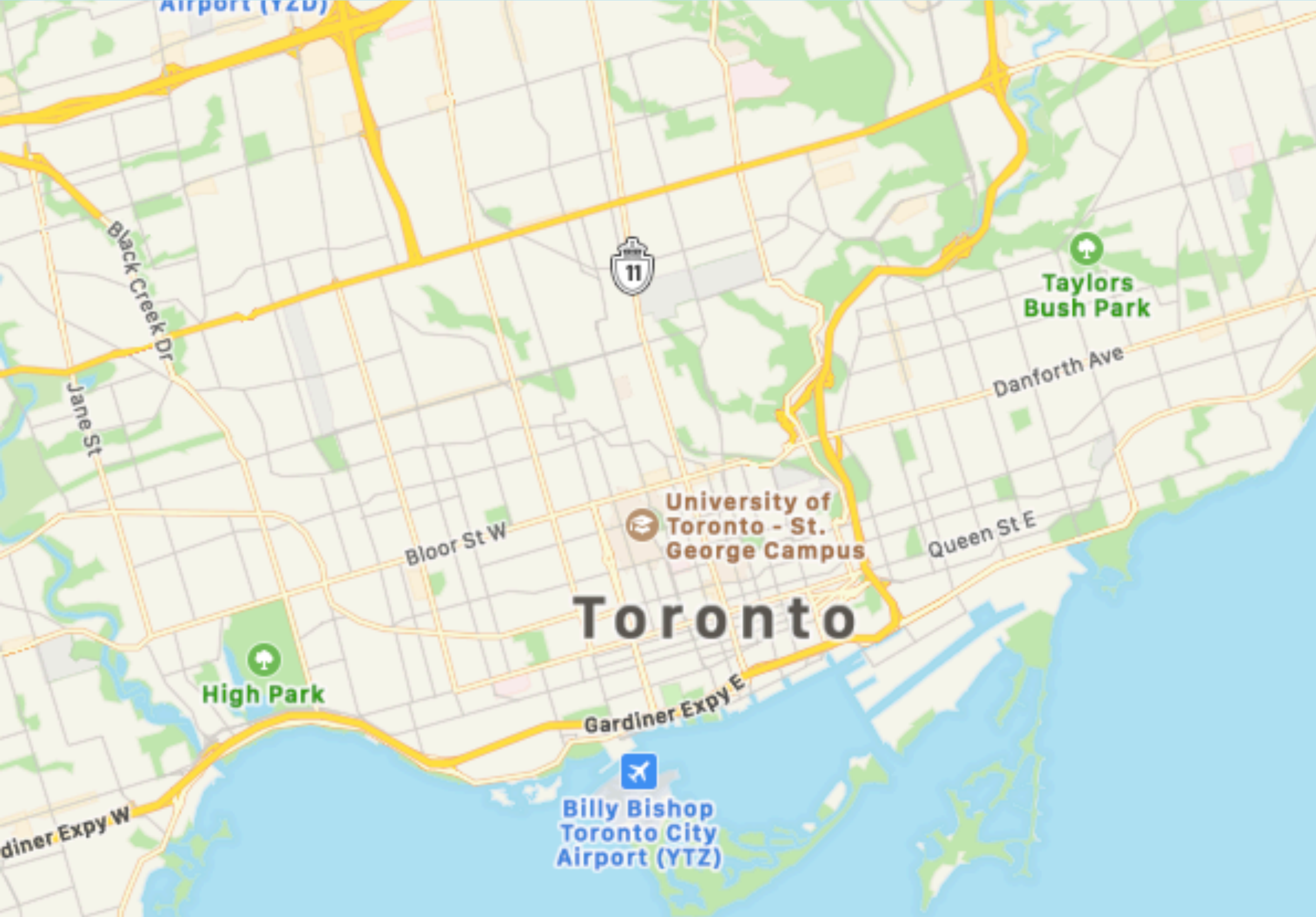

Searching for Best Neighbourhood to Open Steakhouse in Toronto, Ontario

Segment and Cluster Neighborhoods in Toronto, Ontario to find best neighbourhood to open steakhouse

Subha Halder

31 Oct 2020

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1. Introduction

1.1 Background

Toronto, the capital of the province of Ontario, is a major Canadian city along Lake Ontario's northwestern shore. It's a dynamic metropolis with a core of soaring skyscrapers, all dwarfed by the iconic, free-standing CN Tower. Toronto is a city with population of 2.7 million and has a high population density. Being such a crowded city leads the owners of shops and social sharing places in the city where the population is dense. When I think of it by the investor, I expect from them to prefer the districts where there is a dense commerce available, which typically means high population density and high median household income. However, it is difficult to obtain such information that will guide investors in this direction, nowadays. This project seeks to provide stakeholders and investors the guidance require to open restaurant in a crowded commercial capital.

