## Find the Best Neighbourhood to live in Toronto

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## Content

- Introduction
- Data Used
- Process
- Result
- Conclusion

### Introduction

 This project is designed to show features of each neighbourhoods in Toronto and provide those who want to move to Toronto an idea of which neighbourhood to live in.

### Data Used

- The Crime Data is from the Toronto Police
- GPS Coordinates of each neighbourhoods were extracted from the table provided in Week 3 Assignment and merged with the Crime Data
- Datas regarding to the most common venues of each neighbourhood is from the use of Foursquare API

	Α	В	С	D	Е	F	G	Н		J
1	Hood_ID	Neighbourl	Total_2018	Population	Longitude	Latitude	Borough	PostalCode	Rate	
2	1	West Huml	1035	37722	-79.594054	43.7067483	Etobicoke	M9W	3%	
3	2	Mount Oliv	427	35443	-79.588437	43.7394164	Etobicoke	M9V	1%	
4	3	Thistletowr	131	10788	-79.588437	43.7394164	Etobicoke	M9V	1%	
5	4	Rexdale-Ki	177	11043	-79.594054	43.7067483	Etobicoke	M9W	2%	
6	5	Elms Old R	133	10524	-79.594054	43.7067483	Etobicoke	M9W	1%	
7	6	Kingsview	218	23440	-79.532242	43.696319	Etobicoke	M9P	1%	
8	7	Willowridg	211	23205	-79.554724	43.6889054	Etobicoke	M9R	1%	
9	8	Humber He	97	12196	-79.532242	43.696319	Etobicoke	M9P	1%	
10	9	Edenbridge	91	15749	-79.532242	43.6678556	Etobicoke	M9A	1%	
11	10	Princess-R	63	11812	-79.554724	43.6509432	Etobicoke	M9B	1%	
12	11	Eringate-C	126	20434	-79.554724	43.6509432	Etobicoke	M9B	1%	
13	12	Markland \	56	11387	-79.577201	43.6435152	Etobicoke	M9C	0%	
14	13	Etobicoke \	76	12255	-79.577201	43.6435152	Etobicoke	M9C	1%	
15	14	Islington-C	573	44359	-79.506944	43.6536536	Etobicoke	M8X	1%	
16	15	Kingsway \$	86	9771	-79.506944	43.6536536	Etobicoke	M8X	1%	
17	16	Stonegate	185	26707	-79.501321	43.6056466	Etobicoke	V8M	1%	
18	18	New Toron	160	11399	-79.501321	43.6056466	Etobicoke	V8M	1%	
19	19	Long Branc	111	10485	-79.543484	43.6024137	Etobicoke	W8M	1%	
20	20	Alderwood	90	12873	-79.543484	43.6024137	Etobicoke	W8M	1%	
21	21	Humber Sı	357	13631	-79.565963	43.7563033	North York	M9L	3%	
22	22	Humberme	211	17351	-79.532242	43.7247659	North York	M9M	1%	
23	23	Pelmo Park	170	9566	-79.532242	43.7247659	North York	M9M	2%	
24	24	Black Cree	363	23359	-79.495697	43.7284964	North York	МЗМ	2%	
25	25	Glenfield Ja	391	33593	-79.520999	43.7616313	North York	M3N	1%	
26	26	Downsview	648	38745	-79.495697	43.7284964	North York	МЗМ	2%	
27	27	York Unive	608	30606	-79.487262	43.7679803	North York	M3J	2%	
28	28	Rustic	139	10836	-79.490074	43.7137562	North York	M6L	1%	
29		Maple Leaf		10863	-79.490074	43.7137562	North York	M6L	1%	
30		Brookhavei		19457	-79.476013	43.6911158	North York	M6M	1%	
31	31	Yorkdale G	356	15757	-79.445073	43.709577	North York	M6B	2%	
32	32	Englemoun	172	23950	-79.464763	43.718518	North York	M6A	1%	
22	22	οι · Β	440	40000	70 440050	40 75 40000	N .1 V/ 1	14011	40/	
4	tor	onto_crime_	_data_1	+						

