Report of Clustering and Comparing Venues in the Neighborhoods of New York City and Toronto

1- Introduction and Problem Statement

During this project, i will be the consultant of a company that contact us because they need a list of major venues in the major cities of the world.

This will help in providing our client with right data which suits their business plans.

The first part will consist in study, analize, cluster and compare two very big cities, one in United states of America, New York City, and the other located in Canada, Toronto.

The investigation will consists in compare which business are located in common in both cities, which one of them are more common in both cities, and, in the other hand, which business are not common.

Thos project will enable our client to understand the similarities and differences between the two cities in order to know the differents business of the people in both cities, where is better to have one business or the other because it suits better, and what kind of business is not desirable in each city.

The conclusion of this project will allow our client to know where is better top open new and effective business.

New York City Brief:

New York City (NYC), also known as the City of New York or simply New York (NY), is the most populous city in the United States. With an estimated 2018 population of 8,398,748 distributed over a land area of about 302.6 square miles (784 km2).

A global power city,[14] New York City has been described as the cultural,[15][16][17][18][19] financial,[20][21][22] and media capital of the world,[23][24] and exerts a significant impact upon commerce,[22] entertainment, research, technology, education, politics, tourism, art, fashion, and sports.

Toronto City Brief:

Toronto is the provincial capital of Ontario and the most populous city in Canada, with a population of 2,954,024 as of July 2018.

Toronto is an international Center of business, finance, arts, and culture, and is recognized as one of the most multicultural and cosmopolitan cities in the world.

2-Data Acquisition and Preparation

The data acquisition, cleaning and preparing of the datasets of this project for next stages will be explained, there are two tyhpes of data sets.

A-Neighborhood Data:

This datasets consists in list the names of the neighborhoods of NYC and Toronto, with their location (Latitude and Longitud coordinates). this data have bee provided by IBM.

B- Venues data:

Data that describes the top 100 venues (restaurants, cafes, parks, museums, etc.) in each neighborhood of the two cities. The data should list the venues of each neighborhood with their categories.

This data will be retrieved from Foursquare which is one of the world largest sources of location and venue data.
Foursquare API will be utilized to get and download the data.

A-Neighborhood Data

For each city, data that describes the names of its neighborhoods and their coordinates is needed.

For New York City:

A dataset that specifies the neighborhood data for New York City was provided by the organizers of “Applied Data Science Capstone” course which is provided by IBM.
The dataset is originally a JSON file that specifies the name of each neighborhood, its coordinates—latitude and longitude, its borough, and other data too.

To be able to use the data of this JSON file in the later parts of this project, it should be stored in a Pandas dataframe.

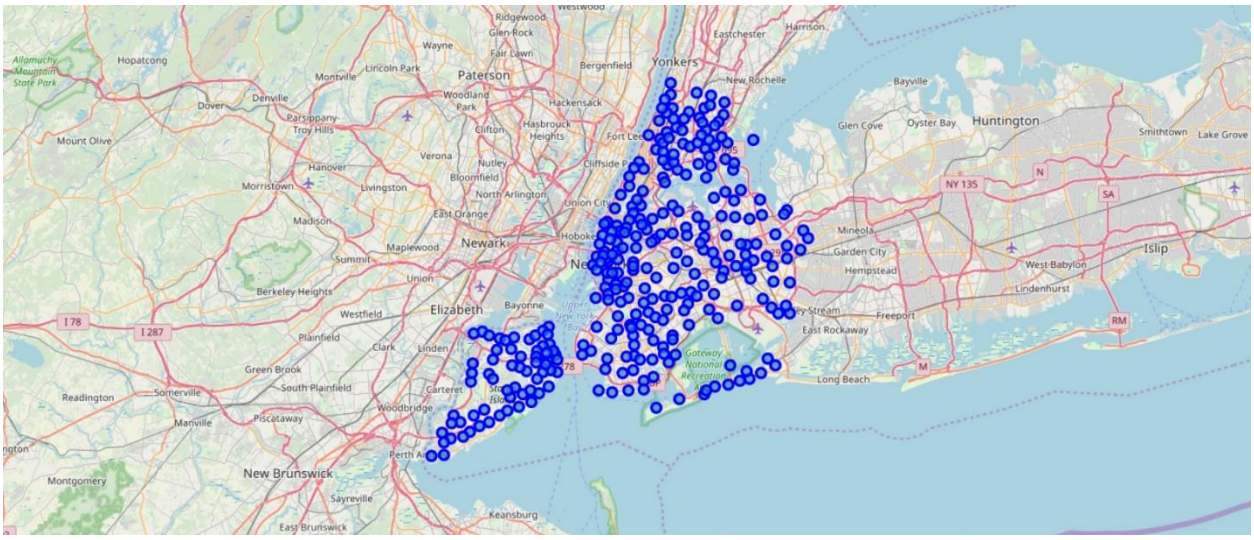
```
[5]: nyc_neighborhoods_data[0]

Out[5]: {'type': 'Feature',
         'id': 'nyu_2451_34572.1',
         'geometry': {'type': 'Point',
          'coordinates': [-73.84720052054902, 40.89470517661]},
         'geometry_name': 'geom',
         'properties': {'name': 'Wakefield',
          'stacked': 1,
          'annoline1': 'Wakefield',
          'annoline2': None,
          'annoline3': None,
          'annoangle': 0.0,
          'borough': 'Bronx',
          'bbox': [-73.84720052054902,
           40.89470517661,
           -73.84720052054902,
           40.89470517661]}}
```

```
[7]: nyc_neighborhoods.head()
```