1.2 Problem

Data that might contribute to determining best neighbourhood to open steakhouse are might be:

- Demographic information, e.g. population, density, age, median household income
- Number of existing popular venues
- Number of existing restaurants/steakhouses

This project aims to predict neighbourhood with high population density and median household income for Toronto City along with best places of most popular venues.

1.3 Interest

This project aims to help restaurant owner, stakeholders of major food-brand determining accurate prediction on best location to open business in Toronto. For others such as chefs and food-enthusiasts this project might also be of interest.

2. Data Acquisition and Data Cleaning

2.1 Data Sources

2016 Toronto census data collected from here, fortunately this dataset doesn't lack any data and an example of the data is provided:

	AREA_S_CD	AREA_NAME	POPULATION	DENSITY (PER SQ KM)	CHILDREN	YOUTH	WORKING_AGE	PRE_RETIREMENT	SENIORS	MEDIAN_HOUSEHOLD_INCOME
0	1	West Humber-Clairville (1)	33312	1117	15	16	42	12	14	70741
1	2	Mount Olive-Silverstone-Jamestown (2)	32954	7291	22	16	41	11	11	55334
2	3	Thistletown-Beaumond Heights (3)	10360	3130	17	13	41	12	17	65459
3	4	Rexdale-Kipling (4)	10529	4229	16	13	41	15	15	63232
4	5	Elms-Old Rexdale (5)	9456	3306	19	15	39	14	14	59576

This dataset contains all relevant information such as neighbourhood name along with population density and median household income and percentage of age demographic living in that neighbourhood.

I also have acquired location data for Toronto city from Geocoder API. I also have acquired a GeoJSON file from here to produce map data. Also to acquire Postal codes I've used web-scrapping from here. These postal codes along with latitude and longitude data acquired from Geocoder API will help us create a data-frame containing all venue, venue category, neighbourhood name, location, neighbourhood location from Foursquare API.

Also different age group spends very differently when it comes to annual spending on restaurants. These data can be found here and it is shown bellow:

	AGE DEMOGRAPHIC	ANUAL SPENDING ($)	SPENDING FREQUENCY
0	YOUTH (UNDER 24)	4073	4.073
1	WORKING AGE (25 to 54)	20804	6.935
2	PRE-Retirement (55 to 64)	6068	6.068
3	SENIOR (65+)	9021	4.510

2.2 Data Cleaning

Data collected from various sources such as table for postal codes along with neighbourhood is combined with data collected from Geocoder API in form of Neighbourhood with location data. A few row of missing data were dropped. Final data-frame has 103 neighbourhood with postal code, borough and coordinate location.

These coordinate location were used to get nearly venues from Foursquare API in radius of 500 meter. Result is the following dataset:

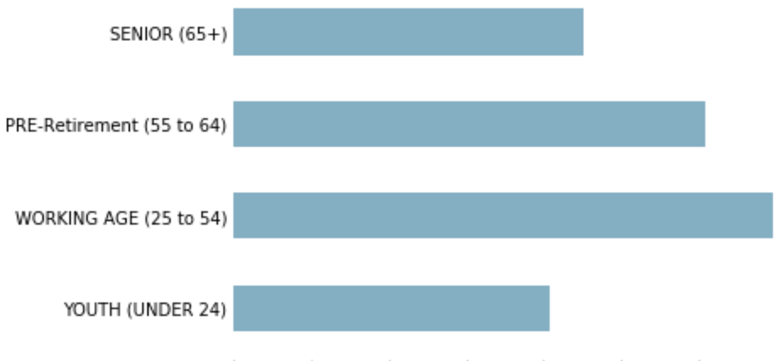
	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Parkwoods	43.753259	-79.329656	Brookbanks Park	43.751976	-79.332140	Park
1	Parkwoods	43.753259	-79.329656	Variety Store	43.751974	-79.333114	Food & Drink Shop
2	Victoria Village	43.725882	-79.315572	Victoria Village Arena	43.723481	-79.315635	Hockey Arena
3	Victoria Village	43.725882	-79.315572	Portugril	43.725819	-79.312785	Portuguese Restaurant
4	Victoria Village	43.725882	-79.315572	Tim Hortons	43.725517	-79.313103	Coffee Shop

