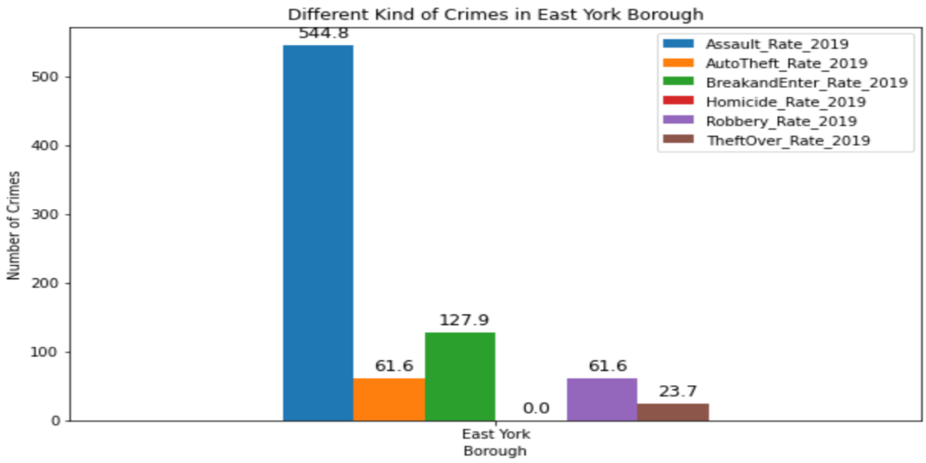
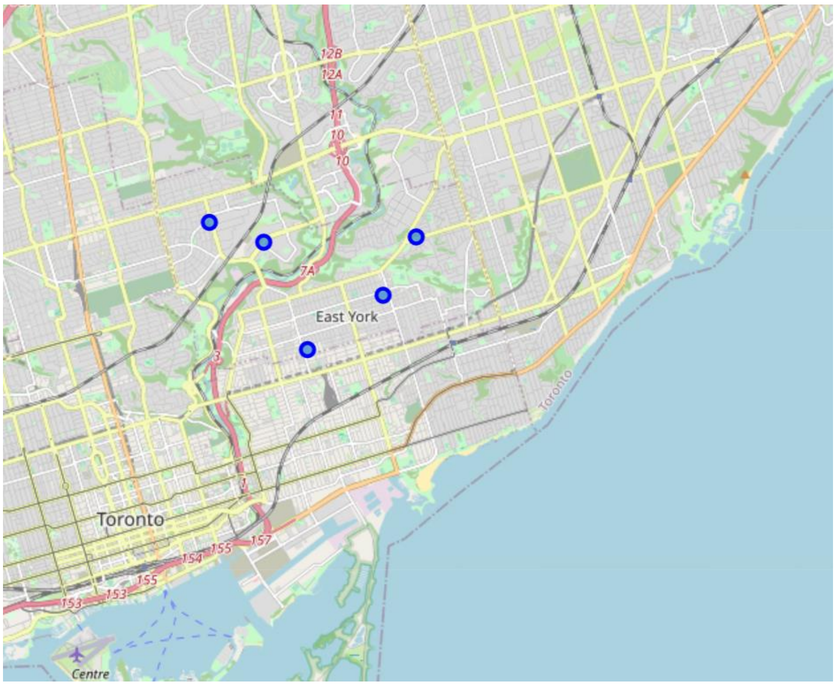


Fig 7 represents the different types of Crime in East York borough

Folium is used to create an interactive map of the East York borough. This is shown below:



The inauguration of a new restaurant should be done in a secure place but also in an area where there are not many others restaurants near in order to attract and get many clients.

4.1 Predictive Modelling: Machine Learning

The realisation of the analysis of the collected data is carried out by performing the one hot encoding technique which is used to convert categorical data into numerical one. The East York borough have numerous neighbourhood which can be analysed individually. Therefore, for each neighbourhood, we recorded the frequency of each venue in the aim to determine which venue has the more client density.