Out[7]:

	Borough	Neighborhood	Latitude	Longitude
0	Bronx	Wakefield	40.894705	-73.847201
1	Bronx	Co-op City	40.874294	-73.829939
2	Bronx	Eastchester	40.887556	-73.827806
3	Bronx	Fieldston	40.895437	-73.905643
4	Bronx	Riverdale	40.890834	-73.912585

Having data of the coordinates of NYC neighborhoods, it is possible to draw a map using Folium Python package of NYC and its neighborhoods. You can see this map below; each circle represents the location of one neighborhood.



For Toronto City:

There is a Wikipedia page titled “List of postal codes of Canada: M”. This page lists the postal codes in Canada that start with the letter M which are the postal codes of Toronto city; it lists the postal codes with the neighborhood and borough name associated with each postal code.
To download this web page and extract the relevant data from it, Pandas read_html() functions can be used. It reads HTML tables on a web page in a list of dataframes.

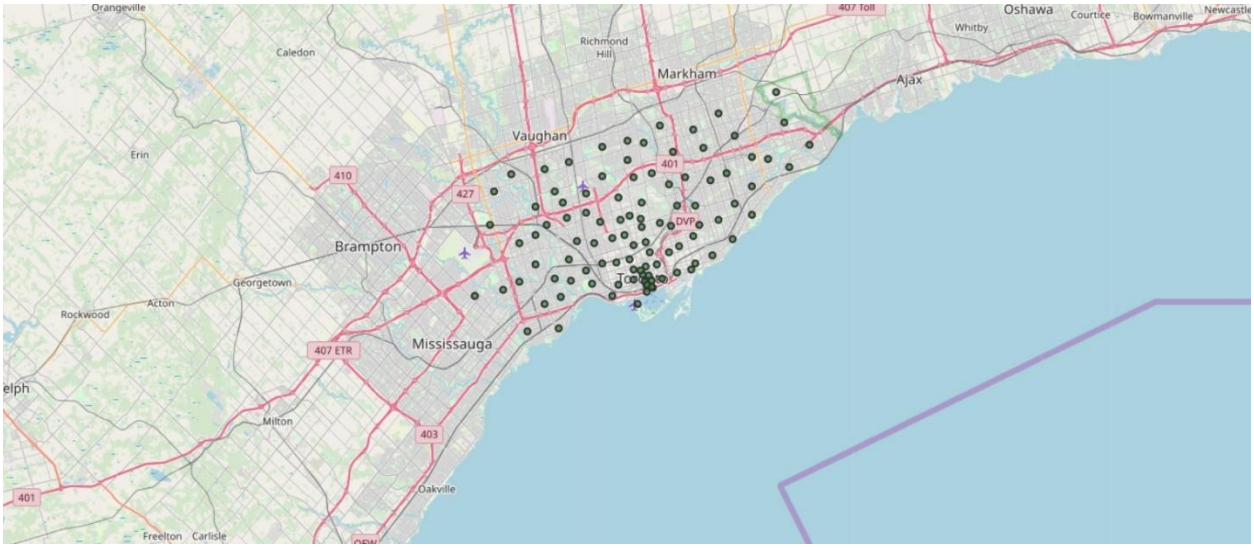
Another dataset that lists the neighborhoods and their postal codes, Latitudes, Longitudes should be used so the combination of the two datasets produces the desired results.

```
In [49]: tor_neighborhoods.head()
```