### Process

 The file was first uploaded in notebook and were excluded of those neighbourhoods that have a crime rate greater than 2% (in this case not safe enough)

	First exlude those Neighbourhoods with Crime Rate greater than 2%												
In [2]:	toronto=df[df.Rate<='2%'] toronto												
Out[2]:	Hood_ID		Neighbourhood	Total_2018	Population	Longitude	Latitude	Borough	PostalCode	Rate			
	1	2	Mount Olive-Silverstone- Jamestown	427	35443	-79.588437	43.739416	Etobicoke	M9V	1%			
	2 3 3 4		Thistletown Beaumond Heights	131	10788	-79.588437	43.739416	Etobicoke	M9V	1%			
			Rexdale-Kipling	177	11043	-79.594054	43.706748	Etobicoke	M9W	2%			
	<b>4</b> 5		Elms Old Rexdale	133	10524	-79.594054	43.706748	Etobicoke	M9W	1%			
	<b>5</b> 6		Kingsview Village-The Westway	218	23440	-79.532242	43.696319	Etobicoke	М9Р	1%			
	6	7	Willowridg-Martingrove-Richview	211	23205	-79.554724	43.688905	Etobicoke	M9R	1%			
	7	8	Humber Heights-Westmount	97	12196	-79.532242	43.696319	Etobicoke	М9Р	1%			
	8	9	Edenbridge-Humber Valley	91	15749	-79.532242	43.667856	Etobicoke	М9А	1%			
	9	10	Princess-Rosethorn	63	11812	-79.554724	43.650943	Etobicoke	М9В	1%			
	10	11	Eringate-Centennial-West Deane	126	20434	-79.554724	43.650943	Etobicoke	М9В	1%			
	11	12	Markland Wood	56	11387	-79.577201	43.643515	Etobicoke	М9С	0%			
	12	13	Etobicoke West Mall	76	12255	-79.577201	43.643515	Etobicoke	М9С	1%			

 After generating a map with the neighbourhoods showed as blue points on Toronto map. The Foursquare API is then used to explore the venues of each neighbourhoods.

#### Get the top 100 venues within a radius of 500m in each Neighbourhood

```
In [6]: def getNearbyVenues(names, latitudes, longitudes, radius=500):
            venues list=[]
            for name, lat, lng in zip(names, latitudes, longitudes):
                print(name)
                url = 'https://api.foursquare.com/v2/venues/explore?&client id={}&client secret={}&v={}
                    CLIENT ID,
                     CLIENT SECRET,
                    VERSION,
                     lat,
                     lnq,
                     500,
                     100)
                results = requests.get(url).json()["response"]['groups'][0]['items']
                venues list.append([(
                     name,
                     lat,
                     lnq,
                     v['venue']['name'],
                    v['venue']['location']['lat'],
                    v['venue']['location']['lng'],
                    v['venue']['categories'][0]['name']) for v in results])
```