From the Foursquare API, we obtained the different types of Venue names and Categories in the East York Borough.

	Neighbourhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Category
7	Parkview Hill, Woodbine Gardens	43.706397	-79.309937	Harvey's	Fast Food Restaurant
27	Woodbine Heights	43.695344	-79.318389	Little Coxwell Restaurant	Thai Restaurant
41	Woodbine Heights	43.695344	-79.318389	Thai Fusion	Thai Restaurant
44	Woodbine Heights	43.695344	-79.318389	Kouzina	Greek Restaurant
56	Leaside	43.709060	-79.363452	The Leaside Pub	Restaurant
60	Leaside	43.709060	-79.363452	Kintako Japanese Restaurant	Sushi Restaurant
75	Leaside	43.709060	-79.363452	Mt Everest Restaurant	Indian Restaurant

Afterwards, we proceeded with the One Hot encoding to analyse each neighbourhood in the East York.

	Neighbourhood	Afghan Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant	Ethiopian Restaurant	Fast Food Restaurant	Greek Restaurant	Indian Restaurant	Italian Restaurant	Japanese Restaurant	Mexican Restaurant	Middle Eastern Restaurant
7	Parkview Hill, Woodbine Gardens	0	0	0	0	0	0	1	0	0	0	0	0	0
27	Woodbine Heights	0	0	0	0	0	0	0	0	0	0	0	0	0
41	Woodbine Heights	0	0	0	0	0	0	0	0	0	0	0	0	0
44	Woodbine Heights	0	0	0	0	0	0	0	1	0	0	0	0	0
56	Leaside	0	0	0	0	0	0	0	0	0	0	0	0	0

Then, we extract each neighbourhood of the East York along with the top 5 most common venues in order to have a precise idea with venues have more client density.