Out[49]:

	PostalCode	Borough	Neighborhood	Latitude	Longitude
0	M1B	Scarborough	Rouge, Malvern	43.806686	-79.194353
1	M1C	Scarborough	Highland Creek, Rouge Hill, Port Union	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

As with NYC, you can see a map of Toronto city and its neighborhoods; each circle represents the location of one neighborhood or a group of neighborhoods that share the same coordinates.



B- Venues Data:

For each city, data that describes the venues of its neighborhoods and the categories of these venues is needed.
Venues data will be retrieved from Foursquare which is a popular source of location and venue data.
Foursquare API service will be utilized to access and download venues data.
To retrieve data from Foursquare using their API, a URL should be prepared and used to request data related a specific location.

An example URL is the following:

https://api.foursquare.com/v2/venues/search?
&client_id=1234&client_secret=1234&v=20180605&
ll=40.89470517661,-73.84720052054902&radius=500&limit=100

where search indicates the API endpoint used, client_id and client_secret are credentials used to access the API service and are obtained when registering a Foursquare developer account, v indicates the API version to use, ll indicates the latitude and longitude of the desired location, radius is the maximum distance in meters between the specified location and the retrieved venues,
and limit is used to limit the number of returned results if necessary.

Then create a function that takes as input the names, latitudes, and longitudes of the neighborhoods, and returns a dataframe with information about each neighborhood and its venues.
It creates an API URL for each neighborhood and retrieves data about the venues of that neighborhoods from Foursquare.
After retrieving the venue data, venues whose category is “Building”, “Office”, “Bus Line”, “Bus Station”, “Bus Stop”, or “Road” were excluded because they are not expected to add analytical value in this project.

For New York City

NYC neighborhood data retrieved data about more than **23,700** venues in NYC neighborhoods.

```
(23753, 7)
```

Out[18]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Wakefield	40.894705	-73.847201	Shell	40.894187	-73.845862	Gas Station
1	Wakefield	40.894705	-73.847201	Pitman Deli	40.894149	-73.845748	Food
2	Wakefield	40.894705	-73.847201	Julio C Barber Shop 2	40.892648	-73.855725	Salon / Barbershop
3	Wakefield	40.894705	-73.847201	Carvel Ice Cream	40.890487	-73.848568	Ice Cream Shop
4	Wakefield	40.894705	-73.847201	Lollipops Gelato	40.894123	-73.845892	Dessert Shop

Different numbers of venues were found in different neighborhoods:

```
In [*]: nyc_venues.groupby('Neighborhood').size()
```

```
Out[19]: Neighborhood
Allerton                                  83
Annadale                                  77
Arden Heights                             69
Arlington                                 71
Arrochar                                  78
Arverne                                   80
Astoria                                   73
Astoria Heights                           63
Auburndale                                61
Bath Beach                                84
Battery Park City                         88
Bay Ridge                                 87
Bay Terrace, Queens                       81
Bay Terrace, Staten Island                76
Baychester                                79
Bayside                                   85
Bayswater                                 80
Bedford Park                              68
Bedford Stuyvesant                        85
```

For Toronto

Similar to what has been done for NYC, a dataframe that describes the venues of Toronto neighborhoods was created.

The dataframe contains data for more than **7,800** venues in Toronto.

```
(7870, 7)
```

Out[54]:

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
1	Rouge, Malvern	43.806686	-79.194353	Shell	43.803227	-79.192414	Gas Station
2	Rouge, Malvern	43.806686	-79.194353	Subway	43.801095	-79.200304	Sandwich Place
3	Rouge, Malvern	43.806686	-79.194353	Wendy's	43.802008	-79.198080	Fast Food Restaurant
4	Rouge, Malvern	43.806686	-79.194353	Tim Hortons	43.802000	-79.198169	Coffee Shop
5	Rouge, Malvern	43.806686	-79.194353	Tim Hortons / Esso	43.801863	-79.199296	Coffee Shop

