Capstone project - Battle of Neighbourhoods (Week1)

Introduction/ Problem

London, the capital of England and the United Kingdom, is a 21st-century city with history stretching back to Roman times. At its centre stand the imposing Houses of Parliament, the iconic 'Big Ben' clock tower and Westminster Abbey, site of British monarch coronations. Across the Thames River, the London Eye observation wheel provides panoramic views of the South Bank cultural complex, and the entire city. London is one of the most ethnically diverse cities in the world. A 2000 survey of school children reported there were over 300 languages spoken at home. At the 2011 census, London had a population of 8,173,941. Of this number 44.9% were White British. 37% of the population were born outside the UK, including 24.5% born outside of Europe

Toronto is the capital city of the Canadian province of Ontario. With a recorded population of 2,731,571 in 2016, it is the most populous city in Canada and the fourth most populous city in North America. The city is the anchor of the Golden Horseshoe, an urban agglomeration of 9,245,438 people (as of 2016) surrounding the western end of Lake Ontario, while the Greater Toronto Area (GTA) proper had a 2016 population of 6,417,516. Toronto is an international centre of business, finance, arts, and culture, and is recognized as one of the most multicultural and cosmopolitan cities in the world.

The aim of this project is to create a comparison of the two cities toronto and london. This could help travelers and tourists understand the similarity or dissimilarity between the two. This can also help immigration of people where the neighbourhoods similar to what they preferred and stayed before can be seen and compared to. It also shows the diversity of the two cities and what the most common venues are for sightseeing or public visits

Data

We require geolocation data for both London and Toronto. Postal codes in each city serve as a starting point. Using Postal codes we use can find out the neighbourhoods, boroughs, venues and their most popular venue categories. I have used the wikipedia pages to collect the postal codes of the cities and use foursquare to accumulate the venues and plot them on the map.
https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M
https://en.wikipedia.org/wiki/List_of_areas_of_London

Methodology

The methodology performed for both the cities are similar thus helping us in the comparison

- Importing the postal codes for each city using wikipedia

```
In [51]: wiki_london_data = pd.read_html(wiki_london_url.text)
wiki_london_data
wiki_london_data = wiki_london_data[1]
wiki_london_data
```

Out[51]:

	Location	London borough	Post town	Postcode district	Dial code	OS grid ref
0	Abbey Wood	Bexley, Greenwich [7]	LONDON	SE2	020	TQ465785
1	Acton	Ealing, Hammersmith and Fulham[8]	LONDON	W3, W4	020	TQ205805
2	Addington	Croydon[8]	CROYDON	CR0	020	TQ375645
3	Addiscombe	Croydon[8]	CROYDON	CR0	020	TQ345665
4	Albany Park	Bexley	BEXLEY, SIDCUP	DA5, DA14	020	TQ478728
...	...	...	...	...	...	...
528	Woolwich	Greenwich	LONDON	SE18	020	TQ435795
529	Worcester Park	Sutton, Kingston upon Thames	WORCESTER PARK	KT4	020	TQ225655
530	Wormwood Scrubs	Hammersmith and Fulham	LONDON	W12	020	TQ225815
531	Yeading	Hillingdon	HAYES	UB4	020	TQ115825
532	Yiewsley	Hillingdon	WEST DRAYTON	UB7	020	TQ063804

533 rows × 6 columns

```
In [5]: wiki_data = wiki_data[0]
wiki_data
```

Out[5]:

	Postal Code	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
...	...	...	...
175	M5Z	Not assigned	Not assigned
176	M6Z	Not assigned	Not assigned
177	M7Z	Not assigned	Not assigned
178	M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,...
179	M9Z	Not assigned	Not assigned

180 rows × 3 columns

- Locational data

We now have the geographical co-ordinates of the London Neighbourhoods.