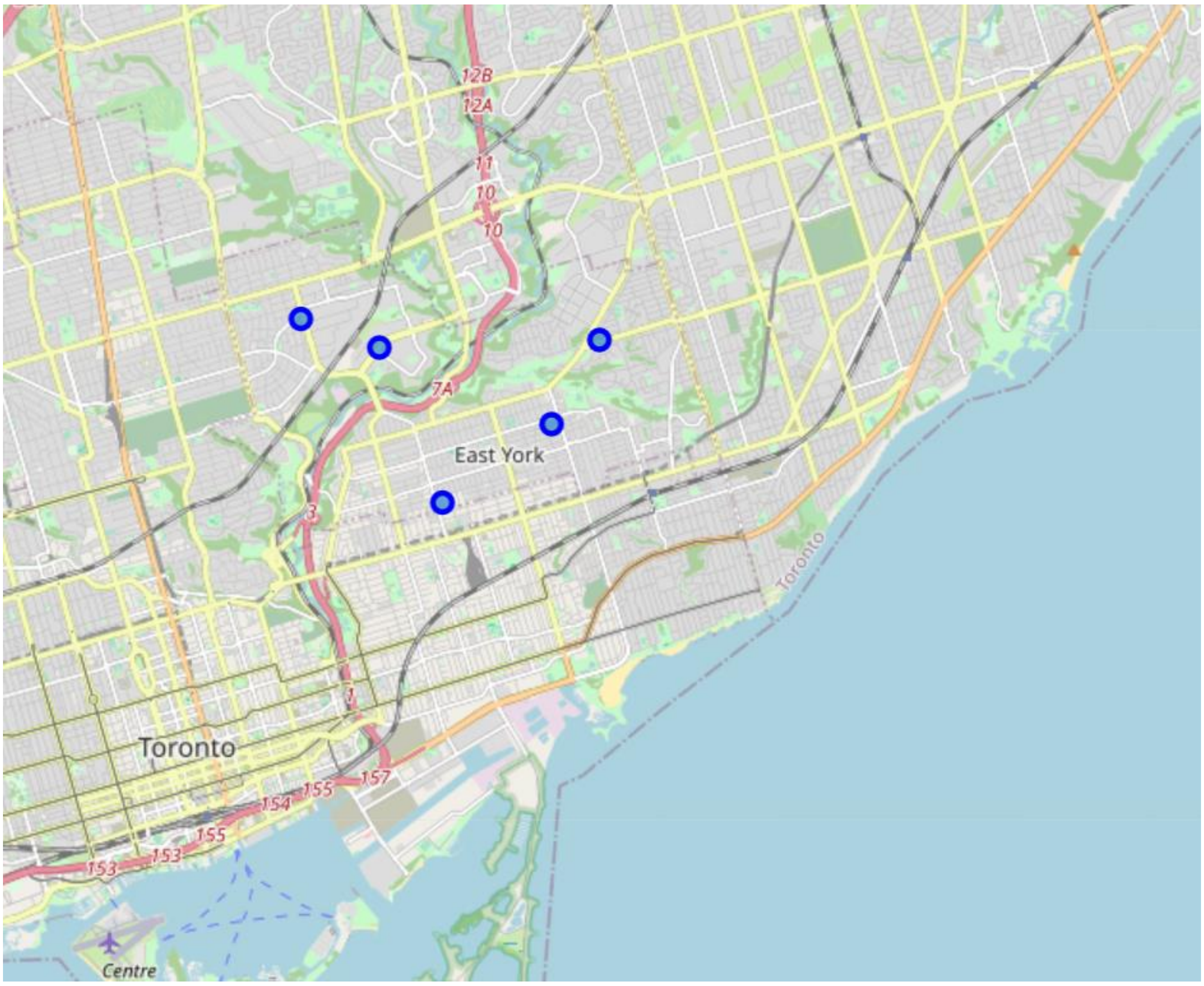
```
----East Toronto, Broadview North (Old East York)----
                        venue  freq
0           Greek Restaurant  0.28
1       Ethiopian Restaurant  0.10
2       Fast Food Restaurant  0.10
3        American Restaurant  0.07
4  Middle Eastern Restaurant  0.07


----Leaside----
                  venue  freq
0            Restaurant  0.29
1    Italian Restaurant  0.14
2   Japanese Restaurant  0.14
3      Sushi Restaurant  0.14
4     Indian Restaurant  0.14


----Parkview Hill, Woodbine Gardens----
                   venue  freq
0   Fast Food Restaurant   1.0
1      Afghan Restaurant   0.0
2    Japanese Restaurant   0.0
3     Turkish Restaurant   0.0
4        Thai Restaurant   0.0


----Thorncliffe Park----
                        venue  freq
0           Indian Restaurant  0.23
1           Afghan Restaurant  0.15
2          Turkish Restaurant  0.15
3   Middle Eastern Restaurant  0.15
4        Fast Food Restaurant  0.08


----Woodbine Heights----
                  venue  freq
0       Thai Restaurant  0.67
1      Greek Restaurant  0.33
2     Afghan Restaurant  0.00
3   Japanese Restaurant  0.00
4    Turkish Restaurant  0.00
```

Proceeding with these data, we want to extract the neighbourhood with its 10th most common venues. Therefore, we can analyse these data to figure out the preference of the population regarding to the different types of restaurant.

	Neighbourhood	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	East Toronto, Broadview North (Old East York)	Greek Restaurant	Ethiopian Restaurant	Fast Food Restaurant	American Restaurant	Middle Eastern Restaurant	Vietnamese Restaurant	Indian Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant
1	Leaside	Restaurant	Italian Restaurant	Sushi Restaurant	Mexican Restaurant	Japanese Restaurant	Indian Restaurant	Fast Food Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant
2	Parkview Hill, Woodbine Gardens	Fast Food Restaurant	Vietnamese Restaurant	Indian Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant	Ethiopian Restaurant	Greek Restaurant	Italian Restaurant
3	Thorncliffe Park	Indian Restaurant	Afghan Restaurant	Middle Eastern Restaurant	Turkish Restaurant	Asian Restaurant	Fast Food Restaurant	Italian Restaurant	Restaurant	Mexican Restaurant	Japanese Restaurant
4	Woodbine Heights	Thai Restaurant	Greek Restaurant	Vietnamese Restaurant	Indian Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant	Ethiopian Restaurant	Fast Food Restaurant

