Setting up a Restaurant in a Multicultural Country

Background (Problem Statement)

Food touches people's soul and the demands of different varieties of cuisine in multicultural cities increase. This leads to business opportunities to appeal the multicultural audience. The aim of this project is to understand the common occurrence of restaurant types and evaluate the decision to open a profitable restaurant that serve cuisines that match with the taste of the city. Here, we focus on two similar size and population density multi-cultural cities – Singapore and Toronto. Singapore has a city area of 728.3km^2 with density population 7804/km^2 from 2019 estimate. Toronto city area, on the other hand, is 630.2 km^2 with density population 4334/km^2.

Data Overview

We obtain the list of neighborhoods in Toronto and Singapore via Wikipedia. Using Geocoder package, we can obtain the geographical location of the neighborhoods. Then, with Foursquare, we can explore the venues in these locations pertaining to restaurants. We filter the restaurants out of the top 10 venues to find out the cuisines offered by these restaurants

Data Acquisition

Step 1: List of Areas in Both Countries via Wikipedia

Singapore	Toronto
https://en.wikipedia.org/wiki/Regions_of_Singapore	https://en.wikipedia.org/w/index.php?title=List_of_postal_codes_of_Canada:_M&oldid=1011037969
Table 1: The URL where data is extracted.	

The names of area from each city are extracted from these sources for the respective countries.

Step 2: Geocoder package to Find Geographical Location

Singapore	Toronto

Region	Latitude	Longitude
The City	1.333108	103.819499
Tampines	1.333108	103.943571
Woodlands	1.333108	103.786216
Seletar	1.333108	103.877379
Jurong East	1.333108	103.742294

PostalCode	Borough	Neighborhood	Latitude	Longitude
M3A	North York	Parkwoods	43.75245	-79.32991
M4A	North York	Victoria Village	43.73057	-79.31306
M5A	Downtown Toronto	Regent Park, Harbourfront	43.65512	-79.36264
M6A	North York	Lawrence Manor, Lawrence Heights	43.72327	-79.45042
M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.66253	-79.39188
...	...	...	...	...
M8X	Etobicoke	The Kingsway, Montgomery Road, Old Mill North	43.65319	-79.51113
M4Y	Downtown Toronto	Church and Wellesley	43.66659	-79.38133
M7Y	East Toronto	Business reply mail Processing Centre, South C...	43.64869	-79.38544
M8Y	Etobicoke	Old Mill South, King's Mill Park, Sunnylea, Hu...	43.63278	-79.48945
M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,...	43.62513	-79.52681

Table 2: Adding latitude and longitude to the data frame

With Geocoder and the data extracted from step 1, we find the latitude and longitude of the geographical locations

Step 3: Foursquare to Extract Venue and Venue Category from Geographical Location

Singapore

name	categories	lat	lng
Mr Teh Tarik Eating House	Food Court	1.378301	103.836725
Charcos The Flaming Chicken	Australian Restaurant	1.378220	103.836871
Selera Rasa Nasi Lemak	Malay Restaurant	1.380600	103.835820
Coffee Sense 咖啡鄉	Food Court	1.377207	103.837049
Thomson Green Playground	Playground	1.378758	103.832444

Toronto

name	categories	lat	lng
Philosopher's Walk	Park	43.666894	-79.395597
Koerner Hall	Concert Hall	43.667983	-79.395962
Tiffany & Co.	Jewelry Store	43.669135	-79.393484
Royal Ontario Museum	Museum	43.668367	-79.394813
ROM Museum Store	Gift Shop	43.668514	-79.394879

Table 3: Add venue and venue category in the data frame

Foursquare provides the details of the locations based on the latitude and longitude information obtained in step 2.

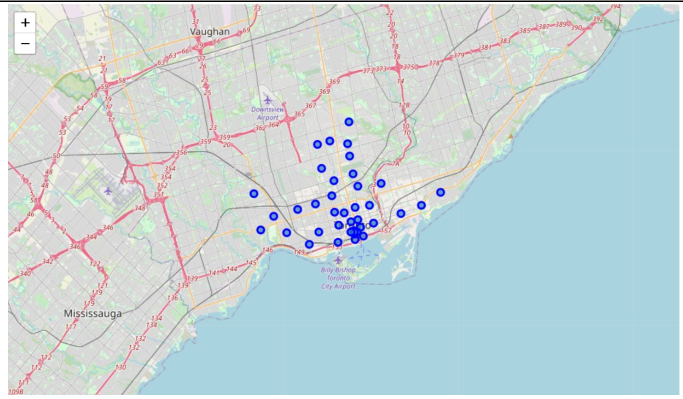
Data Clean up

All the data is extracted and organized into data frames in step 1 (Table 2). The Toronto data frame requires additional data clean up before analyzing the trend.

