Toronto's Neighborhoods Recommender System

Titus Chin Jun Hong
tituschin@tutanota.com
+60 14 980 5623

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1. Introduction

According to CIC News [1], Canada welcomed more than 341,000 immigrants in 2019 and Toronto has successfully attracted nearly 118,000 immigrants which contribute to almost 35% of the total number of immigrants. **The statistics indicate that most of the immigrants prefer to settle in Toronto over other cities.** Why? VisaPlace [2] has listed out 10 reasons for this question. For me, the most convincing reason is Toronto is Canada's business and financial capital, that's why immigrants prefer it.

Toronto is Canada's largest city, it has 6 boroughs which are Etobicoke, North York, East York, Central Toronto, York and Scarborough. These 6 boroughs can be further divided into 140 neighborhoods. According to City of Toronto [3], Toronto is one of the most multicultural cities in the world due to its large population of immigrants all over the world, each Toronto's neighborhood might be quite different from one another. **Therefore, out of 140 neighborhoods in Toronto, how can immigrants decide which neighborhood suits them best?** This is exactly what I want to resolve in this project.

In this project, I will try to build a Toronto's neighborhoods recommender system based on 4 factors including job opportunities, cost of living, safety and culture. So, who would be interested in this recommender system? I can say that at least 118,000 people would and I believe that this number will be growing in the future. And of course, I can't wait to find out which neighborhood suit me best too because I wish to migrate to Canada and settle in Toronto in the future. How about you?

2. Data

Previously, I mentioned that the Toronto's neighborhoods recommender system is built on job opportunities, cost of living, safety and culture. In this section, I will explain why these factors are important, describe the data that will be used and their source, import and clean the data, and finally show the complete dataframes that will be used to create the Toronto's neighborhoods recommender system.

2.1 Factors to consider while deciding where to settle

- **Job opportunities**: We have to make a living to support ourselves or our family. And I bet we wish to get our dream job right? So, we need to know what are the common jobs for each neighborhood.
- **Cost of living**: We would like to buy our dream house but how much does it cost? Curious of how much should we earn to afford to live in a specific neighborhood? To answer these questions, we need to know the average house price and household income for each neighborhood.
- **Safety**: We wish to live in a safe and peaceful area but how can we determine if the area is safe? To answer these questions, we need to know the crime rate for each neighborhood.
- **Culture**: We will talk and eat everyday. If possible, we would like to communicate in our favorite language and eat our favorite food right? And it's even better if our favorite things are just around us. So, it's important to know what are the language spoken most often at home and what are the popular food in each neighborhood.

2.2 Description of data and data source

Table 2.1: Description of data and data source

No.	Data	Data Description	Data Source
I.	Common jobs	These data show the common jobs for each neighborhood. The data categorize jobs according to North American Industry Classification System (NAICS) 2012. For example: 54-Professional, scientific and technical services, 23-Construction, etc.	I extracted the data from the **2016 Toronto Neighborhood Profiles** [4]. City of Toronto uses the 2016 Canadian Census to provide a portrait of the demographic, social and economic characteristics of the people and households in each Toronto's neighborhood.
II.	Average house price and household income	These data show the average house price and household income for each neighborhood in Canadian Dollar (CAD). The composite Housing Affordability Index (HAI) for each neighborhood is also calculated.	I scraped the data current as of October 2020 from **Realosophy** [5]. Realosophy is a real estate brokerage company that helps their customers make better decision based on data.
III.	Crime rate	These data show the crime rate for each neighborhood. The types of crimes included in the data are assault, auto theft, homicide, theft over, break and enter, and robbery.	I get the data from the **Toronto Neighborhood Crime Rates Boundary File** [6] by calling a REST API from Toronto Police Service. The file contains the 2014-2019 crime data by neighborhood.
IV.	Language spoken most often at home	These data show the language spoken most often at home in each neighborhood. For example: English, Spanish, Italian, French, etc.	I extracted the data from the **2016 Toronto Neighborhood Profiles** [4].
V.	Boundaries of neighborhoods	These data contain the boundary, latitude and longitude coordinate of each neighborhood in geojson file. We will use these data to create the boundary of each neighborhood on a map. The latitude and longitude coordinates of each neighborhood are needed to get the popular food data.	I get the data from **Boundaries of Toronto's Neighborhoods** [7]. City of Toronto made the data available on its open data portal.
VI.	Popular food	These data show the popular food categories around each neighborhood according to Foursquare API. For example: Italian restaurant, Korean restaurant, Japanese restaurant, etc.	I get the data through **Foursquare API** [8]. Foursquare is a location technology platform dedicated to improve how people move through the real world.