We proceed with Merging our source data with the geographical co-ordinates to make our dataset ready for the next stage

In [64]:
```
london_merged = pd.concat([df1,lat_uk.astype(float), lng_uk.astype(float)], axis=1)
london_merged.columns= ['borough','town','post_code','latitude','longitude']
london_merged
```

Out[64]:

	borough	town	post_code	latitude	longitude
0	Bexley, Greenwich	LONDON	SE2	51.49245	0.12127
1	Ealing, Hammersmith and Fulham	LONDON	W3, W4	51.51324	-0.26746
6	City	LONDON	EC3	51.51200	-0.08058
7	Westminster	LONDON	WC2	51.51651	-0.11968
9	Bromley	LONDON	SE20	51.41009	-0.05683
...	...	...	...	...	...
523	Redbridge	LONDON	IG8, E18	51.58977	0.03052
524	Redbridge, Waltham Forest	LONDON, WOODFORD GREEN	IG8	51.50642	-0.12721
527	Barnet	LONDON	N12	51.61592	-0.17674
528	Greenwich	LONDON	SE18	51.48207	0.07143
530	Hammersmith and Fulham	LONDON	W12	51.50645	-0.23691

310 rows × 5 columns

Co-ordinates for London Getting the geocode for London to help visualize it on the map

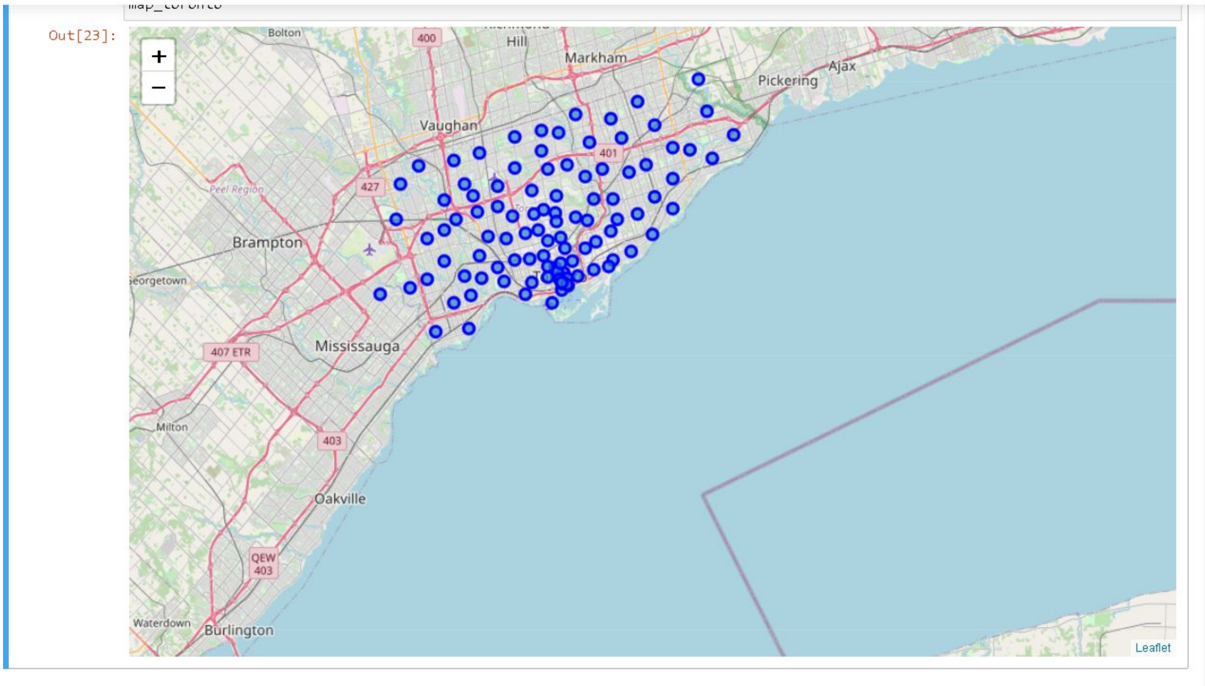
In [14]:
```
coor = pd.read_csv("https://cocl.us/Geospatial_data")
coor
```

