Exploring the Neighbourhoods of Toronto –
What is the best place to open a new Indian Restaurant?

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1. Business problem and Background

1.1 Problem statement: Potential success of opening an Indian restaurant in Toronto, Canada

Toronto is one of the most populous Canadian cities and is home to a large number of immigrants. As a result of this, it has diverse neighborhoods such as Greektown, Koreatown, Little Italy, and Little India. More than half of Indian immigrants in Canada reside in Toronto, and therefore there is a great demand for Indian food.

Due to the this, starting an Indian restaurant can potentially be a great idea given that it will be profitable to the owner. Through the course of this capstone project, we will evaluate the business idea of opening an Indian restaurant. Through geospatial data analysis, we can analyze the neighborhoods in Toronto by looking at current data about the success of restaurants.

1.2 Target Audience

Who will be more interested in this project? What type of clients or a group of people would be benefitted?

1. **Business owners who are thinking of opening a restaurant:**
   This can be a detailed reference for anyone wishing the open an Indian restaurant and can help in decision making related to neighborhoods, ambience, and other geographical factors.

2. **Data scientists and Business analysts:**
   The variety of stages such as data cleaning, exploratory data analysis, and machine learning undertaken in this project can help other Data scientists who want to analyze the neighborhoods of Toronto. By using the conclusions and insights yielded in this project, the operations can be extended, and further analysis can also be performed.

3. **Indian residents and tourists of Toronto:**
   Since the report focuses on Indian restaurants, the conclusion from this report can help Indians looking for eatery options in Toronto.

2. Data Acquisition and Cleaning

2.1 Data sources

1. **Information on Toronto's neighborhoods** (Postal code, borough, name of neighborhood)
   https://en.wikipedia.org/w/index.php?title=List_of_postal_codes_of_Canada:_M&oldid=1012118802

2. **Geographical coordinates of neighborhoods:**
   https://cocl.us/Geospatial_data%E2%80%9D

3. **Foursquare API - Information about venues in Toronto:**
   Collecting the name, category, latitude, and longitude to see existing venues present
   https://developer.foursquare.com/docs/

4. **Demographics of Toronto's neighborhoods by ethnicity:**
   This dataset will give an insight into the distribution of Indians in Toronto and help identify neighborhoods where opening an Indian restaurant can attract most customers
   https://en.m.wikipedia.org/wiki/Demographics_of_Toronto#Ethnic_diversity

2.2 Data Cleaning

1. **Scraping information on Toronto's neighborhoods:**

   I web scraped this data from Wikipedia's page on Toronto's neighborhoods. The data frame consisted of three columns – Postal code, Borough, Neighborhood.

   BeautifulSoup was used to scrape this data:

Out[128]:

	Postalcode	Borough	Neighbourhood
0	M1A	Not assigned	Not assigned
1	M2A	Not assigned	Not assigned
2	M3A	North York	Parkwoods
3	M4A	North York	Victoria Village
4	M5A	Downtown Toronto	Regent Park, Harbourfront

However, there were a few problems with the dataset. First, there were a few cells which were not assigned a Borough. Hence, I only processed cells which were assigned a Borough. Secondly, there were multiple neighborhoods for one postal code. This caused duplication of rows and hence I combined these 2 rows into one, where different neighborhoods for a given postal code would be separated by a comma. Lastly, there were quite a few cells were assigned a borough but not a neighborhood. In that case, the neighborhood was made the same as borough.

After making these iterations, this was the final dataframe:

Out[184]:

	Postalcode	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

2. **Extracting geographical coordinates of each neighborhood**

   In this step, I imported the csv file Geospatial_data.csv downloaded from here and merged it with the dataframe made in the previous step.

   The dataframe was merged based on the common column of Postal code as follows:

In [195]:
```
geo_data=geo_merged[['Postalcode','Borough','Neighbourhood','Latitude','Longitude']]
toronto_data = geo_data
toronto_data.head()
```

Out[195]:

	Postalcode	Borough	Neighbourhood	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

3. **Leveraging Foursquare API for information on venues**

   Foursquare API is an online tool which helps extract information about various venues present across neighborhoods. For this project, I used foursquare API to find the type of venue present in each neighborhood in Toronto, along with the latitudes and longitudes of the venue.