Different numbers of venues were found in different neighborhoods

```
[55]: #Let's check how many venues were returned for each neighborhoo
      tor_venues.groupby('Neighborhood').size()
```

```
)ut[55]: Neighborhood
Adelaide, King, Richmond                                                                    82
Agincourt                                                                                   75
Agincourt North, L'Amoreaux East, Milliken, Steeles East                                    58
Albion Gardens, Beaumond Heights, Humbergate, Jamestown, Mount Olive, Silverstone, South Steeles, Thistletown    95
Alderwood, Long Branch                                                                      81
Bathurst Manor, Downsview North, Wilson Heights                                             81
Bayview Village                                                                             80
Bedford Park, Lawrence Manor East                                                           86
Berczy Park                                                                                 68
Birch Cliff, Cliffside West                                                                 74
Bloordale Gardens, Eringate, Markland Wood, Old Burnhamthorpe                               73
Brockton, Exhibition Place, Parkdale Village                                                67
Business Reply Mail Processing Centre 969 Eastern                                           70
CFB Toronto, Downsview East                                                                 57
CN Tower, Bathurst Quay, Island airport, Harbourfront West, King and Spadina, Railway Lands, South Niagara    98
Cabbagetown, St. James Town                                                                 90
Caledonia-Fairbanks                                                                         84
Canada Post Gateway Processing Centre                                                       65
Cedarbrae                                                                                   77
Central Bay Street                                                                          88
Chinatown, Grange Park, Kensington Market                                                   92
Christie                                                                                    79
Church and Wellesley                                                                        81
Clairlea, Golden Mile, Oakridge                                                             72
Clarks Corners, Sullivan, Tam O'Shanter                                                     86
```

3-Exploratory Data Analysis:

In this section, the datasets produced in the previous section will be explored via effective visualizations to understand the data better.
In fact, no venue data was returned for the postal-code areas that contain these neighborhoods. Remember that previously the records that represent neighborhoods that share the same postal code were merged together.

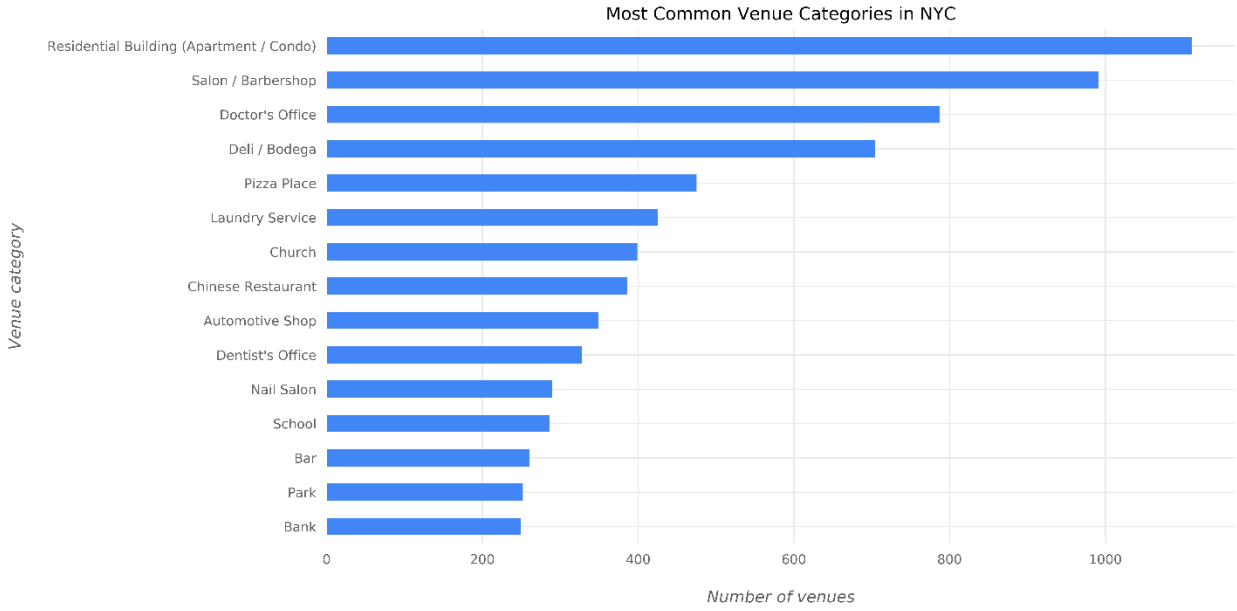
A- Most Common Venue Categories

What are the categories that have more venues than the others in NYC and Toronto? To answer this question, the number of occurrences is counted for each venue category for NYC and for Toronto.
After doing so, a bar plot can be used to visualize the popularity of the most common venue categories in each city.