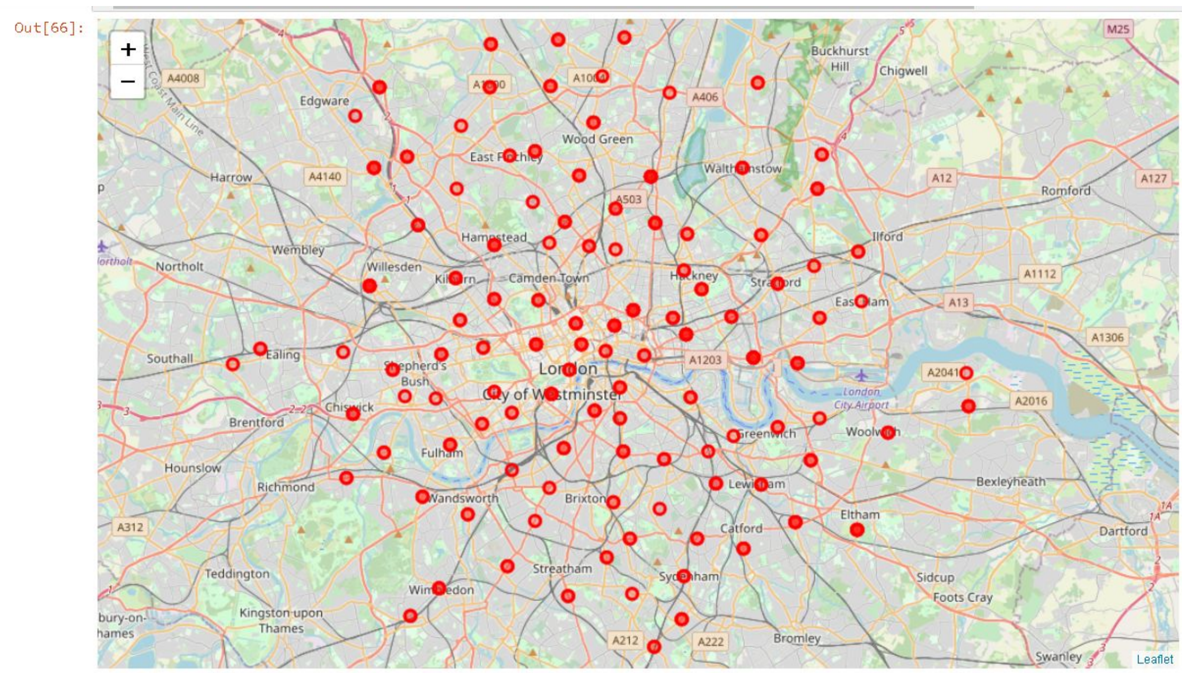
Out[14]:

	Postal Code	Latitude	Longitude
0	M1B	43.806686	-79.194353
1	M1C	43.784535	-79.160497
2	M1E	43.763573	-79.188711
3	M1G	43.770992	-79.216917
4	M1H	43.773136	-79.239476
...	...	...	...
98	M9N	43.706876	-79.518188
99	M9P	43.696319	-79.532242
100	M9R	43.688905	-79.554724
101	M9V	43.739416	-79.588437
102	M9W	43.706748	-79.594054

103 rows × 3 columns

● Plotting the neighbourhoods in the map. The first map is toronto and the subsequent map is london