Assumptions in Toronto Data

1. Borough with not assigned are omitted in data analysis
2. Extract boroughs contain 'Toronto' in it

With the cleaned data from step 1, we use the Geocoder package to obtain the latitude and longitude of the locations in both cities. We add two latitude and longitude columns in each of the data frame and use map folium to display the location of interest on the map (Figure 1).

<table>
<tr><td colspan="2">Map Around the Region of Interest</td></tr>
<tr><td>Singapore</td><td>Toronto</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Figure 1</td></tr>
</table>

Next, we use the Foursquare API to provide the local venue and its corresponding categories within 500-meter radius for Toronto (5000-meter radius for Singapore)*.

* After this initial investigation, I discover there is another data set that split Singapore into more neighborhood from the initial dataset used. For the interest in time, I shall use the initial data set. This project can be improved later.

Data Exploration

After organizing the data, we can analyze it based on the venue category. First, we convert the categorical data to numerical data for Machine Learning purposes using "One hot encoding".

	Yoga Studio	American Restaurant	Antique Shop	Aquarium	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	BBQ Joint	...	Theater	Theme Restaurant	Toy / Game Store	Trail	Train Station	Vegetarian / Vegan Restaurant
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

Table 4: A data frame (Toronto example) containing the frequency of the venue corresponding where the index indicates the corresponding row of cleaned data frame as shown in Table 3

	Neighborhood	Yoga Studio	American Restaurant	Antique Shop	Aquarium	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	...	Theater	Theme Restaurant	Toy / Game Store
0	Berczy Park	0.000000	0.000000	0.000000	0.000000	0.033333	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	0.000000
1	Brockton, Parkdale Village, Exhibition Place	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033333	0.000000	0.000000	...	0.000000	0.000000	0.000000
2	Business reply mail Processing Centre, South C...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033333	0.000000	...	0.066667	0.000000	0.000000
3	CN Tower, King and Spadina, Railway Lands,	0.033333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.033333	0.000000	...	0.000000	0.000000	0.000000

Table 5: Create a data frame with the neighborhood with its corresponding mean of the number of occurrenc for each category.

Then, we group the rows by neighborhood and take the mean of the number of occurrences for each category (Table 5)

	Neighborhood	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	Berczy Park	Seafood Restaurant	Farmers Market	Cocktail Bar	Beer Bar	Coffee Shop	Café	Bistro	Restaurant	Jazz Club	Pharmacy
1	Brockton, Parkdale Village, Exhibition Place	Gift Shop	Coffee Shop	Italian Restaurant	Furniture / Home Store	Restaurant	Bakery	Sandwich Place	Japanese Restaurant	Breakfast Spot	Café
2	Business reply mail Processing Centre, South C...	Coffee Shop	Café	Concert Hall	Theater	Restaurant	Sushi Restaurant	Mediterranean Restaurant	Lounge	Opera House	Japanese Restaurant
3	CN Tower, King and Spadina, Railway Lands, Har...	Italian Restaurant	Park	Gym / Fitness Center	Restaurant	Yoga Studio	Sandwich Place	Brewery	Ramen Restaurant	Café	Caribbean Restaurant
4	Central Bay Street	Coffee Shop	Clothing Store	Plaza	Pizza Place	Park	Sandwich Place	Bubble Tea Shop	Ramen Restaurant	Poke Place	Café