1- New York City

bar plot of the most common venues in NYC.
We can see that the most common category is:

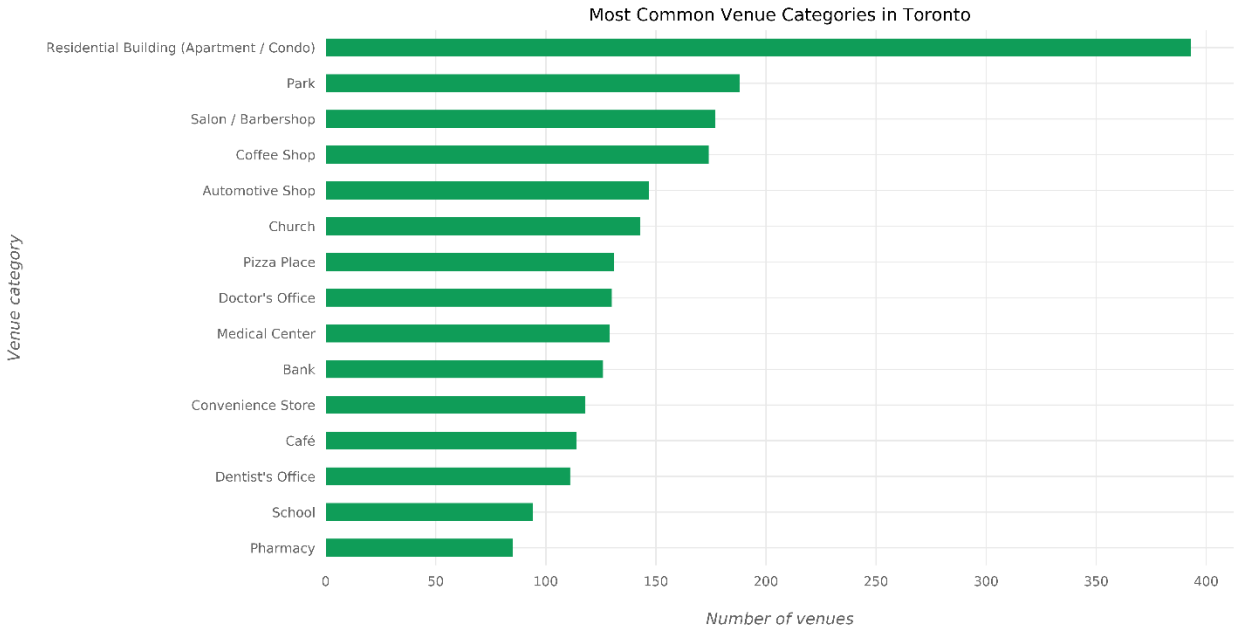
1. "**Residential Building (Apartment / Condo)"** with more than 1200 venues in NYC; this means that there are ~1200 residential buildings in NYC.
2. **"Salon / Barbershop"** appears with more than 900 venues.
3. **"Doctors Office"** category.



2- Toronto

bar plot of the most common venues in Toronto.
For Toronto, the most common category is:

1. **“Residential Building (Apartment / Condo)”** with almost 400 venues.
2. **“Park”** category with almost 200 venues
3. **“Salon/Barbershop”** with around 175 venues.