- Getting venues using foursquare

```
In [68]: venues_in_London = getNearbyVenues(london_merged['borough'], london_merged['latitude'], london_merged['longitude'])

Bexley, Greenwich
Ealing, Hammersmith and Fulham
City
Westminster
Bromley
Islington
Islington
Barnet
Enfield
Wandsworth
Southwark
City
Richmond upon Thames
Barnet
Islington
Wandsworth
Westminster
Bromley
Newham
Ealing
Westminster
Lewisham
Camden
Southwark
Tower Hamlets
Bexley
City
Lewisham
Greenwich
Tower Hamlets
Camden
Haringey
Tower Hamlets
Haringey
```

```
In [26]: venues_in_toronto = getNearbyVenues(data['Neighbourhood'], data['Latitude'], data['Longitude'])

Parkwoods
Victoria Village
Regent Park, Harbourfront
Lawrence Manor, Lawrence Heights
Queen's Park, Ontario Provincial Government
Islington Avenue, Humber Valley Village
Malvern, Rouge
Don Mills
Parkview Hill, Woodbine Gardens
Garden District, Ryerson
Glencairn
West Deane Park, Princess Gardens, Martin Grove, Islington, Cloverdale
Rouge Hill, Port Union, Highland Creek
Don Mills
Woodbine Heights
St. James Town
Humewood-Cedarvale
Eringate, Bloordale Gardens, Old Burnhamthorpe, Markland Wood
Guildwood, Morningside, West Hill
The Beaches
Berczy Park
Caledonia-Fairbanks
Woburn
Leaside
Central Bay Street
Christie
Cedarbrae
Hillcrest Village
Bathurst Manor, Wilson Heights, Downsview North
Thorncliffe Park
Richmond, Adelaide, King
```

- Grouping neighbourhoods by venues, the venues that we previously got using Foursquare API was used to group

In [71]:
```
venues_in_London.groupby('Venue Category').max()
```

Out[71]:

Venue Category	Neighbourhood	Neighbourhood Latitude	Neighbourhood Longitude	Venue
African Restaurant	Westminster	51.52587	-0.08808	Red Sea Restaurant
American Restaurant	Waltham Forest	51.63261	0.02912	Spielburger
Antique Shop	Kensington and Chelsea	51.51244	-0.20639	Alice's
Arepa Restaurant	Tower Hamlets	51.52669	-0.06257	Arepa & Co
Argentinian Restaurant	Wandsworth	51.61568	-0.09568	The Argentine Grill
...	...	...	...	...
Wings Joint	Camden and Islington	51.54187	-0.12273	Wingmans
Women's Store	Kensington and ChelseaHammersmith and Fulham	51.55457	-0.11478	Vivien of Holloway
Xinjiang Restaurant	Southwark	51.47480	-0.09313	Silk Road
Yoga Studio	Westminster	51.55457	-0.06257	yogahaven
Zoo Exhibit	Camden	51.53354	-0.14606	Penguin Beach

257 rows × 4 columns

In [30]:
```
venues_in_toronto.groupby('Venue Category').max()
```

Out[30]:

Venue Category	Neighbourhood	Neighbourhood Latitude	Neighbourhood Longitude	Venue
Accessories Store	Lawrence Manor, Lawrence Heights	43.718518	-79.464763	Ardene Shoes Outlet
Airport	Downsview	43.737473	-79.394420	Toronto Downsview Airport (YZD)
Airport Food Court	CN Tower, King and Spadina, Railway Lands, Har...	43.628947	-79.394420	Billy Bishop Café
Airport Gate	CN Tower, King and Spadina, Railway Lands, Har...	43.628947	-79.394420	Gate 8
Airport Lounge	CN Tower, King and Spadina, Railway Lands, Har...	43.628947	-79.394420	Porter Lounge
...	...	...	...	...
Warehouse Store	Thorncliffe Park	43.705369	-79.349372	Costco
Wine Bar	Studio District	43.659526	-79.340923	Paris Paris Bar
Wings Joint	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	Wingporium
Women's Store	Caledonia-Fairbanks	43.689026	-79.453512	Maximum Woman
Yoga Studio	University of Toronto, Harbord	43.715383	-79.321558	YogaSpace