Table 6: A data frame with the 10 top-most common venue for each neighborhood

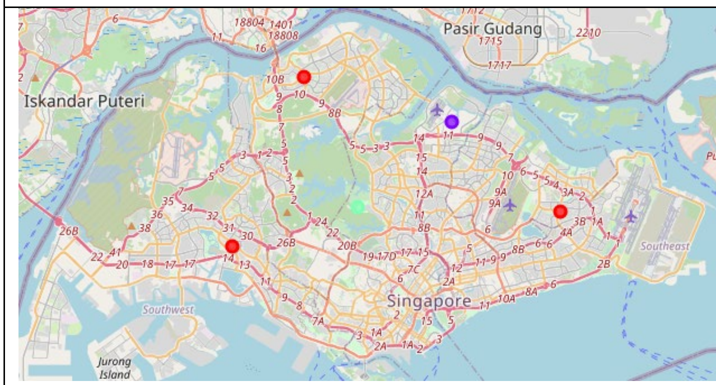
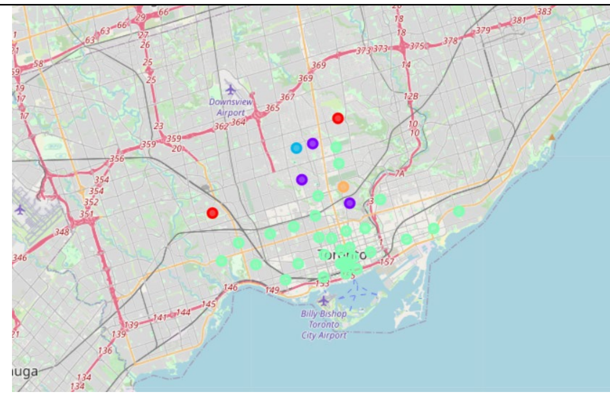
Finally, we look at the types of venues for the top 10 most common venue for each neighborhood

Methodology

k-means clustering

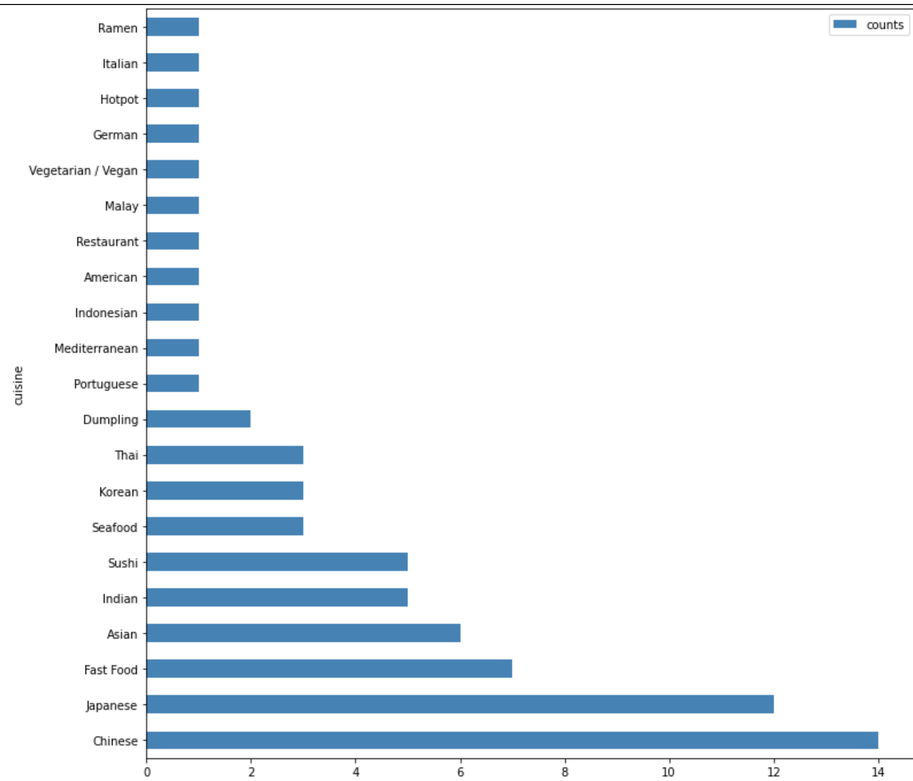
With the sorted data frame (Table 6), we are using the k-means clustering to cluster neighborhoods in 5 cluster for Toronto and 3 clusters for Singapore. Then, we examine the occurrence of restaurants types from the top 10 most common venues.