2.3 Import data and data wrangling

In this section, I will briefly explain how to obtain the data and the steps of data wrangling for each dataframe. The codes for importing data and data wrangling can be found in my notebook entitled **Toronto's Neighborhoods Recommender System** [9].

I. Common jobs data

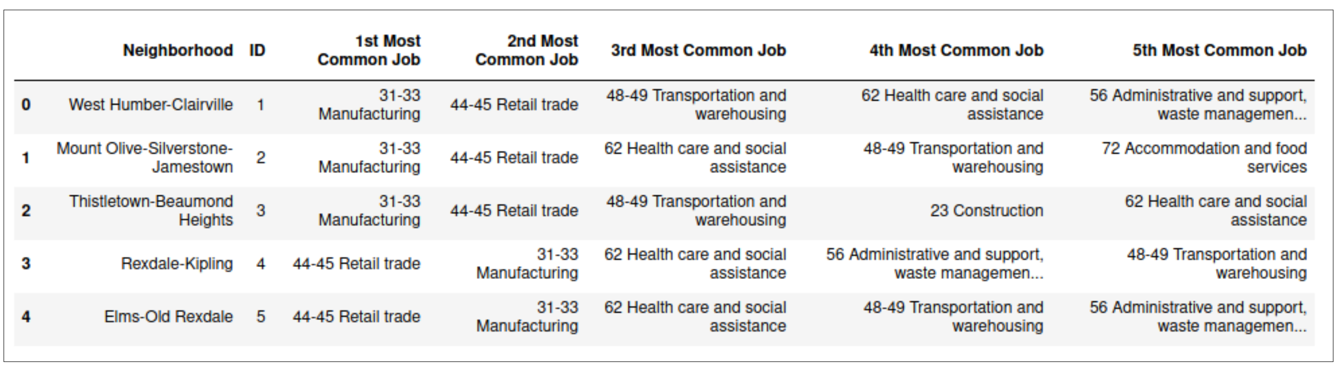
a) Import pandas library.

b) Read the 2016 Toronto Neighborhood Profiles [4] into toronto_df and clean the dataframe.

c) Extract the common jobs data for each neighborhood from toronto_df into jobs_df and clean the dataframe.

d) Define a function called get_top5_elements to return a dataframe of top 5 common elements.

e) Use the get_top5_elements function to get the top 5 common jobs for each neighborhood and save the data into top5_jobs_df. Figure 2.1 shows the first 5 rows of the top5_jobs_df.



	Neighborhood	ID	1st Most Common Job	2nd Most Common Job	3rd Most Common Job	4th Most Common Job	5th Most Common Job
0	West Humber-Clairville	1	31-33 Manufacturing	44-45 Retail trade	48-49 Transportation and warehousing	62 Health care and social assistance	56 Administrative and support, waste managemen...
1	Mount Olive-Silverstone-Jamestown	2	31-33 Manufacturing	44-45 Retail trade	62 Health care and social assistance	48-49 Transportation and warehousing	72 Accommodation and food services
2	Thistletown-Beaumond Heights	3	31-33 Manufacturing	44-45 Retail trade	48-49 Transportation and warehousing	23 Construction	62 Health care and social assistance
3	Rexdale-Kipling	4	44-45 Retail trade	31-33 Manufacturing	62 Health care and social assistance	56 Administrative and support, waste managemen...	48-49 Transportation and warehousing
4	Elms-Old Rexdale	5	44-45 Retail trade	31-33 Manufacturing	62 Health care and social assistance	48-49 Transportation and warehousing	56 Administrative and support, waste managemen...

Figure 2.1: First 5 rows of the top5_jobs_df

f) Sum up all the jobs for each neighborhood and save the data to a new column called 'Any Job'.

g) Define a function called data_normalization to normalize the data.

h) Use the data_normalization function to normalize the jobs_df. Figure 2.2 shows the first 5 rows of the jobs_df.