   Foursquare returned a JSON file which I then imported and converted into a dataframe. After doing this, I filtered the top 100 venues around a 1km radius for each neighborhood.

In [268]:
```
toronto_venues.head()
```

Out[268]:

	Neighbourhood	Neighbourhood Latitude	Neighbourhood 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	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497	Scarborough Historical Society	43.788755	-79.162438	History Museum
3	Guildwood, Morningside, West Hill	43.763573	-79.188711	RBC Royal Bank	43.766790	-79.191151	Bank
4	Guildwood, Morningside, West Hill	43.763573	-79.188711	G & G Electronics	43.765309	-79.191537	Electronics Store

4. **Ethnic diversity of Toronto's neighborhoods:**

   Since we are focusing on Indian restaurants in Toronto, factoring for the Indian population in each neighborhood would help us get a better idea of which locality would be suitable in order to set up an Indian restaurant.

   To do this, I scraped the data from Wikipedia's page of Ethnic diversities of Toronto. I identified 4 main parts of Toronto which had a considerable amount of Indian crowd. These are:

1. Toronto and East York:

	Riding	Population	Ethnic Origin #1	Ethnic Origin 1 %	Ethnic Origin #2	Ethnic Origin 2 %	Ethnic Origin #3	Ethnic Origin 3 %	Ethnic Origin #4	Ethnic Origin 4 %	Ethnic Origin #5	Ethnic Origin 5 %	Ethnic Origin #6	Ethnic Origin 6 %	Ethnic Origin #7	Ethnic Origin 7 %	Ethnic Origin #8	Et O
0	Spadina-Fort York	114315	English	16.4	Chinese	16.0	Irish	14.6	Canadian	14.0	Scottish	13.2	French	7.70	German	7.6	NaN	
1	Beaches-East York	108435	English	24.2	Irish	19.9	Canadian	19.7	Scottish	18.9	French	8.7	German	8.40	NaN	NaN	NaN	
2	Davenport	107395	Portuguese	22.7	English	13.6	Canadian	12.8	Irish	11.5	Italian	11.1	Scottish	11.00	NaN	NaN	NaN	
3	Parkdale-High Park	106445	English	22.3	Irish	20.0	Scottish	18.7	Canadian	16.1	German	9.8	French	8.88	Polish	8.5	NaN	
4	Toronto-Danforth	105395	English	22.9	Irish	19.5	Scottish	18.7	Canadian	18.4	Chinese	13.8	French	8.86	German	8.8	Greek	

2. North York:

	Riding	Population	Ethnic Origin #1	Ethnic Origin 1 %	Ethnic Origin #2	Ethnic Origin 2 %	Ethnic Origin #3	Ethnic Origin 3 %	Ethnic Origin #4	Ethnic Origin 4 %	Ethnic Origin #5	Ethnic Origin 5 %	Ethnic Origin #6	Ethnic Origin 6 %	Ethnic Origin #7	Ethnic Origin 7 %	Ethnic Origin #8	Et O
0	Willowdale	117405	Chinese	25.9	Iranian	12.1	Korean	10.6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	Eglinton-Lawrence	112925	Canadian	14.7	English	12.6	Polish	12.0	Filipino	11.0	Scottish	9.7	Italian	9.5	Irish	9.2	Russian	
2	Don Valley North	109060	Chinese	32.4	East Indian	7.3	Iranian	7.3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	Humber River-Black Creek	107725	Italian	12.8	East Indian	9.2	Jamaican	8.5	Vietnamese	8.0	Canadian	7.4	NaN	NaN	NaN	NaN	NaN	
4	York Centre	103760	Filipino	17.0	Italian	13.4	Russian	9.5	Canadian	8.6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