Cluster	
Singapore	Toronto
3 clusters Red- Cluster0	5 clusters Red- Cluster0

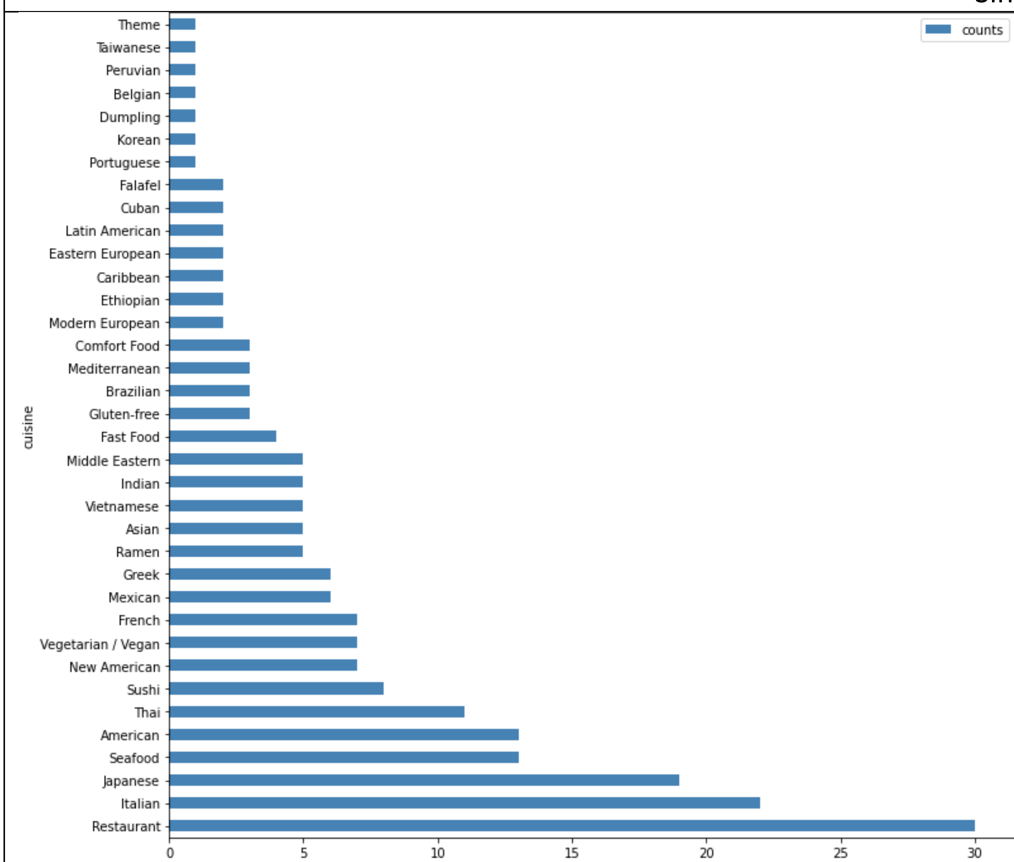
<table>
<tr><td>Purple-Cluster1
Green= Cluster2</td><td>Purple-Cluster1
Blue= Cluster2
Green – Cluster3
Yellow-Cluster4</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Figure 2</td></tr>
</table>

Data Analysis

Before we delve into the analysis of the cluster, let's look at the counts of the restaurant type in both cities. (Figure 3). In Singapore, there are 21 different types of restaurants with the Chinese cuisine as the highest occurrences, follow by Japanese cuisine. Toronto, on the other hand, has 37 different types of restaurant with Italian as the highest occurrences (although "Restaurant" is the highest. Here, we omit this part of the data as it has no cuisine type).



Singapore

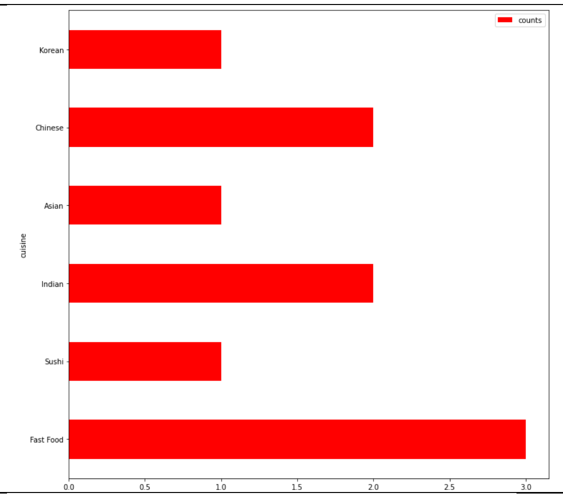


Toronto

Figure 3. The number

Next, we shall look the occurrence of restaurant types within the top 10 most common venues in their clusters.