235 rows × 4 columns

Max number of venues grouped by its venue category

- One hot encoding

One Hot encoding

In [72]:
```
London_venue_cat = pd.get_dummies(venues_in_London[['Venue Category']], prefix="", prefix_sep="")
London_venue_cat
```

Out[72]:

	African Restaurant	American Restaurant	Antique Shop	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Art Museum	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	...	Video Game Store	Vietnamese Restaurant	Warehouse Store
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
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0
3	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
6751	0	0	0	0	0	0	0	0	0	0	...	0	0	0
6752	0	0	0	0	0	0	0	0	0	0	...	0	0	0
6753	0	0	0	0	0	0	0	0	0	0	...	0	0	0
6754	0	0	0	0	0	0	0	0	0	0	...	0	0	0
6755	0	0	0	0	0	0	0	0	0	0	...	0	0	0

6756 rows × 257 columns

One Hot Encoding

In [31]:
```
toronto_onehot = pd.get_dummies(venues_in_toronto[['Venue Category']], prefix="", prefix_sep="")
toronto_onehot
```

Out[31]:

	Accessories Store	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antique Shop	Aquarium	...	Train Station	Turkish Restaurant	Vegetarian / Vegan Restaurant	Video Game Store
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
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0
3	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1311	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1312	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1313	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1314	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0
1315	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0

1316 rows × 235 columns

- Top 10 common venues in each neighbourhood

In [77]:
```
# create a new dataframe for London
neighborhoods_venues_sorted_london = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted_london['Neighbourhood'] = London_grouped['Neighbourhood']

for ind in np.arange(London_grouped.shape[0]):
    neighborhoods_venues_sorted_london.iloc[ind, 1:] = return_most_common_venues(London_grouped.iloc[ind, :], num_top_venue

neighborhoods_venues_sorted_london.head()
```

Out[77]:

	Neighbourhood	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	Barnet	Coffee Shop	Café	Grocery Store	Pub	Supermarket	Italian Restaurant	Pharmacy	Bus Stop	Turkish Restaurant	Indian Restaurant
1	Barnet, Brent, Camden	Gym / Fitness Center	Convenience Store	Clothing Store	Supermarket	Bus Station	Fountain	Food Truck	French Restaurant	Food Service	Fast Food Restaurant
2	Bexley	Supermarket	Historic Site	Train Station	Platform	Coffee Shop	Convenience Store	Park	Bus Stop	Construction & Landscaping	Golf Course
3	Bexley, Greenwich	Park	Sports Club	Bus Stop	Golf Course	Convenience Store	Construction & Landscaping	Historic Site	Flower Shop	Fish & Chips Shop	Fishing Store
4	Bexley, Greenwich	Supermarket	Historic Site	Coffee Shop	Platform	Convenience Store	Train Station	Flower Shop	Fast Food Restaurant	Fish & Chips Shop	Fishing Store

Out[37]:

	Neighbourhood	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	Agincourt	Lounge	Breakfast Spot	Latin American Restaurant	Clothing Store	Yoga Studio	Dim Sum Restaurant	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant
1	Alderwood, Long Branch	Pizza Place	Gym	Sandwich Place	Coffee Shop	Skating Rink	Pub	Distribution Center	Dim Sum Restaurant	Diner	Discount Store
2	Bathurst Manor, Wilson Heights, Downsview North	Bank	Coffee Shop	Pharmacy	Mobile Phone Shop	Bridal Shop	Diner	Sandwich Place	Deli / Bodega	Restaurant	Supermarket
3	Bayview Village	Café	Bank	Chinese Restaurant	Japanese Restaurant	Yoga Studio	Falafel Restaurant	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant
4	Bedford Park, Lawrence Manor East	Sandwich Place	Italian Restaurant	Coffee Shop	Pizza Place	Thai Restaurant	Indian Restaurant	Pub	Sushi Restaurant	Japanese Restaurant	Restaurant