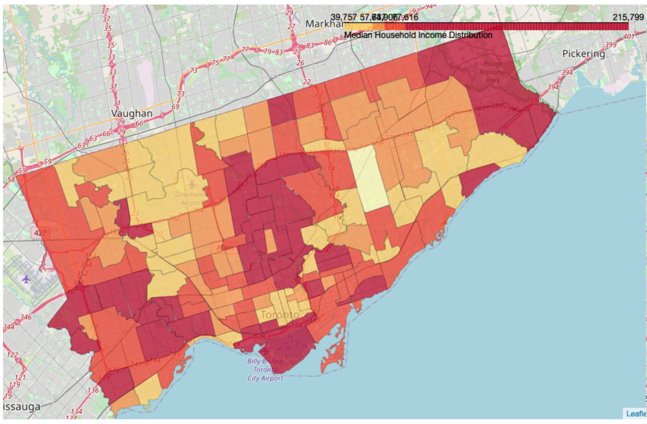
In total data for 2136 venues of 103 neighbourhoods were collected. Using this I've created a data-frame with only "Steakhouse" as Venue Category, and another data-frame of all venues excluding restaurants and steakhouses.

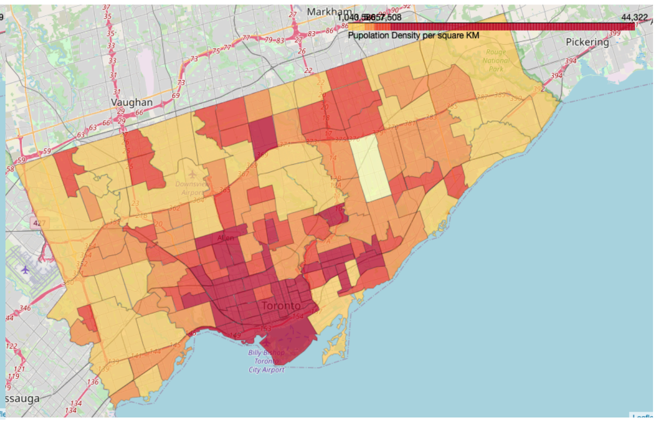
Now for census data, I've used the GeoJson file to better understand population density and median household income of different neighbourhood. I've come to realise that different age group spend very differently when come to outdoor dining.

2.3 Feature Selection

This bar diagram shows spending frequency (in USD) of different age group. Next two map shown bellow are density distribution and median household income distribution respectively.





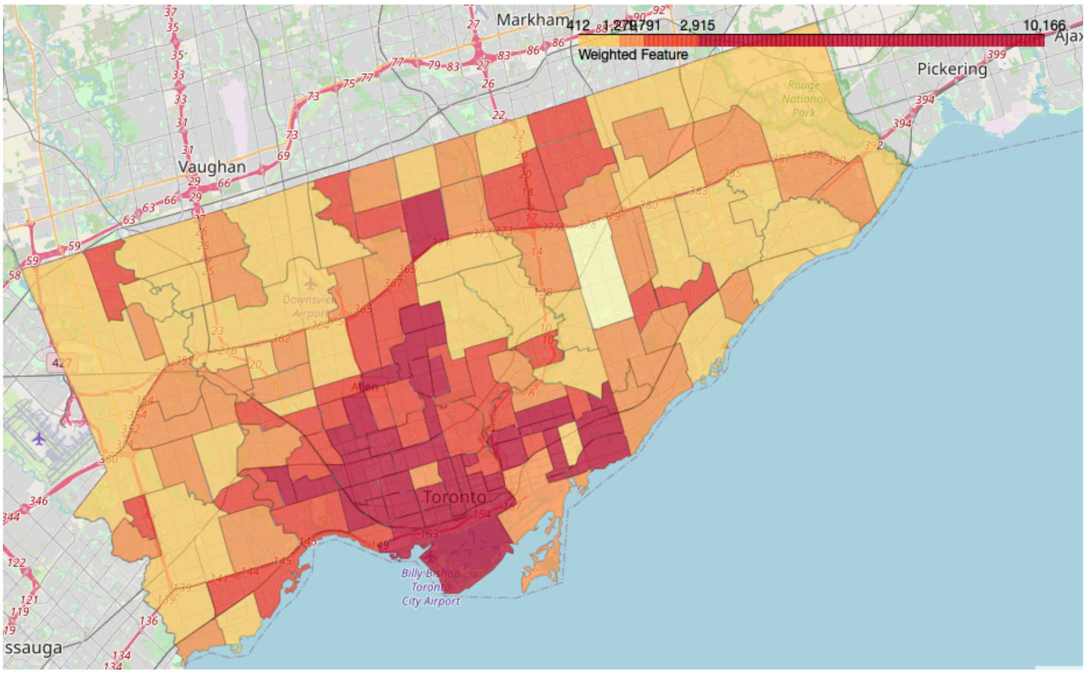


Median Household Income Distribution

Density Distribution

The two distributions varies very widely. So I've decided to use another Weighted feature:

$$WeightedFeature = [\sum(PercentageAgeGroup) \times (SpendingFrequency)] \times Density \times Income$$