Singapore

<table>
<tr><td>Cluster 0</td><td>
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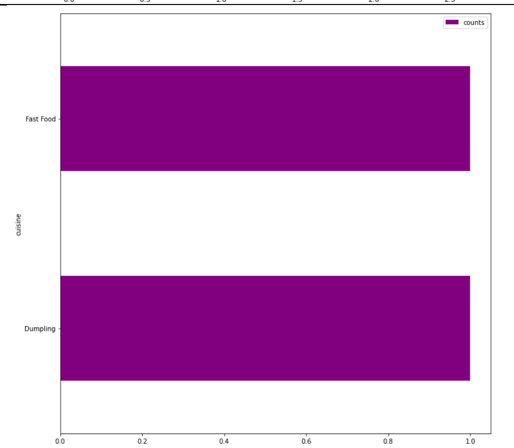
<tr><td>Cluster 1</td><td>
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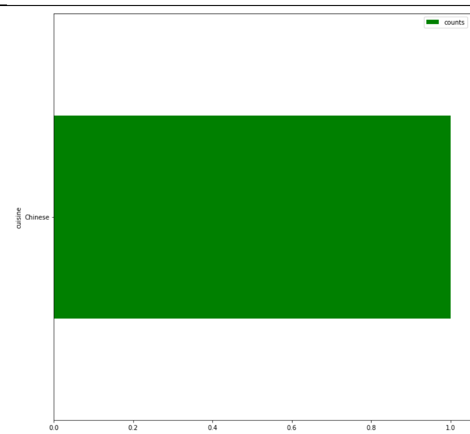
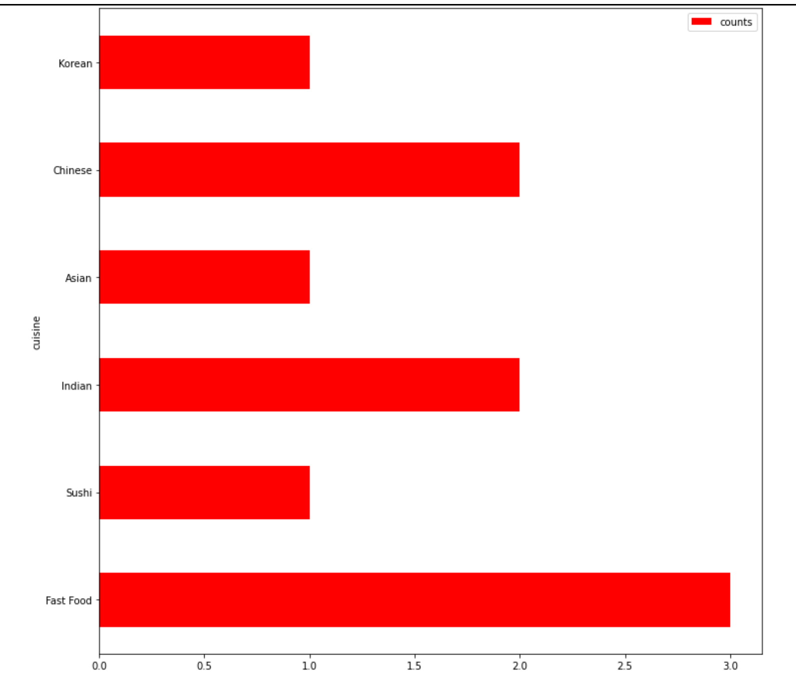
<tr><td>Cluster 2</td><td>
</td></tr>
<tr><td colspan="2">Table 7: The occurences of restaurant types in the respective cluster for Singapore</td></tr>
</table>

We can see the cluster0 for Singapore has the highest occurrence of restaurant. Among this cluster, the fast-food chain is the most common, follow by Chinese and Indian cuisine.