	Neighborhood	ID	11 Agriculture, forestry, fishing and hunting	21 Mining, quarrying, and oil and gas extraction	22 Utilities	23 Construction	31-33 Manufacturing	41 Wholesale trade	44-45 Retail trade	48-49 Transportation and warehousing	51 Information and cultural industries	52 Finance and insurance	53 Real estate and rental and leasing	Profe s te s
0	West Humber-Clairville	1	0.333	0.108	0.18	0.492	1.000	0.486	0.680	1.000	0.125	0.078	0.182	
1	Mount Olive-Silverstone-Jamestown	2	0.667	0.054	0.06	0.451	0.952	0.439	0.532	0.732	0.097	0.052	0.114	
2	Thistletown-Beaumond Heights	3	0.000	0.054	0.08	0.218	0.243	0.155	0.215	0.274	0.038	0.021	0.046	
3	Rexdale-Kipling	4	0.417	0.000	0.08	0.206	0.215	0.165	0.221	0.265	0.030	0.023	0.065	
4	Elms-Old Rexdale	5	0.000	0.000	0.00	0.144	0.180	0.147	0.182	0.248	0.034	0.021	0.055	

Figure 2.2: First 5 rows of the jobs_df

II. Average house price and household income data

a) Import selenium, time and BeautifulSoup libraries.

b) Define a function called get_neighborhood_websites to scrape each neighborhood's name and website by borough.

c) Use get_neighborhood_websites function to scrape all neighborhoods' names and websites from Realosophy [5], then save the data into website_df.

d) Import numpy library.

e) Define a function called get_number_only to get the average house price or household income in numerical results.

f) Use selenium webdriver and BeautifulSoup to navigate through all the websites stored in the website_df and scrape the average house price and household income for each neighborhood into website_df.

g) Group website_df by neighborhood ID and save the data into houseprice_df.

h) Calculate the composite Housing Affordability Index (HAI) for each neighborhood by using Equation 2.1 [10].

$$Housing\ Affordability\ Index\ (HAI) = \frac{median\ household\ income}{qualifying\ income}\ x\ 100 \qquad \text{Equation 2.1}$$

i) The assumptions made to calculate the Housing Affordability Index (HAI) are:

- The average house price and household income are equal to the median house price and household income.
- The effective mortgage rates is 2% [11].
- Home buyers make a 20% down payment [12].
- The maximum monthly mortgage payment is 25% of gross monthly income.

j) If a neighborhood's Housing Affordability Index (HAI) is higher than 100, it means that most of the residents are able to afford a house in the neighborhood, the greater the HAI, the higher the housing affordability. However, if a neighborhood's HAI is lower than 100, it means that most of the residents are unable to afford a house in the neighborhood, the lower the HAI, the lower the housing affordability.

k) Save the results of Housing Affordability Index (HAI) into a new column called 'HAI'.

l) Define a function called data_binning to categorize the data into three bins namely High, Medium and Low.

m) Use the data_binning function to categorize the houseprice_df. Figure 2.3 shows the first 5 rows of the houseprice_df.

	Neighborhood	ID	Avg House Price	Avg Household Income	HAI	Avg House Price Categories	Avg Household Income Categories	HAI Categories
0	West Humber-Clairville	1	587000	94000	112.825	Low (<964,000)	Low (<106,666)	High (>100)
1	Mount Olive-Silverstone-Jamestown	2	578000	79000	96.297	Low (<964,000)	Low (<106,666)	Medium (76-100)
2	Thistletown-Beaumond Heights	3	898000	94000	73.751	Low (<964,000)	Low (<106,666)	Low (<76)
3	Rexdale-Kipling	4	744000	91000	86.175	Low (<964,000)	Low (<106,666)	Medium (76-100)
4	Elms-Old Rexdale	5	600000	82000	96.289	Low (<964,000)	Low (<106,666)	Medium (76-100)

Figure 2.3: First 5 rows of the houseprice_df

III. Crime rate data

a) Import requests and json_normalize libraries.

b) Get the crimes data from the Toronto Neighborhood Crime Rates Boundary File [6] by calling a REST API from Toronto Police Service , save the data into crime_df and clean the dataframe.

c) Calculate the crime rate for each neighborhood by using Equation 2.2 [13].

$$crime\ rate\ =\ \frac{number\ of\ crimes}{population}\ x\ 100,000\ people \qquad \text{Equation 2.2}$$

d) Sum up all the crime rate for each neighborhood and save the data into a new column called 'All Crimes'.

e) Use data_binning function to categorize crime_df. Figure 2.4 shows the first 5 rows of the crime_df.