B-Most Widespread Venue Categories:

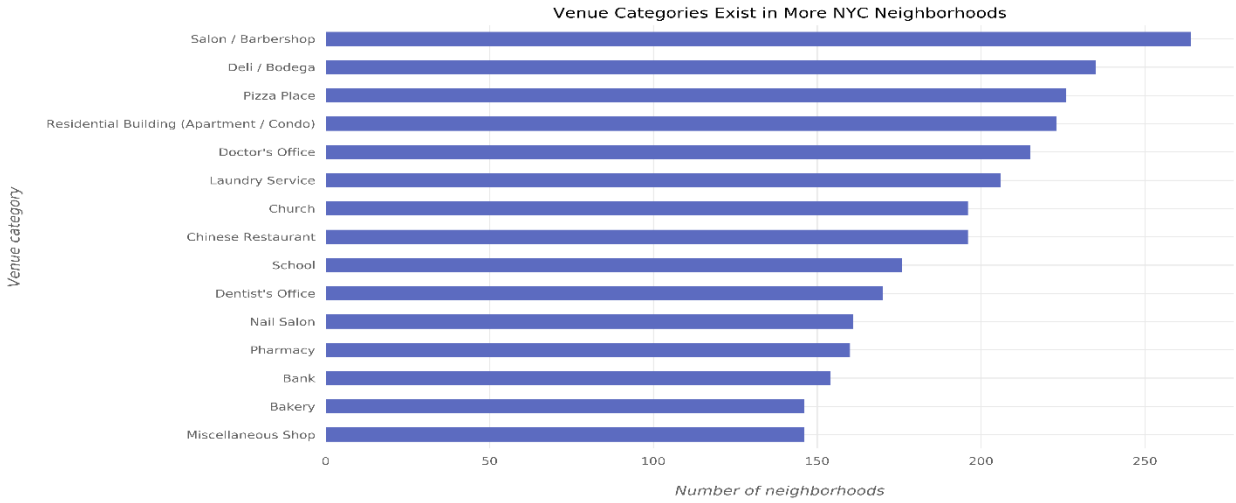
Now another question is to be answered:
What are the venue categories that exist in more neighborhood?

This question is different than the one mentioned in the first question.
To explain the difference with an example, suppose that there are 15 venues with the category **“Salon / Barbershop”** and that these venues exist in 7 neighborhoods only out of 80 neighborhoods; also suppose that there are 10 venues with the category **“Restaurant”** and that these venues exist in 10 neighborhoods—each one of them in a different neighborhood. Then it can be said that the **“Salon / Barbershop”** category is more common than **“Restaurant”** category because there are more venues under this category, and it can be said that the **“Restaurant”** category is more widespread than the **“Salon / Barbershop”** category because venues under this category exist in more neighborhoods than the other category.

1-New York City

The most widespread venue categories in NYC. It can be seen that the order of categories this time is different than that of the most common categories.

1. **“Salon / Barbershop”;** Salons and barbershops exist in more than 250 neighborhoods out of the 306 neighborhoods.
2. the **“Deli / Bodega”** category with venues in almost 240 neighborhoods.
3. the **“Pizza Place”** category with venues in almost 230 neighborhoods.



2- Toronto

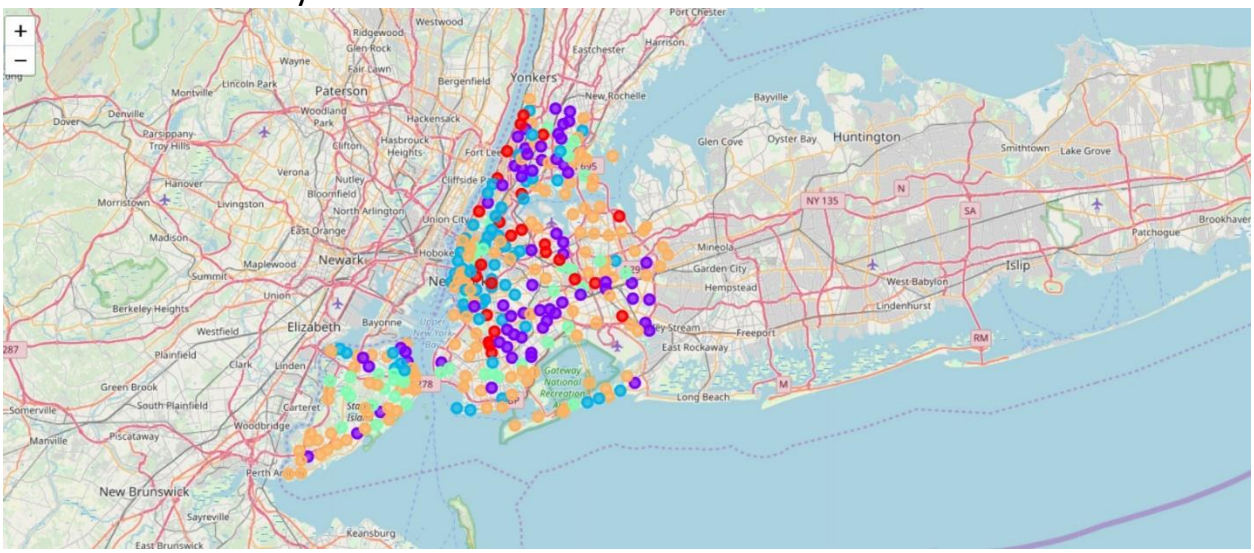
The most widespread venue categories in Toronto. As with NYC, the order of the most-widespread-categories in Toronto differs than the order of the most common categories.