Toronto

<table>
<tr><td>Cluster 0</td><td>
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<tr><td>Cluster 1</td><td>
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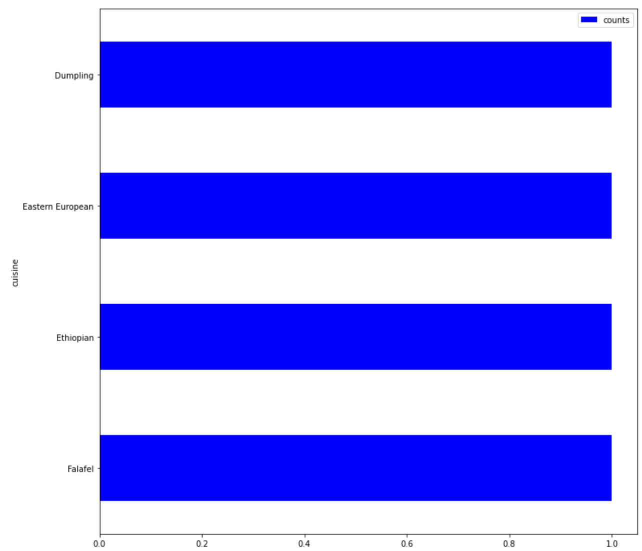
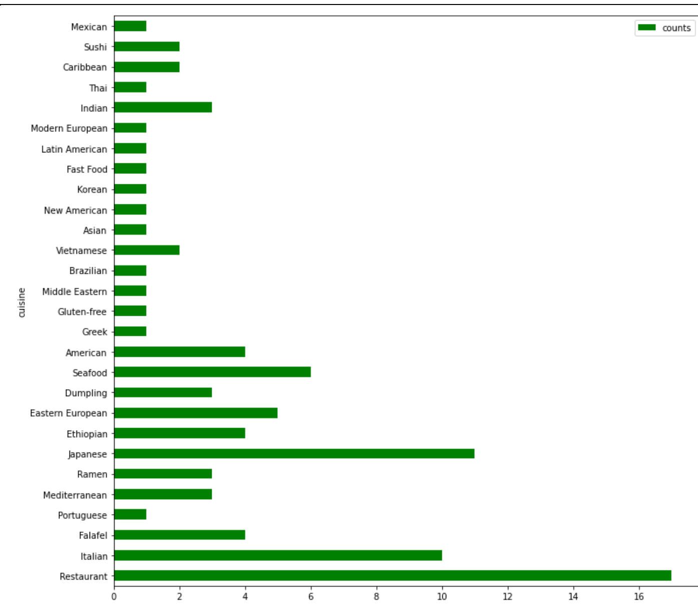
Cluster 2	
Cluster 3	

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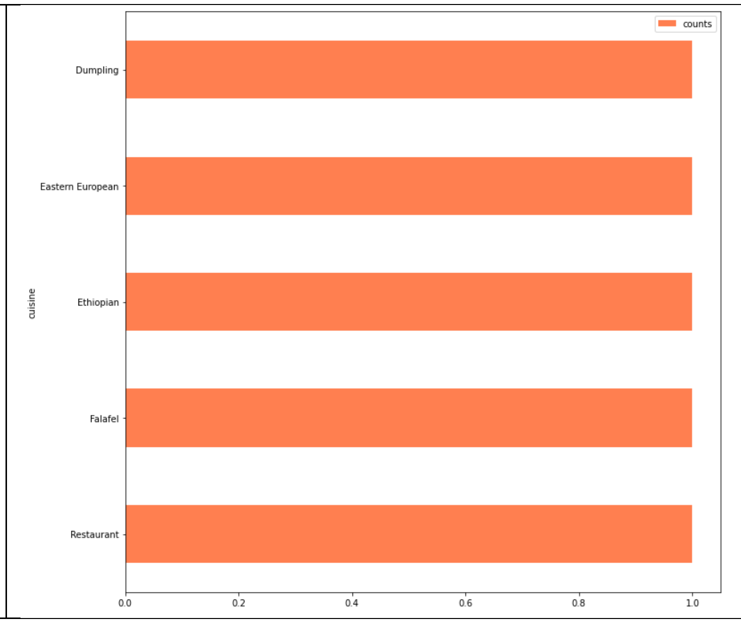
<tr><td>Cluster 4</td><td>
</td></tr>
<tr><td colspan="2">Table 8: The occurences of restaurant types in the respective cluster for Toronto</td></tr>
</table>

We can see the cluster3 for Toronto has the highest occurrence of restaurant. Among this cluster, the Japanese cuisine is the most common, followed by Korean cuisine.

Discussion

Here, we have identified the clusters of areas where restaurants are common in both cities.

Cluster0 from Singapore contains the most restaurants. The most common restaurant occurrence among the top 10 list is fast food although the total number of Chinese cuisine restaurant is the most for the whole Singapore.

For Toronto, cluster3 has the most types of restaurants from top 10 most common occurrence venues. List. Within this top-10 list, Japanese cuisine is the most common although the number of Italian cuisine venues is the highest for Toronto as a whole.

Now, we have identified the most common occurrence of restaurants types in both cities. We can choose not to open these most common restaurants types to avoid competitive and open a different restaurant type.

However, this analysis does have some drawbacks where we did not consider the demographic of the population of both cities. A suggestion for future model is taking the demographic into consideration

Conclusion

In conclusion, this project works on a business problem which uses data science to find a solution. We use python to extract information from the Wikipedia and obtain the coordinate of a location via Geocoder. Finally, we utilize Foursquare to extract information of venues. To further categorize the data set, we use machine learning, specifically k-means clustering to break the cities into different parts for future analysis.