3. Scarborough:

	Riding	Population	Ethnic Origin #1	Ethnic Origin 1 %	Ethnic Origin #2	Ethnic Origin 2 %	Ethnic Origin #3	Ethnic Origin 3 %	Ethnic Origin #4	Ethnic Origin 4 %	Ethnic Origin #5	Ethnic Origin 5 %	Ethnic Origin #6	Ethnic Origin 6 %	Ethnic Origin #7	Ethnic Origin 7 %	Ethnic Origin #8
0	Scarborough Centre	110450	Filipino	13.1	East Indian	12.2	Canadian	11.2	Chinese	10.7	English	7.8	Sri Lankan	7.0	NaN	NaN	NaN
1	Scarborough Southwest	108295	Canadian	16.2	English	14.3	Irish	11.5	Scottish	10.9	Filipino	9.5	East Indian	8.2	Chinese	7.2	NaN
2	Scarborough-Agincourt	104225	Chinese	47.0	East Indian	7.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Scarborough-Rouge Park	101445	East Indian	16.7	Canadian	11.8	Sri Lankan	11.1	English	9.8	Filipino	9.3	Jamaican	8.4	Scottish	7.2	Irish
4	Scarborough-Guildwood	101115	East Indian	18.0	Canadian	11.6	English	9.7	Filipino	8.5	Sri Lankan	7.8	Chinese	7.1	Scottish	7.0	NaN
5	Scarborough North	97610	Chinese	46.6	East Indian	11.8	Sri Lankan	9.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

4. Etobicoke and York:

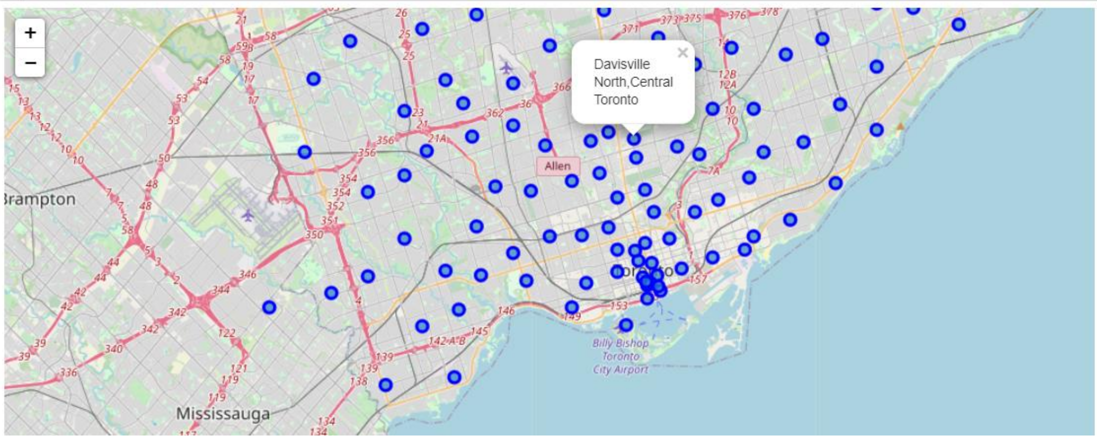
	Riding	Population	Ethnic Origin #1	Ethnic Origin 1 %	Ethnic Origin #2	Ethnic Origin 2 %	Ethnic Origin #3	Ethnic Origin 3 %	Ethnic Origin #4	Ethnic Origin 4 %	Ethnic Origin #5	Ethnic Origin 5 %	Ethnic Origin #6	Ethnic Origin 6 %	Ethnic Origin #7	Ethnic Origin 7 %	Ethni Origi #
0	Etobicoke-Lakeshore	127520	English	17.1	Canadian	15.9	Irish	14.4	Scottish	13.5	Polish	9.2	Italian	9.1	Ukrainian	7.6	Germa
1	Etobicoke North	116960	East Indian	22.2	Canadian	7.9	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Nal
2	Etobicoke Centre	116055	Italian	15.1	English	14.3	Canadian	12.1	Irish	10.8	Scottish	10.4	Ukrainian	8.1	Polish	7.4	Nal
3	York South-Weston	115130	Portuguese	14.5	Italian	12.8	Canadian	8.7	Jamaican	8.4	NaN	NaN	NaN	NaN	NaN	NaN	Nal

3. Exploratory Data Analysis

This section included charting different visualizations and manipulating data (for example – one hot encoding) in order to find the best set of insights for further analysis and arrive at an accurate conclusion.