	Neighborhood	ID	Assault	AutoTheft	Homicide	TheftOver	BreakandEnter	Robbery	All Crimes	Assault Categories	AutoTheft Categories	Homicide Categories	TheftOver Categories	BreakandEr Categoi
0	West Humber-Clairville	1	905	1100	4	156	413	275	2853	Medium (588-1,027)	High (>184)	Medium (2-4)	High (>44)	High (>3
1	Mount Olive-Silverstone-Jamestown	2	776	189	6	13	97	233	1314	Medium (588-1,027)	High (>184)	High (>4)	Low (<26)	Low (<2
2	Thistletown-Beaumond Heights	3	518	244	2	22	183	144	1113	Low (<588)	High (>184)	Medium (2-4)	Low (<26)	Low (<2
3	Rexdale-Kipling	4	652	272	4	16	150	191	1285	Medium (588-1,027)	High (>184)	Medium (2-4)	Low (<26)	Low (<2
4	Elms-Old Rexdale	5	576	198	3	15	111	142	1045	Low (<588)	High (>184)	Medium (2-4)	Low (<26)	Low (<2

Figure 2.4: First 5 rows of the crime_df

IV. Language spoken most often at home data

a) Extract the language spoken most often at home data for each neighborhood from toronto_df into language_df and clean the dataframe.

b) Use the get_top5_elements function to get the top 5 common languages for each neighborhood and save the data into top5_language_df. Figure 2.5 shows the first 5 rows of the top5_language_df.

	Neighborhood	ID	1st Most Common Language	2nd Most Common Language	3rd Most Common Language	4th Most Common Language	5th Most Common Language
0	West Humber-Clairville	1	English	Punjabi (Panjabi)	Gujarati	Spanish	Hindi
1	Mount Olive-Silverstone-Jamestown	2	English	Punjabi (Panjabi)	Gujarati	Assyrian Neo-Aramaic	Arabic
2	Thistletown-Beaumond Heights	3	English	Punjabi (Panjabi)	Spanish	Gujarati	Italian
3	Rexdale-Kipling	4	English	Spanish	Italian	Urdu	Croatian
4	Elms-Old Rexdale	5	English	Spanish	Somali	Italian	Vietnamese

Figure 2.5: First 5 rows of the top5_language_df

c) Normalize the language_df. Figure 2.6 shows the first 5 rows of the language_df.

	Neighborhood	ID	English	French	Montagnais (Innu)	Swampy Cree	Ojibway	Oji-Cree	Ottawa (Odawa)	Dene	Sarsi (Sarcee)	Mohawk	Dakota	Kabyle	Bilen	Oromo	Somali	War Wa
0	West Humber-Clairville	1	0.345	0.123	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000	0.134	
1	Mount Olive-Silverstone-Jamestown	2	0.288	0.136	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000	0.359	
2	Thistletown-Beaumond Heights	3	0.106	0.065	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000	0.052	
3	Rexdale-Kipling	4	0.133	0.084	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.714	0.052	
4	Elms-Old Rexdale	5	0.116	0.039	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.000	0.229	

Figure 2.6: First 5 rows of the language_df

V. Boundaries of neighborhoods data

a) Import the boundary data from Boundaries of Toronto's Neighborhoods [7] into boundary_df and clean the dataframe. Figure 2.7 shows the first 5 rows of the boundary_df.

	Neighborhood	ID	Latitude	Longitude
0	West Humber-Clairville	1	43.716180	-79.596356
1	Mount Olive-Silverstone-Jamestown	2	43.746868	-79.587259
2	Thistletown-Beaumond Heights	3	43.737988	-79.563491
3	Rexdale-Kipling	4	43.723725	-79.566228
4	Elms-Old Rexdale	5	43.721519	-79.548983

Figure 2.7: First 5 rows of the boundary_df

b) Import geocoder and folium libraries.

c) Visualize the boundary data by creating a map called toronto_map using folium library. Figure 2.8 shows the toronto_map.