4.2 K-Means Clustering of the neighbourhoods

To go deeper in the analysis of the collected data of the East York borough, we used the K-Means clustering to cluster the neighbourhood based on the neighbourhood which had similar average of



restaurants. We have use K = 5 to obtain 5 clusters in the East York borough. The python library Folium is used to obtain an interactive map of the 5 clusters.

4.3 Examination of the 5 different clusters in the East York Borough

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
14	East York	0	Thai Restaurant	Greek Restaurant	Vietnamese Restaurant	Indian Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant	Ethiopian Restaurant	Fast Food Restaurant

Cluster 2

	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
29	East York	1	Indian Restaurant	Afghan Restaurant	Middle Eastern Restaurant	Turkish Restaurant	Asian Restaurant	Fast Food Restaurant	Italian Restaurant	Restaurant	Mexican Restaurant	Japanese Restaurant

Cluster 3

	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
8	East York	2	Fast Food Restaurant	Vietnamese Restaurant	Indian Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant	Ethiopian Restaurant	Greek Restaurant	Italian Restaurant

Cluster 4

	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
35	East York	3	Greek Restaurant	Ethiopian Restaurant	Fast Food Restaurant	American Restaurant	Middle Eastern Restaurant	Vietnamese Restaurant	Indian Restaurant	Asian Restaurant	Chinese Restaurant	Dim Sum Restaurant

Cluster 5

	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
23	East York	4	Restaurant	Italian Restaurant	Sushi Restaurant	Mexican Restaurant	Japanese Restaurant	Indian Restaurant	Fast Food Restaurant	American Restaurant	Asian Restaurant	Chinese Restaurant

5.0 Results

From the 5 clusters obtained above we can figure out that:

1. The Toronto Crime Rate dataset has provided the opportunity to identify the borough with the lowest crime rate in order to establish a new restaurant.
2. The East York borough has a variety of different restaurant available to the Toronto's population.
3. For businessmen who are invested in Thai restaurant, according to our data, cluster 1 is the only cluster where the East York's population has a Thai restaurant.
4. Cluster 1 and Cluster 5 are the clusters which have the tendency to have many Asian restaurants.
5. Cluster 4 is an optimal place for the opening of a Mexican restaurant.

6.0 Discussion and Conclusion

According to the data analysis, East York borough is the optimal location for the establishment of a new restaurant. The data extracted provide useful and significant information about the different types of restaurants present in the different neighbourhoods.

All clusters except the cluster 1 are considered to be a potential place for the inauguration of a Thai Restaurant. Cluster 4 is the only cluster which does not possess a Mexican restaurant. Investors can use this information to have decision making about the opening of a Mexican restaurant.

Throughout this project, we have been able to identify the different boroughs with their corresponding neighbourhoods which have the highest crime rate as well as the lowest crime rate in 2019. Thus, we identify the potential borough with the lowest crime rate to see the different types of restaurant which are already there. The objective is also to find a safe place for a new restaurant but also an area where there is not many restaurants.

As a results, stakeholders can use these important information to make a strategic approach and to decide which type of restaurant to inaugurate.

We can conclude that this project provides us to define real life business problem and to solve them in the same way as a data scientist would do. We have been able to develop a methodology in the aim to figure out the borough which has the lowest crim rate in Toronto. However, some drawbacks have been detected and this shows that we could use more datasets about the population density, age and religion in order to have a more precise idea about which type of restaurant we can inaugurate in the neighbourhood.

This project can also be used to detect and solve any real life scenario such as the opening of a new grocery store in the region.