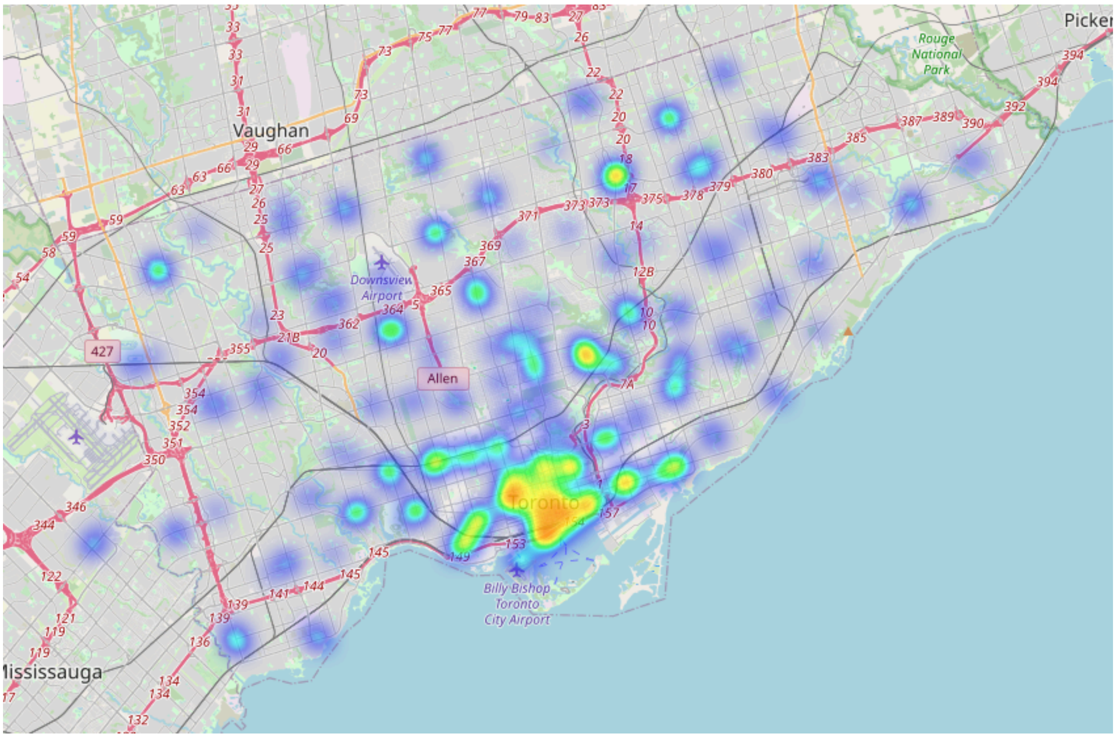


Weighted Feature Distribution

3. Methodology

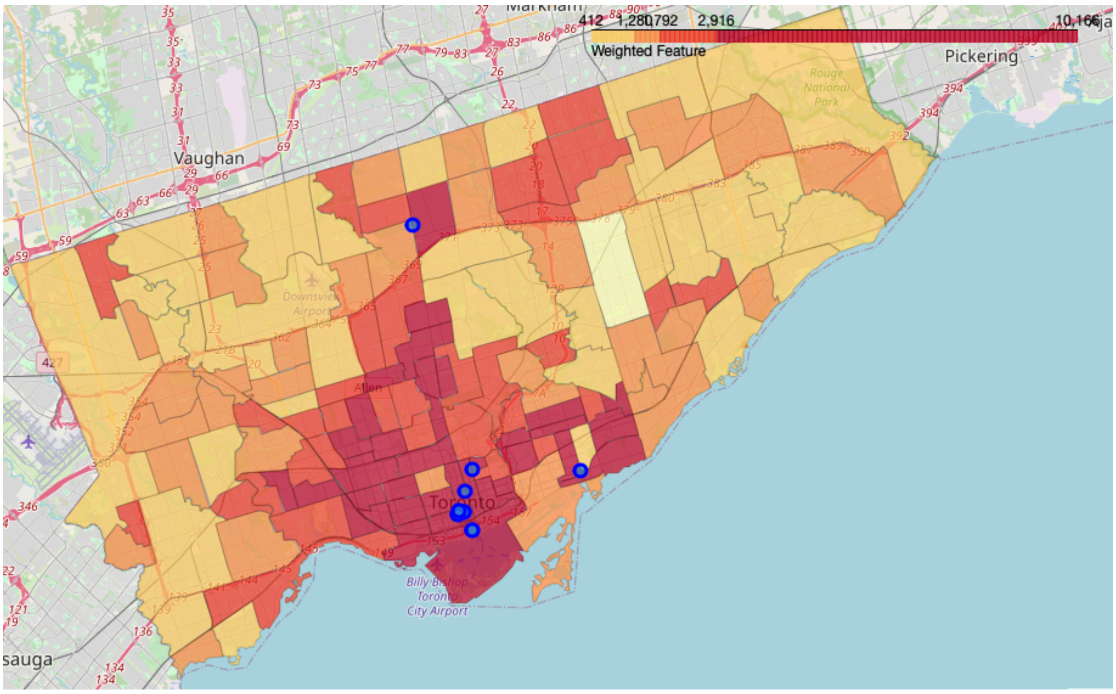
3.1 Heat Map of All Venues excluding restaurants

This heat map is generated with location data of all venues such as parks, malls, markets but excluding any restaurants, such as