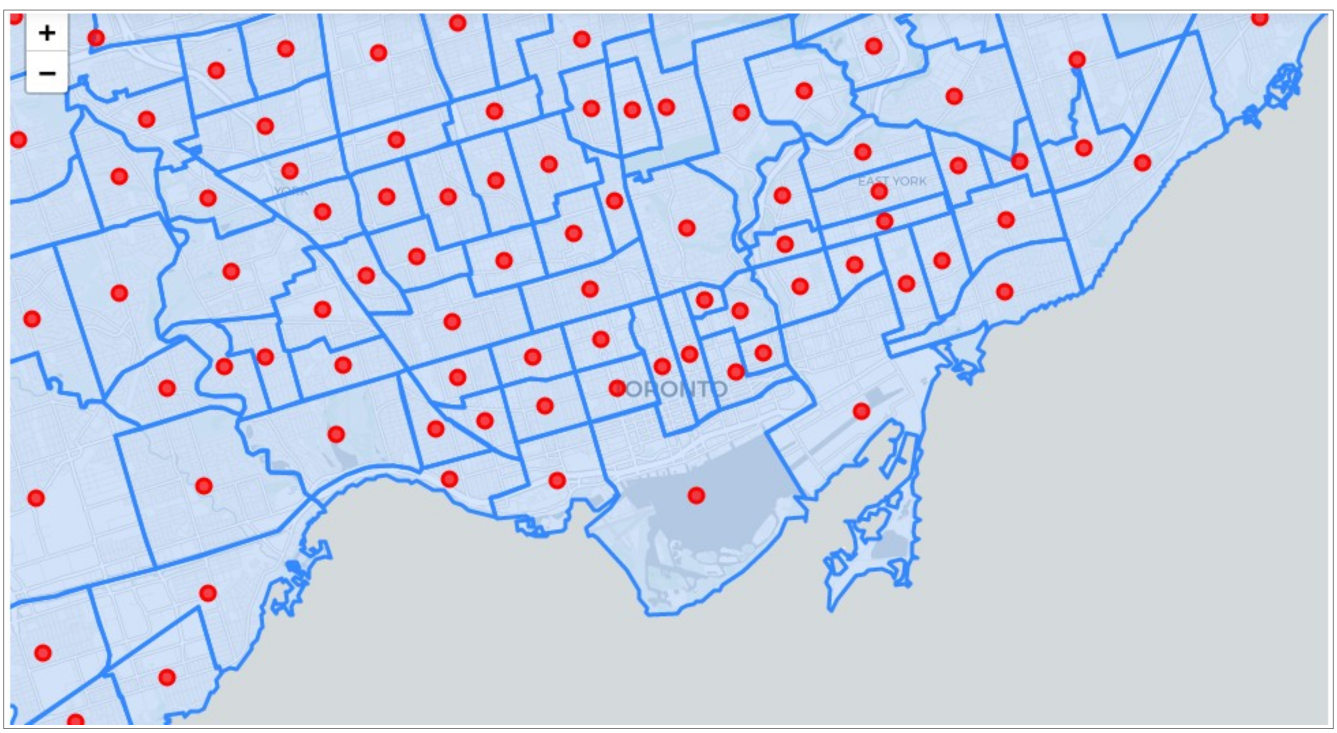


Figure 2.8: The toronto_map

VI. Popular food data

a) Get the popular food categories for each neighborhood using Foursquare API [8] into food_df and clean the dataframe.

b) Convert the popular food categories data into numerical value through one hot encoding.

c) Group food_df by neighborhood ID and clean the dataframe.

d) Use get_top5_elements function to get the top 5 common food categories for each neighborhood and save the data into top5_food_df. Figure 2.9 shows the first 5 rows of the top5_food_df.

	Neighborhood	ID	1st Most Common Food	2nd Most Common Food	3rd Most Common Food	4th Most Common Food	5th Most Common Food
0	West Humber-Clairville	1	Indian Restaurant	Sandwich Place	Restaurant	Chinese Restaurant	Caribbean Restaurant
1	Mount Olive-Silverstone-Jamestown	2	Sandwich Place	Indian Restaurant	Italian Restaurant	Pizza Place	Asian Restaurant
2	Thistletown-Beaumond Heights	3	Sandwich Place	Pizza Place	Indian Restaurant	Vietnamese Restaurant	Fried Chicken Joint
3	Rexdale-Kipling	4	Indian Restaurant	Chinese Restaurant	Restaurant	Sandwich Place	Vietnamese Restaurant
4	Elms-Old Rexdale	5	Sandwich Place	Chinese Restaurant	Indian Restaurant	Vietnamese Restaurant	Pizza Place

Figure 2.9: First 5 rows of the top5_food_df

e) Use data_normalization function to normalize the food_df. Figure 2.10 shows the first 5 rows of the food_df.