 Then analyse each Neighbourhood and take the top 5 most common venues for further analyze.

```
columns.append( { } { } { } Most Common Venue .format(ind+1, indicators[ind]))
               except:
                    columns.append('{}th Most Common Venue'.format(ind+1))
          neighborhoods venues sorted = pd.DataFrame(columns=columns)
          neighborhoods venues sorted['Neighborhood'] = toronto grouped['Neighborhood']
           for ind in np.arange(toronto grouped.shape[0]):
               neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common venues(toronto grouped.iloc[
          neighborhoods venues sorted.head()
Out[13]:
                                  1st Most Common
                                                    2nd Most Common
                                                                      3rd Most Common
                                                                                       4th Most Common
                                                                                                         5th Most Common
                    Neighborhood
                                            Venue
                                                              Venue
                                                                                                  Venue
                                                                                Venue
                                                                                                                   Venue
                    Agincourt North
                                         Playground
                                                                Park
                                                                       Department Store
                                                                                         Falafel Restaurant
                                                                                                               Event Space
           0
                   Agincourt South
           1
                                     Sandwich Place
                                                        Clothing Store
                                                                                           Breakfast Spot
                                                                                                        Dim Sum Restaurant
                                                                               Lounge
                     Malvern West
           2
                       Alderwood
                                         Pizza Place
                                                          Skating Rink
                                                                           Coffee Shop
                                                                                                   Pool
                                                                                                                     Pub
           3
                                              Pub
                                                          Coffee Shop
                                                                            Pizza Place
                                                                                              Bagel Shop
                                                                                                          Convenience Store
                           Annex
                  Banbury Don Mills
                                                                           Coffee Shop
                                              Gym
                                                           Beer Store
                                                                                          Asian Restaurant
                                                                                                             Clothing Store
          neighborhoods venues sorted.shape
Dut[14]: (128, 6)
```

# Lastly, cluster the neighbourhoods into 5 clusters

```
Cluster Neighbourhoods
In [15]:
          kclusters = 5
          toronto grouped clustering = toronto grouped.drop('Neighborhood', 1)
          kmeans = KMeans(n clusters=kclusters, random state=0).fit(toronto grouped clustering)
          kmeans.labels [0:10]
Out[15]: array([3, 2, 2, 2, 2, 2, 2, 2, 2], dtype=int32)
          neighborhoods venues sorted.insert(0, 'Cluster Labels', kmeans.labels ,True)
In [16]:
          toronto merged = toronto
          toronto merged = toronto merged.join(neighborhoods venues sorted.set index('Neighborhood'), on=
          toronto merged.head()
Out[16]:
                                                                                                       1st Most
                                                                                                Cluster
             Hood_ID Neighbourhood Total_2018 Population Longitude
                                                                        Borough PostalCode Rate
                                                                Latitude
                                                                                                       Common
                                                                                                Labels
                                                                                                         Venue
                        Mount Olive-
                                                                                                        Grocery
                   2
                        Silverstone-
                                       427
                                               35443 -79.588437 43.739416 Etobicoke
                                                                                      M9V
                                                                                           1%
                                                                                                   2.0
                                                                                                          Store
                         Jamestown
                         Thistletown
                                                                                                        Grocery
                         Beaumond
                                       131
                                                                                      M9V 1%
                                               10788 -79.588437 43.739416 Ftobicoke
```

## Result

The neighbourhoods were clustered into 5 clusters

	Cluster 1														
In [20]:	to	toronto_merged.loc[toronto_merged['Cluster Labels'] == 0.0, toronto_merged.columns[[1] + list(r													
Out[20]:		Neighbourhood	Latitude	Borough	PostalCode	Rate	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue			
	60	East End Danforth	43.676357	East Toronto	M4E	1%	0.0	Coffee Shop	Health Food Store	Pub	Department Store	Falafel Restaurant			
	61	The Beaches	43.676357	East Toronto	M4E	1%	0.0	Coffee Shop	Health Food Store	Pub	Department Store	Falafel Restaurant			
	35	Woburn	43.770992	Scarborough	M1G	1%	0.0	Coffee Shop	Korean Restaurant	Dim Sum Restaurant	Farmers Market	Falafel Restaurant			

#### Cluster 2

In [21]: pronto\_merged.loc[toronto\_merged['Cluster Labels'] == 1.0, toronto\_merged.columns[[1] + list(rar

Out[21]:

	Neighbourhood	Latitude	Borough	PostalCode	Rate	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
129	Rouge	43.806686	Scarborough	M1B	1%	1.0	Fast Food Restaurant	Women's Store	Dim Sum Restaurant	Farmers Market	Falafel Restaurant
130	Malvern	43.806686	Scarborough	M1B	1%	1.0	Fast Food Restaurant	Women's Store	Dim Sum Restaurant	Farmers Market	Falafel Restaurant