3.1 Leaflet map of Toronto's neighborhoods

I used Folium library to plot a leaflet map of Toronto's neighborhoods:



3.2 Relationship between neighborhood and Indian restaurant

This was important in order to decide which neighborhood would be the most suitable for an Indian restaurant

I used one hot encoding in order to find the relationship between a particular neighborhood and a range of venues in Toronto.

Out[58]:

	Neighbourhood	Accessories Store	Adult Boutique	Afghan Restaurant	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	...	Turkish Restaurant	Vegetarian / Vegan Restaurant	Video Game Store	Vietnamese Restaurant	W
0	Agincourt	0.0	0.0	0.0	0.0	0.0	0.0	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	0.0	...	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	0.0	...	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	0.0	...	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	0.0	...	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
92	Willowdale, Willowdale West	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
93	Woburn	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
94	Woodbine Heights	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
95	York Mills West	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
96	York Mills, Silver Hills	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	

97 rows × 257 columns

By extracting the neighborhood and 'Indian restaurant' column only, I would be able to get a better idea of the neighborhoods favoring an Indian restaurant. Hence, I extracted those 2 columns and merged it with the dataframe generated after data cleaning.

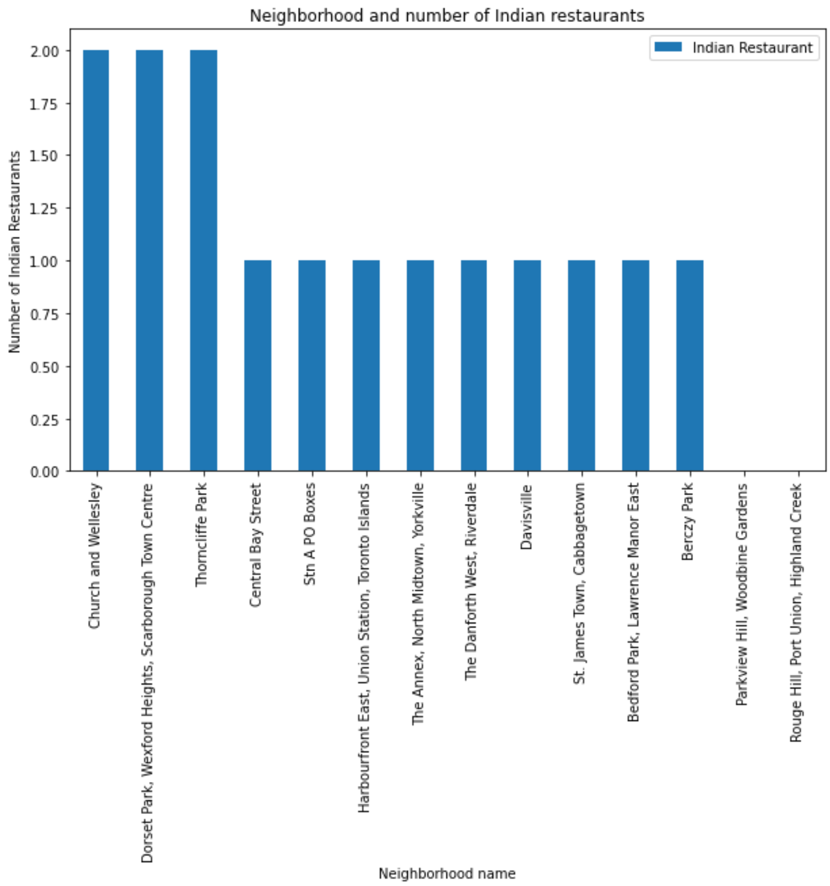
In [33]:
```
toronto_merged = pd.merge(toronto_data, ind_toronto_df, on='Neighbourhood')
toronto_merged
```

Out[33]:

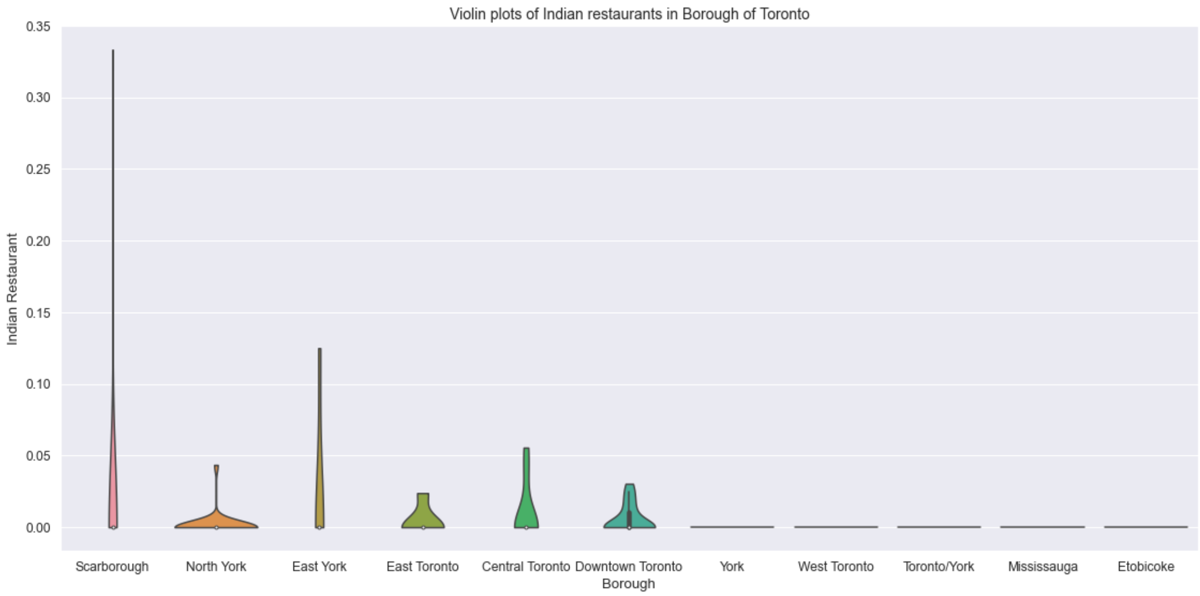
	Postalcode	Borough	Neighbourhood	Latitude	Longitude	Indian Restaurant
0	M1B	Scarborough	Malvern, Rouge	43.806686	-79.194353	0.0
1	M1C	Scarborough	Rouge Hill, Port Union, Highland Creek	43.784535	-79.160497	0.0
2	M1E	Scarborough	Guildwood, Morningside, West Hill	43.763573	-79.188711	0.0
3	M1G	Scarborough	Woburn	43.770992	-79.216917	0.0
4	M1H	Scarborough	Cedarbrae	43.773136	-79.239476	0.0
...	...	...	...	...	...	...
96	M9N	York	Weston	43.706876	-79.518188	0.0
97	M9P	Etobicoke	Westmount	43.696319	-79.532242	0.0
98	M9R	Etobicoke	Kingsview Village, St. Phillips, Martin Grove ...	43.688905	-79.554724	0.0
99	M9V	Etobicoke	South Steeles, Silverstone, Humbergate, Jamest...	43.739416	-79.588437	0.0
100	M9W	Etobicoke	Northwest, West Humber - Clairville	43.706748	-79.594054	0.0

101 rows × 6 columns

This dataframe helped me visualize the density of Indian restaurants across various neighborhoods in Toronto.



I also drew a violin plot so that we can identify which boroughs have densely populated Indian restaurants.



3.3 Relationship between neighborhood and Indian population

This relationship would be instrumental in finding an ideal location for opening and Indian restaurant as a neighborhood with a greater Indian population would always have a higher demand for Indian restaurant – ensuring more scope for the restaurant's customer base to grow.