American, Indian, French etc., along with all steakhouses. The heat map is superimposed on Toronto map.

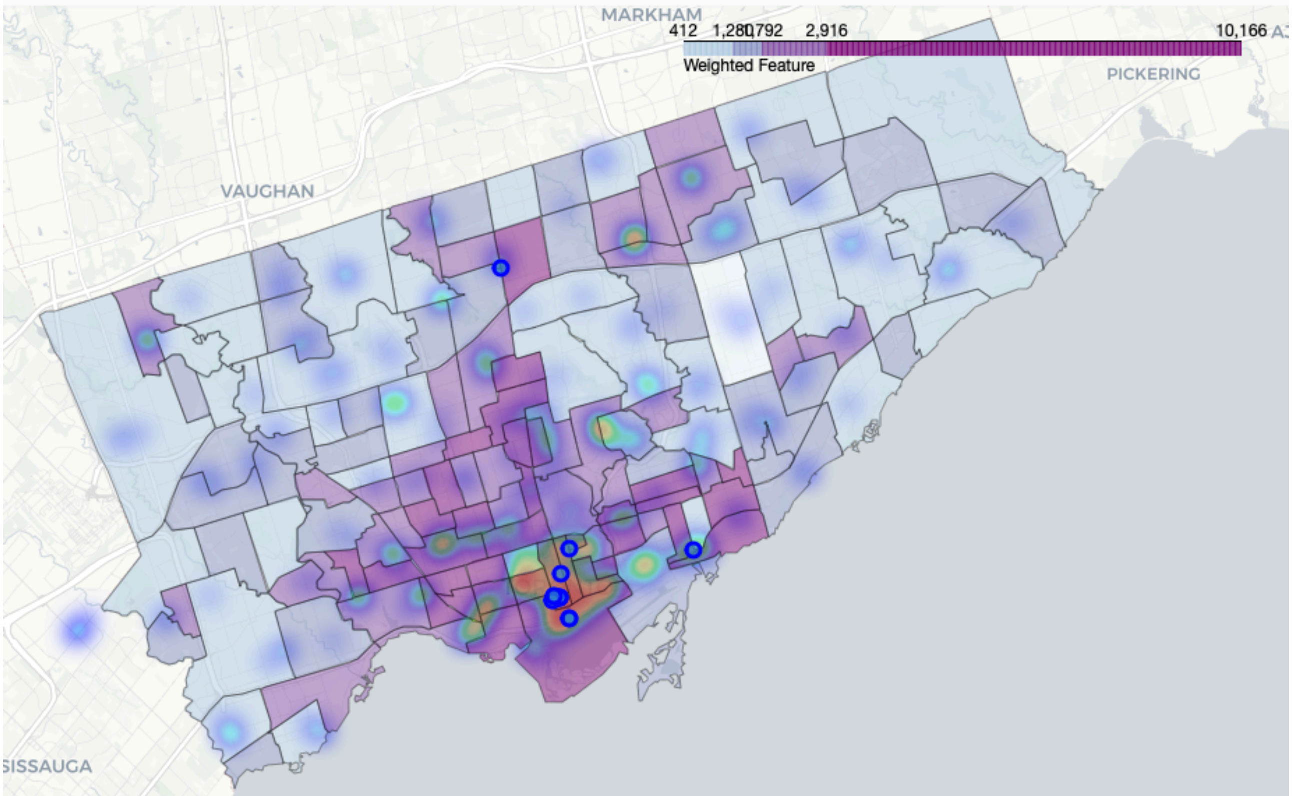


3.2 Map of All Steakhouses with Weighted Feature

The map of All steakhouses, marked with blue, is superimposed on Weighted Feature Map of Toronto Neighbourhood.