Lets make a model to cluster

- Verification of clusters of each city

In [85]:
```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 2, london_data_nonan.columns[[1] + list(range(5, london_data_n
```

Out[85]:

	town	Cluster Labels	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
121	LONDON	2	Gym / Fitness Center	Convenience Store	Clothing Store	Supermarket	Bus Station	Fountain	Food Truck	French Restaurant	Food Service	Fast Food Restaurant

In [86]:
```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 3, london_data_nonan.columns[[1] + list(range(5, london_data_n
```

Out[86]:

	town	Cluster Labels	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	LONDON	3	Supermarket	Historic Site	Coffee Shop	Platform	Convenience Store	Train Station	Flower Shop	Fast Food Restaurant	Fish & Chips Shop	Fishing Store
9	LONDON	3	Supermarket	Convenience Store	Fast Food Restaurant	Hotel	Grocery Store	Park	Bus Stop	Café	Gastropub	Bistro
29	BECKENHAM, LONDON	3	Supermarket	Convenience Store	Fast Food Restaurant	Hotel	Grocery Store	Park	Bus Stop	Café	Gastropub	Bistro
45	BEXLEYHEATH, LONDON	3	Supermarket	Historic Site	Train Station	Platform	Coffee Shop	Convenience Store	Park	Bus Stop	Construction & Landscaping	Golf Course

In [87]:
```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 4, london_data_nonan.columns[[1] + list(range(5, london_data_n
```

Out[87]:

	town	Cluster Labels	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
10	LONDON	4	Coffee Shop	Pub	Café	Vietnamese Restaurant	Cocktail Bar	Food Truck	Burger Joint	Grocery Store	Bike Shop	Park
12	LONDON	4	Coffee Shop	Pub	Café	Vietnamese Restaurant	Cocktail Bar	Food Truck	Burger Joint	Grocery Store	Bike Shop	Park
14	BARNET, LONDON	4	Coffee Shop	Café	Grocery Store	Pub	Supermarket	Italian Restaurant	Pharmacy	Bus Stop	Turkish Restaurant	Indian Restaurant
15	LONDON	4	Coffee Shop	Fast Food Restaurant	Italian Restaurant	Pizza Place	Supermarket	Gym / Fitness Center	Grocery Store	Turkish Restaurant	Pub	Sandwich Place
16	LONDON	4	Pub	Coffee Shop	Indian Restaurant	Bar	Portuguese Restaurant	Café	Pizza Place	Burger Joint	Gym / Fitness Center	Gym
...	...	...	...	...	...	...	...	...	...	...	...	...
522	LONDON	4	Café	Pub	Coffee Shop	Park	Grocery Store	French Restaurant	Food & Drink Shop	Train Station	Hardware Store	South American Restaurant
523	LONDON	4	Pub	Grocery Store	Coffee Shop	Café	Bar	Bridal Shop	BBQ Joint	Seafood Restaurant	Park	Pizza Place
527	LONDON	4	Coffee Shop	Café	Grocery Store	Pub	Supermarket	Italian Restaurant	Pharmacy	Bus Stop	Turkish Restaurant	Indian Restaurant
528	LONDON	4	Pub	Grocery Store	Indian Restaurant	Bus Stop	Coffee Shop	Construction & Landscaping	Turkish Restaurant	Gym / Fitness Center	Golf Course	Middle Eastern Restaurant
530	LONDON	4	Café	Pub	Grocery Store	Park	Coffee Shop	Gastropub	Thai Restaurant	Bakery	Convenience Store	Climbing Gym

In [88]:
```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 5, london_data_nonan.columns[[1] + list(range(5, london_data_n
```