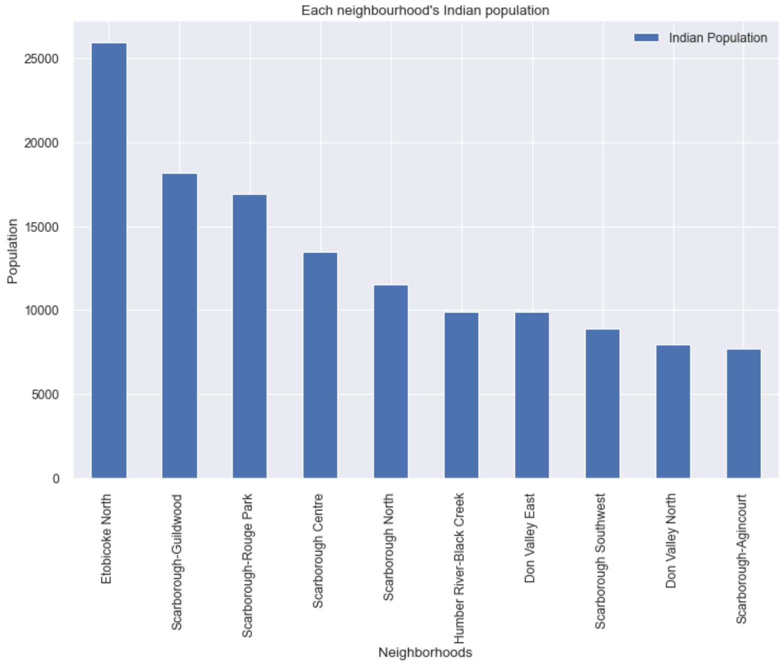
I extracted 2 key values – riding population and Indian population percentage – for each riding from the ethnic diversity Wikipedia table and applied the following formula:

$$Indian\ population = \frac{Indian\ population\ by\ percentage}{100} \times 100$$

Further, I complied these metrics into the following table:

	Ethnicity	Percentage	Population	Riding
5	East Indian	7.4	104225.0	Scarborough-Agincourt
6	East Indian	16.7	101445.0	Scarborough-Rouge Park
7	East Indian	18.0	101115.0	Scarborough-Guildwood
8	East Indian	11.8	97610.0	Scarborough North
9	East Indian	22.2	116960.0	Etobicoke North

Using the dataframe, the following bar plot was plotted:



This relationship helps us identify neighborhoods with a high density of Indian population. This is a key factor in our analysis since an Indian restaurant situated in a densely populated neighborhood is more likely to get more customer visits – which contributes to the success of the restaurant.

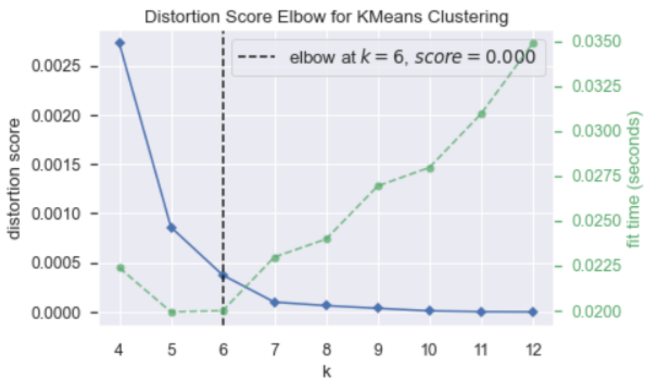
4. Predictive modelling

4.1 Machine learning

Since I was using K-means clustering for our predictive model, the first step included identifying the most accurate 'K' value. K-means clustering is used to find groups which have not been explicitly conveyed by the data, and hence is the most ideal in this case.

In [122]:
```
model = KMeans()
visualizer = KElbowVisualizer(model, k=(4,13))

visualizer.fit(ind_toronto_df_cluster)
visualizer.show()
```