### Cluster 3

In [22]: pronto\_merged.loc[toronto\_merged['Cluster Labels'] == 2.0, toronto\_merged.columns[[1] + list(ran

	Neighbourhood	Latitude	Borough	PostalCode	Rate	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
1	Mount Olive- Silverstone- Jamestown	43.739416	Etobicoke	M9V	1%	2.0	Grocery Store	Coffee Shop	Fried Chicken Joint	Sandwich Place	Discount Store
2	Thistletown Beaumond Heights	43.739416	Etobicoke	M9V	1%	2.0	Grocery Store	Coffee Shop	Fried Chicken Joint	Sandwich Place	Discount Store
3	Rexdale-Kipling	43.706748	Etobicoke	M9W	2%	2.0	Drugstore	Rental Car Location	Women's Store	Department Store	Falafel Restaurant
4	Elms Old Rexdale	43.706748	Etobicoke	M9W	1%	2.0	Drugstore	Rental Car Location	Women's Store	Department Store	Falafel Restaurant
5	Kingsview Village-The Westway	43.696319	Etobicoke	M9P	1%	2.0	Pizza Place	Intersection	Chinese Restaurant	Sandwich Place	Middle Eastern Restaurant
6	Willowridg- Martingrove-	43.688905	Etobicoke	M9R	1%	2.0	Pizza Place	Mobile Phone	Park	Bus Line	Falafel

#### Cluster 4

In [23]: toronto\_merged.loc[toronto\_merged['Cluster Labels'] == 3.0, toronto\_merged.columns[[1] + list(r

Out[23]:

:	Neighbourhood	Latitude	Borough	PostalCode	Rate	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th N Comı V€
13	Islington-City Centre West	43.653654	Etobicoke	M8X	1%	3.0	Park	River	Women's Store	Dessert Shop	Fa Restau
14	Kingsway South	43.653654	Etobicoke	M8X	1%	3.0	Park	River	Women's Store	Dessert Shop	Fa Restau
39	Bridle Path Sunnybrook York Mills	43.728020	North York	M4N	1%	3.0	Park	Bus Line	Swim School	Women's Store	Dim : Restau
43	Parkwoods Donalda	43.753259	North York	МЗА	1%	3.0	Park	Food & Drink Shop	Bus Stop	Fast Food Restaurant	Wom S
56	Old East York	43.685347	East York	M4J	1%	3.0	Park	Coffee Shop	Convenience Store	Dim Sum Restaurant	Farr Ma
57	Danforth East York	43.685347	East York	M4J	1%	3.0	Park	Coffee Shop	Convenience Store	Dim Sum Restaurant	Farr Ma
67	Blake Jones	43.685347	East York	M4J	1%	3.0	Park	Coffee Shop	Convenience Store	Dim Sum Restaurant	Farr Ma
90	Corso Italia Davenport	43.689026	York	M6E	1%	3.0	Park	Women's Store	Market	Pharmacy	Fast F Restau
05	Oakwood Village	43.689026	York	M6E	1%	3.0	Park	Women's Store	Market	Pharmacy	Fast F Restai

### Cluster 5

In [24]: toronto\_merged.loc[toronto\_merged['Cluster Labels'] == 4.0, toronto\_merged.columns[[1] + list(r

Out[24]:

	Neighbourhood	Latitude	Borough	PostalCode	Rate	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
9	Princess- Rosethorn	43.650943	Etobicoke	М9В	1%	4.0	Bank	Women's Store	Fish & Chips Shop	Fast Food Restaurant	Farmers Market
10	Eringate- Centennial-West Deane	43.650943	Etobicoke	М9В	1%	4.0	Bank	Women's Store	Fish & Chips Shop	Fast Food Restaurant	Farmers Market

### Conclusion

 The user of the project can choose the ultimate neighbourhoods to live in according to his/her preferences.

# Thank you