Out[88]:

	town	Cluster Labels	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
1	LONDON	5	Grocery Store	Indian Restaurant	Park	Breakfast Spot	Train Station	Flower Shop	Fast Food Restaurant	Fish & Chips Shop	Fishing Store	Flea Market
61	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
69	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
100	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
138	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
218	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
261	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
270	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
320	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
358	LONDON	5	Grocery Store	Sandwich Place	Fast Food Restaurant	Café	Pharmacy	Warehouse Store	Convenience Store	Chinese Restaurant	Zoo Exhibit	Fish & Chips Shop
378	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
443	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub
519	LONDON	5	Grocery Store	Café	Sandwich Place	Warehouse Store	Indian Restaurant	Convenience Store	Pharmacy	Chinese Restaurant	Fast Food Restaurant	Pub

In [84]:
```
london_data_nonan.loc[london_data_nonan['Cluster Labels'] == 1, london_data_nonan.columns[[1] + list(range(5, london_data_n
```

Out[84]:

	town	Cluster Labels	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
6	LONDON	1	Coffee Shop	Hotel	Falafel Restaurant	Vietnamese Restaurant	Gym / Fitness Center	Food Truck	Wine Bar	Beer Bar	Pub	Cocktail Bar
7	LONDON	1	Coffee Shop	Hotel	Theater	Pub	Restaurant	French Restaurant	Café	Sandwich Place	Juice Bar	Sporting Goods Shop
18	LONDON	1	Coffee Shop	Hotel	Falafel Restaurant	Vietnamese Restaurant	Gym / Fitness Center	Food Truck	Wine Bar	Beer Bar	Pub	Cocktail Bar
28	LONDON	1	Coffee Shop	Hotel	Theater	Pub	Restaurant	French Restaurant	Café	Sandwich Place	Juice Bar	Sporting Goods Shop
35	LONDON	1	Coffee Shop	Hotel	Theater	Pub	Restaurant	French Restaurant	Café	Sandwich Place	Juice Bar	Sporting Goods Shop
49	LONDON	1	Coffee Shop	Hotel	Falafel Restaurant	Vietnamese Restaurant	Gym / Fitness Center	Food Truck	Wine Bar	Beer Bar	Pub	Cocktail Bar
68	LONDON	1	Bookstore	Ice Cream Shop	Women's Store	Japanese Restaurant	Bakery	Restaurant	Plaza	Boxing Gym	Clothing Store	Coffee Shop

Cluster 1

```
In [45]: toronto_merged_nonan.loc[toronto_merged_nonan['Cluster Labels'] == 0, toronto_merged_nonan.columns[[1] + list(range(5, toro
```

Out[45]:

	Borough	Cluster Labels	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
1	North York	0.0	Pizza Place	Hockey Arena	French Restaurant	Coffee Shop	Portuguese Restaurant	Dim Sum Restaurant	Diner	Discount Store	Distribution Center	Donut Shop
2	Downtown Toronto	0.0	Coffee Shop	Park	Café	Breakfast Spot	Theater	Bakery	French Restaurant	Performing Arts Venue	Chocolate Shop	Pub
3	North York	0.0	Clothing Store	Furniture / Home Store	Accessories Store	Coffee Shop	Shoe Store	Event Space	Athletics & Sports	Boutique	Vietnamese Restaurant	Dim Sum Restaurant
4	Downtown Toronto	0.0	Coffee Shop	Yoga Studio	Park	Beer Bar	Smoothie Shop	Sandwich Place	Café	Portuguese Restaurant	Chinese Restaurant	Persian Restaurant
7	North York	0.0	Gym	Japanese Restaurant	Restaurant	Coffee Shop	Beer Store	Dim Sum Restaurant	Sporting Goods Shop	Discount Store	Café	Caribbean Restaurant
...	...	...	...	...	...	...	...	...	...	...	...	...
97	Downtown Toronto	0.0	Café	Coffee Shop	Restaurant	Seafood Restaurant	Pizza Place	Steakhouse	Speakeasy	Pub	Japanese Restaurant	Bakery