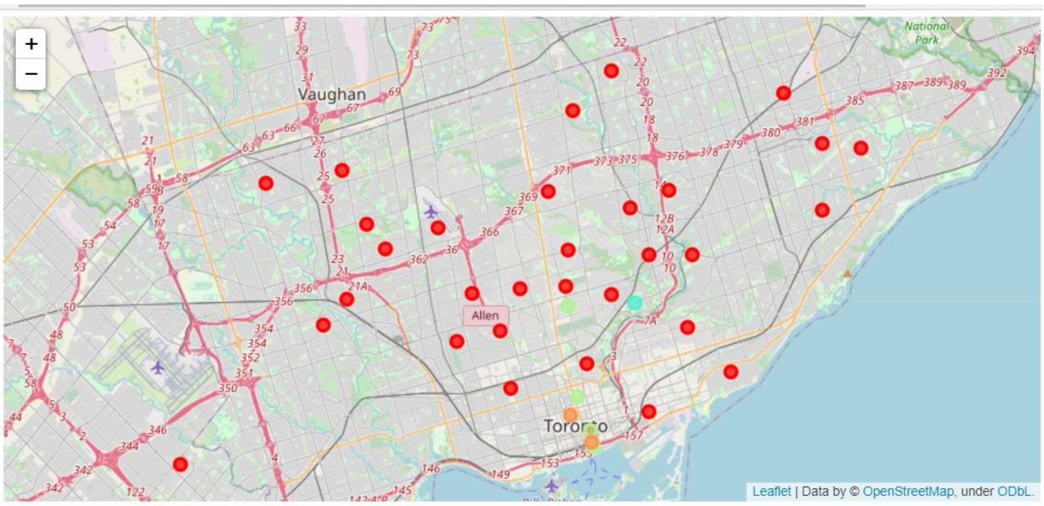
Out[122]: `<matplotlib.axes._subplots.AxesSubplot at 0x2205df99d00>`

This distortion score elbow helped us analyze the most ideal K value, which in this case was 6.

The predive model was fitted to our data and produced the following table which rendered the cluster labels for each location:

	Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant
34	M6G	Downtown Toronto	Christie	43.669542	-79.422564	0.0	0.0
35	M7R	Mississauga	Canada Post Gateway Processing Centre	43.636966	-79.615819	0.0	0.0
36	M9L	North York	Humber Summit	43.756303	-79.565963	0.0	0.0
37	M9N	York	Weston	43.706876	-79.518188	0.0	0.0
38	M9P	Etobicoke	Westmount	43.696319	-79.532242	0.0	0.0

Using this, we could produce a cluster map for the neighborhoods:



4.2 Analyzing the clusters

The clusters ranged from 0 to 5, with cluster 0 containing the neighborhoods with the lowest Indian population and cluster 5 comprising of neighborhoods with the greatest Indian population.

Cluster 0 (red color):

In [176]:
```
toronto_merged.loc[toronto_merged['Cluster Labels'] == 0]
```
Out[176]:

	Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant
0	M1G	Scarborough	Woburn	43.770992	-79.216917	0.0	0.0
1	M1H	Scarborough	Cedarbrae	43.773136	-79.239476	0.0	0.0
2	M1J	Scarborough	Scarborough Village	43.744734	-79.239476	0.0	0.0
3	M1S	Scarborough	Agincourt	43.794200	-79.262029	0.0	0.0
4	M2H	North York	Hillcrest Village	43.803762	-79.363452	0.0	0.0
5	M2K	North York	Bayview Village	43.786947	-79.385975	0.0	0.0
6	M2P	North York	York Mills West	43.752758	-79.400049	0.0	0.0
7	M3A	North York	Parkwoods	43.753259	-79.329656	0.0	0.0
8	M3B	North York	Don Mills	43.745906	-79.352188	0.0	0.0
9	M3C	North York	Don Mills	43.725900	-79.340923	0.0	0.0
10	M3K	North York	Downsview	43.737473	-79.464763	0.0	0.0
11	M3L	North York	Downsview	43.739015	-79.506944	0.0	0.0

Cluster 1:

In [177]:
```
toronto_merged.loc[toronto_merged['Cluster Labels'] == 1]
```
Out[177]:

Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant

Cluster 2:

In [178]:
```
toronto_merged.loc[toronto_merged['Cluster Labels'] == 2]
```
Out[178]:

Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant

Cluster 1 and 2 had no rows, which shows that there were no neighborhoods classified for that cluster.