3.3 HeatMap of venues excluding restaurants with Steakhouses Marked
This map of all steakhouses and heat map of all venues excluding any restaurants shows that almost all steakhouses are located in Downtown Toronto, where the Weighted Feature is also highest. Downtown has highest concentration of popular venues. Let's confirm this theory with further analysis.



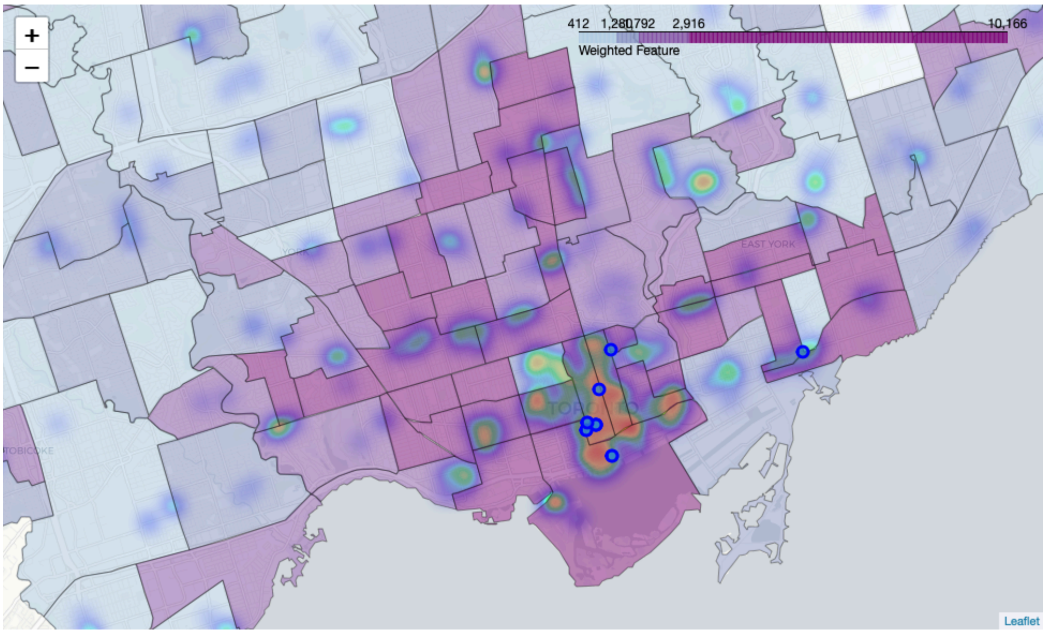
3.4 Analysis of Each Borough
Now I have a Dataframe containing each neighbourhoods of each borough:

	Postal Code	Borough	Neighbourhood	Latitude	Longitude
0	M3A	North York	Parkwoods	43.753259	-79.329656
1	M4A	North York	Victoria Village	43.725882	-79.315572
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494

Grouping this Dataframe by Borough and counting total neighbourhoods, gives us neighbourhood count of each borough. Now, by leveraging Foursquare API, I can call all nearby venue names of every borough, and use shape feature to get the neighbourhood count for each borough. Iterating this for every borough I got a list containing integer that describes total number of neighbourhoods of every borough. I can now finally append that list to the above data-frame. By doing this, we now have a data-frame as follows:

	Borough	Neighborhood_Count	Venue Count
0	North York	24	239
1	Downtown Toronto	19	1248
2	Scarborough	17	89
3	Etobicoke	12	74
4	Central Toronto	9	104
5	West Toronto	6	153
6	East Toronto	5	119
7	East York	5	77
8	York	5	336
9	Mississauga	1	13

As seen in this table Downtown Toronto has the highest number of venues, ie. 1248 venues spread across 19 neighbourhoods. York comes second as it has 336 venues spread across only 5 venues. For frequency count at which venue appears per neighbourhood, York has higher count that Downtown Toronto. But for Weighted Feature, Downtown is higher than York. So I've decided that I'll use explore Downtown Toronto further.