	Neighborhood	ID	Afghan Restaurant	African Restaurant	American Restaurant	Asian Restaurant	BBQ Joint	Bagel Shop	Bakery	Bistro	Brazilian Restaurant	Breakfast Spot	Burger Joint	Burrito Place	Café	Cajun Creol Restauran
0	West Humber-Clairville	1	1.0	0.0	0.667	0.667	0.00	0.0	0.125	0.0	0.0	0.2	0.500	0.0	0.000	0.(
1	Mount Olive-Silverstone-Jamestown	2	0.0	0.5	0.000	1.000	0.25	0.0	0.250	0.0	0.0	0.0	0.333	0.0	0.067	0.(
2	Thistletown-Beaumond Heights	3	0.0	0.5	0.000	1.000	0.00	0.0	0.125	0.0	0.0	0.2	0.333	0.0	0.067	0.(
3	Rexdale-Kipling	4	0.0	0.5	0.333	1.000	0.00	0.0	0.125	0.0	0.0	0.2	0.333	0.0	0.067	0.(
4	Elms-Old Rexdale	5	0.0	0.5	0.333	1.000	0.00	0.0	0.375	0.0	0.0	0.2	0.333	0.0	0.067	0.(

Figure 2.10: First 5 rows of the food_df

2.4 Complete dataframes for Toronto's neighborhoods recommender system

Use reduce and merge built-in function to merge all the dataframes required to build a Toronto's neighborhoods recommender system. Figure 2.11 and Figure 2.12 show the first 5 rows of the complete_df and the complete_top5_df respectively. With these data, now we are ready to build a Toronto's neighborhoods recommender system!

```
This dataframe consists of 140 rows and 262 columns!
```

	Neighborhood	ID	Latitude	Longitude	11 Agriculture, forestry, fishing and hunting	21 Mining, quarrying, and oil and gas extraction	22 Utilities	23 Construction	31-33 Manufacturing	41 Wholesale trade	44-45 Retail trade	48-49 Transportation and warehousing	51 Information and cultural industries	in:
0	West Humber-Clairville	1	43.716180	-79.596356	0.333	0.108	0.18	0.492	1.000	0.486	0.680	1.000	0.125	
1	Mount Olive-Silverstone-Jamestown	2	43.746868	-79.587259	0.667	0.054	0.06	0.451	0.952	0.439	0.532	0.732	0.097	
2	Thistletown-Beaumond Heights	3	43.737988	-79.563491	0.000	0.054	0.08	0.218	0.243	0.155	0.215	0.274	0.038	
3	Rexdale-Kipling	4	43.723725	-79.566228	0.417	0.000	0.08	0.206	0.215	0.165	0.221	0.265	0.030	
4	Elms-Old Rexdale	5	43.721519	-79.548983	0.000	0.000	0.00	0.144	0.180	0.147	0.182	0.248	0.034	

Figure 2.11: First 5 rows of the complete_df

```
This dataframe consists of 140 rows and 19 columns!
```

	Neighborhood	ID	Latitude	Longitude	1st Most Common Job	2nd Most Common Job	3rd Most Common Job	4th Most Common Job	5th Most Common Job	1st Most Common Language	2nd Most Common Language	3rd Most Common Language	4th I Com Langu
0	West Humber-Clairville	1	43.716180	-79.596356	31-33 Manufacturing	44-45 Retail trade	48-49 Transportation and warehousing	62 Health care and social assistance	56 Administrative and support, waste managemen...	English	Punjabi (Panjabi)	Gujarati	Spa
1	Mount Olive-Silverstone-Jamestown	2	43.746868	-79.587259	31-33 Manufacturing	44-45 Retail trade	62 Health care and social assistance	48-49 Transportation and warehousing	72 Accommodation and food services	English	Punjabi (Panjabi)	Gujarati	Ass Ara
2	Thistletown-Beaumond Heights	3	43.737988	-79.563491	31-33 Manufacturing	44-45 Retail trade	48-49 Transportation and warehousing	23 Construction	62 Health care and social assistance	English	Punjabi (Panjabi)	Spanish	Gu
3	Rexdale-Kipling	4	43.723725	-79.566228	44-45 Retail trade	31-33 Manufacturing	62 Health care and social assistance	56 Administrative and support, waste managemen...	48-49 Transportation and warehousing	English	Spanish	Italian	
4	Elms-Old Rexdale	5	43.721519	-79.548983	44-45 Retail trade	31-33 Manufacturing	62 Health care and social assistance	48-49 Transportation and warehousing	56 Administrative and support, waste managemen...	English	Spanish	Somali	It

Figure 2.12: First 5 rows of the complete_top5_df

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