Cluster 3 (blue color):

In [179]:
```
toronto_merged.loc[toronto_merged['Cluster Labels'] == 3]
```
Out[179]:

	Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant
18	M4H	East York	Thorncliffe Park	43.705369	-79.349372	3.0	0.125

Cluster 4 (light green color):

In [180]:
```
toronto_merged.loc[toronto_merged['Cluster Labels'] == 4]
```

Out[180]:

	Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant
22	M4S	Central Toronto	Davisville	43.704324	-79.388790	4.0	0.037037
24	M4Y	Downtown Toronto	Church and Wellesley	43.665860	-79.383160	4.0	0.030303
26	M5C	Downtown Toronto	St. James Town	43.651494	-79.375418	4.0	0.025000
27	M5E	Downtown Toronto	Berczy Park	43.644771	-79.373306	4.0	0.021277

Cluster 5 (orange color):

In [180]:
```
toronto_merged.loc[toronto_merged['Cluster Labels'] == 4]
```

Out[180]:

	Postalcode	Borough	Neighbourhood	Latitude	Longitude	Cluster Labels	Indian Restaurant
22	M4S	Central Toronto	Davisville	43.704324	-79.388790	4.0	0.037037
24	M4Y	Downtown Toronto	Church and Wellesley	43.665860	-79.383160	4.0	0.030303
26	M5C	Downtown Toronto	St. James Town	43.651494	-79.375418	4.0	0.025000
27	M5E	Downtown Toronto	Berczy Park	43.644771	-79.373306	4.0	0.021277

5. Results and Discussion

5.1 Results

We have now reached the end of the project. In this project, we identified a business problem of finding a suitable neighborhood to open an Indian restaurant. As part of this analysis, we looked at geographical data such as latitude and longitudes of various neighborhoods and venues in addition to identifying correlations between the Indian population and number of Indian restaurants. In order to develop a tool which performs accurately in a real-world scenario, we curated data from a variety of sources before reaching our findings.

The findings were:

- Out of all ridings, Scarborough-Guildwood, Scarborough-Rough Park, Scarborough-Centre, Scarborough-north, Humber River-Black Creek, Don Valley East, Scarborough Southwest, Don Valley North, Scarborough-Agincourt are densely populated with Indian crowd.

- After examining the clusters, we saw that East York, Central Toronto, and Downtown Toronto already have many Indian restaurants. Therefore, it is best to consider other boroughs such as Scarborough, North York, East Toronto, Mississauga and Etobicoke for the new restaurant's location.

- After a detailed and careful analysis, it is a great idea to open a new Indian restaurant in Scarborough borough since there is a high Indian population which can potentially attract more customers and a lesser competition since there are very few Indian restaurants in the neighborhoods.

5.2 Discussion

To conclude, Scarborough is the best location as there is potentially a great demand for Indian food but currently not enough supply as there are very few Indian restaurants for a large number of Indians. Due to this, competition will be minimal along with a higher customer base.

However, there are a few drawbacks of our analysis. First, the ethnic diversity distribution is from 2016 Census and is not up to date. Also, the data obtained is completely based on that obtained from Foursquare's API. Moreover, we could also try a supervised machine learning technique and train it is using labelled data which might render a higher accuracy.

Even though there is a lot of scope of improvement, our current analysis definitely provides us with valuable insights which can give businesses an idea of an ideal location for their restaurant. This tool can help drive such business decisions.

6. Conclusion

Throughout the course of this project, I got the chance of identifying and solving a real-life business problem. I applied my learnings from the previous courses of IBM's data science professional certificate such as using different python libraries to scrape, clean, manipulate and visualize data. This taught me a structured process of extracting insights from raw data.

I also used Foursquare API and scraped Wikipedia to get various datasets needed for analysis. After obtaining and cleaning this data, I moved on to the exploratory data analysis stage where I used Seaborn and Matplotlib to visualize the data and find the correlations between metrics which would help me in the last stage. Here, we used machine learning to extract outputs from a given data and presented it using a Folium map.

This project can be used in other such scenarios such as opening a different restaurant or recreational venue. I hope this project acts as a steppingstone to tackle more complex, real life challenges.