3.5 Analyse Downtown Toronto Neighbourhood

I've used data-frame containing postal code for each neighbourhood to get location data for all neighbourhood in Downtown Toronto. Data looks like this:

	Postal Code	Borough	Neighbourhood	Latitude	Longitude
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636
4	M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government	43.662301	-79.389494
9	M5B	Downtown Toronto	Garden District, Ryerson	43.657162	-79.378937
15	M5C	Downtown Toronto	St. James Town	43.651494	-79.375418
20	M5E	Downtown Toronto	Berczy Park	43.644771	-79.373306

3.5.1 Clustering Neighbourhoods of Downtown Toronto

I've used KMeans from sklearn package to cluster neighbourhoods. First I've dropped all venues that are not in Downtown from Venues data-frame. Then created a onehot table of venues in downtown. Then used the groupby feature to create a frequency chart of each venue category for all neighbourhoods in downtown. Here's the top of the chart:

	Neighborhood	Yoga Studio	Afghan Restaurant	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	...	Theater	Theme Restaurant	Toy / Game Store	Trail	Train Station	Vege / Resta
0	Berczy Park	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.000000	...	0.000000	0.000000	0.00	0.0	0.00	0.0
1	CN Tower, King and Spadina, Railway Lands, Har...	0.000000	0.000000	0.0625	0.0625	0.0625	0.125	0.125	0.0625	0.000000	...	0.000000	0.000000	0.00	0.0	0.00	0.0
2	Central Bay Street	0.014706	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.000000	...	0.000000	0.000000	0.00	0.0	0.00	0.0
3	Christie	0.000000	0.000000	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.000000	...	0.000000	0.000000	0.00	0.0	0.00	0.0
4	Church and Wellesley	0.026667	0.013333	0.0000	0.0000	0.0000	0.000	0.000	0.0000	0.013333	...	0.013333	0.013333	0.00	0.0	0.00	0.0

The chart contains total 19 neighbourhoods and 213 venue category. From this I've created a data-frame to display top 10 venues for each neighbourhood. Top values of data-frame is shown bellow:

	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	Coffee Shop	Seafood Restaurant	Cocktail Bar	Bakery	Cheese Shop	Beer Bar	Restaurant	Farmers Market	Hotel	Italian Restaurant
1	CN Tower, King and Spadina, Railway Lands, Har...	Airport Lounge	Airport Service	Boutique	Sculpture Garden	Plane	Rental Car Location	Coffee Shop	Bar	Harbor / Marina	Boat or Ferry
2	Central Bay Street	Coffee Shop	Café	Sandwich Place	Italian Restaurant	Salad Place	Burger Joint	Japanese Restaurant	Department Store	Thai Restaurant	Bubble Tea Shop
3	Christie	Grocery Store	Café	Park	Candy Store	Nightclub	Coffee Shop	Restaurant	Italian Restaurant	Athletics & Sports	Baby Store
4	Church and Wellesley	Coffee Shop	Japanese Restaurant	Gay Bar	Sushi Restaurant	Restaurant	Yoga Studio	Men's Store	Mediterranean Restaurant	Hotel	Pub