1. the **“Coffee Shop”** category with venues in more than 80 neighborhoods.
2. the **“Residential Building (Apartment / Condo)”** category with venues in almost 80 neighborhoods.
3. **“Salon\Barbershop”** with venues in almost 75 neighborhoods.

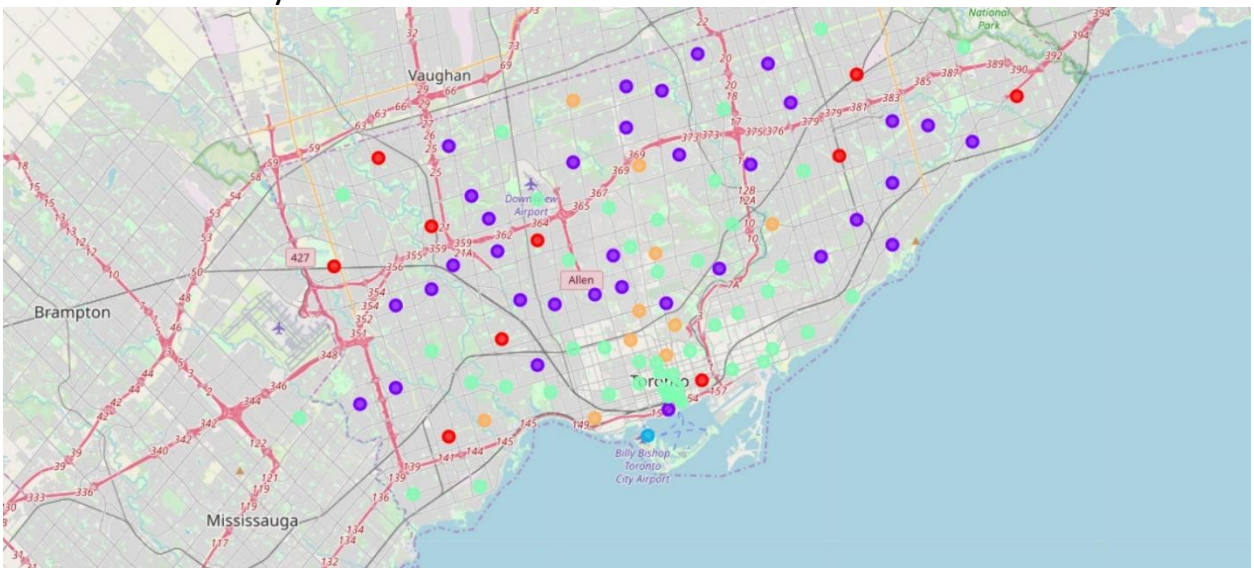
4-Cluster Analysis:

The clustering algorithm grouped neighborhoods of NYC and Toronto in 5 clusters based on the similarity between their venues.
These clusters will be investigated to see the most common categories in each of them.
You can see the distribution of each category in each cluster and this give you hints about business locations preferences.

1. New York City Clusters:



2. Toronto City Clusters:



5-Conclusions:

In this project, the neighborhoods of New York City and Toronto were clustered into multiple groups based on the categories (types) of the venues in these neighborhoods.
The results showed that there are venue categories that are more common in some cluster than the others; the most common venue categories differ from one cluster to the other.
The results also showed the most common venues categories in each city along with the widespread of each category so by using the clustering algorithm the project can detect the distribution of similar venues or business category on map.
By these results you have the best and widespread business category and also their location in each city and this can be applied on the major cities around the world.
I think a deeper analysis can be done according to our client's business category and also using more data sources can give the project more intuition and prediction of each business category future.