Cluster 2

```
In [46]: toronto_merged_nonan.loc[toronto_merged_nonan['Cluster Labels'] == 1, toronto_merged_nonan.columns[[1] + list(range(5, toro
```

Out[46]:

	Borough	Cluster Labels	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	North York	1.0	Park	Food & Drink Shop	Yoga Studio	Dessert Shop	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop
21	York	1.0	Park	Women's Store	Pool	Yoga Studio	Department Store	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop
32	Scarborough	1.0	Playground	Jewelry Store	Yoga Studio	Dessert Shop	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop
35	East York	1.0	Park	Coffee Shop	Convenience Store	Yoga Studio	Dessert Shop	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore
52	North York	1.0	Piano Bar	Park	Deli / Bodega	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop	Dog Run	Distribution Center

Cluster 3

```
In [47]: toronto_merged_nonan.loc[toronto_merged_nonan['Cluster Labels'] == 2, toronto_merged_nonan.columns[[1] + list(range(5, toro
```

Out[47]:

	Borough	Cluster Labels	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
6	Scarborough	2.0	Fast Food Restaurant	Print Shop	Department Store	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop	Dog Run

Cluster 4

```
In [48]: toronto_merged_nonan.loc[toronto_merged_nonan['Cluster Labels'] == 3, toronto_merged_nonan.columns[[1] + list(range(5, toro
```

Out[48]:

	Borough	Cluster Labels	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
57	North York	3.0	Baseball Field	Furniture / Home Store	Yoga Studio	Farmers Market	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop
101	Etobicoke	3.0	Baseball Field	Yoga Studio	Fast Food Restaurant	Falafel Restaurant	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore	Donut Shop

Cluster 5

```
In [49]: toronto_merged_nonan.loc[toronto_merged_nonan['Cluster Labels'] == 4, toronto_merged_nonan.columns[[1] + list(range(5, toro
```

Out[49]:

	Borough	Cluster Labels	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
12	Scarborough	4.0	Bar	Home Service	Yoga Studio	Dim Sum Restaurant	Falafel Restaurant	Event Space	Electronics Store	Eastern European Restaurant	Dumpling Restaurant	Drugstore
62	Central Toronto	4.0	Garden	Home Service	Department Store	Event Space	Electronics Store	Eastern European	Dumpling Restaurant	Drugstore	Donut Shop	Dog Run

Result and Discussion

The neighbourhoods of London are very multicultural. There are a lot of different cuisines including Indian, Italian, Turkish and Chinese. London seems to take a step further in this direction by having a lot of Restaurants, bars, juice bars, coffee shops, Fish and Chips shops and Breakfast spots. It has a lot of shopping options too with that of the Flea markets, flower shops, fish markets, Fishing stores, clothing stores. The main modes of transport seem to be Buses and trains. For leisure, the neighbourhoods are set up to have lots of parks, golf courses, zoo, gyms and Historic sites. Overall, the city of London offers a multicultural, diverse and certainly an entertaining experience.

Toronto is comparatively smaller in area. Although due to the high migration rate we can see that Toronto is also multicultural and most of the immigrants are from India, China, Europe. Thus the cuisines are also similar to london. Toronto has a lot of pizza places, coffee shops, parks European restaurants, Vietnamese restaurants, Chinese restaurants, donut shops, drug stores.

The observations I made are that London seems to be a bigger city with more of a larger cultural diversity, Toronto comparatively seems more a more passive city with beautiful tourist spots too.

Conclusion

The purpose of this project was to explore the cities of London and Toronto to see how attractive it is to potential tourists and migrants. We explored both the cities based on their postal codes and then extrapolated the common venues present in each of the neighbourhoods finally concluding with clustering similar neighbourhoods together. We could see that each of the neighbourhoods in both the cities have a wide variety of experiences to offer which is unique in it's own way. The cultural diversity is quite evident which also gives the feeling of a sense of inclusion.