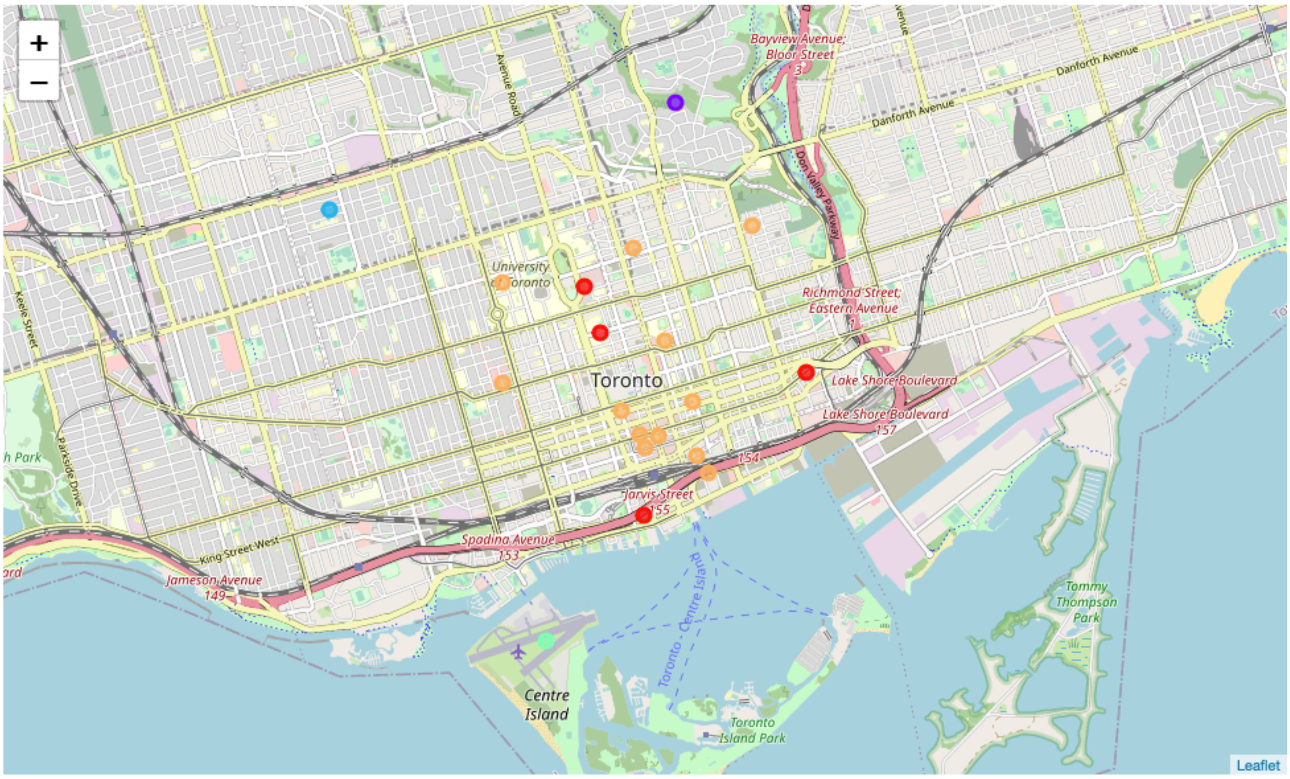
3.5.2 Run KMean to cluster neighbourhood into 5 clusters

I've decided to cluster the neighbourhoods into 5 clusters. After running clusters I've merged the data-frame with previous another data-frame containing location data for each neighbourhood. Column heads are shown below:

```
Postal Code                object
Borough                    object
Neighbourhood              object
Latitude                  float64
Longitude                 float64
Cluster Labels              int64
1st Most Common Venue      object
2nd Most Common Venue      object
3rd Most Common Venue      object
4th Most Common Venue      object
5th Most Common Venue      object
6th Most Common Venue      object
7th Most Common Venue      object
8th Most Common Venue      object
9th Most Common Venue      object
10th Most Common Venue     object
dtype: object
```

3.5.3 Visualising Clusters

We can visualise 5 clusters in a map:



This map suggests that green cluster has the highest number of venues. The chart below suggests that this cluster is where most commerce occurs. Hence, we can conclude that this cluster is where stakeholders should target to open business. So to further analyse it I've decided to cluster the Downtown Toronto neighbourhood by venues, this time excluding all restaurants. The cluster is shown bellow:

	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
9	Downtown Toronto	4	Clothing Store	Coffee Shop	Café	Bubble Tea Shop	Cosmetics Shop	Japanese Restaurant	Ramen Restaurant	Hotel	Italian Restaurant	Lingerie Store
15	Downtown Toronto	4	Coffee Shop	Café	Cocktail Bar	Restaurant	Gastropub	American Restaurant	Beer Bar	Gym	Seafood Restaurant	Farmers Market
20	Downtown Toronto	4	Coffee Shop	Seafood Restaurant	Cocktail Bar	Bakery	Cheese Shop	Beer Bar	Restaurant	Farmers Market	Hotel	Italian Restaurant
30	Downtown Toronto	4	Coffee Shop	Café	Gym	Restaurant	Hotel	Bar	Thai Restaurant	Clothing Store	Sushi Restaurant	Juice Bar
42	Downtown Toronto	4	Coffee Shop	Hotel	Restaurant	Café	Salad Place	Seafood Restaurant	American Restaurant	Japanese Restaurant	Italian Restaurant	Bar

3.6 Exploring Downtown Neighbourhoods Excluding Restaurants

Dataframe used to cluster neighbourhoods before can be used here, after dropping all venues containing restaurants and steakhouses. Then I've created a onehot table of venues in downtown and used groupby feature to create a frequency chart of each venue category for all neighbourhoods in downtown. The chart contains total 19 neighbourhoods and 169 venue category. From this I've created a data-frame to display top 10 venues for each neighbourhood. Top values of data-frame is shown bellow:

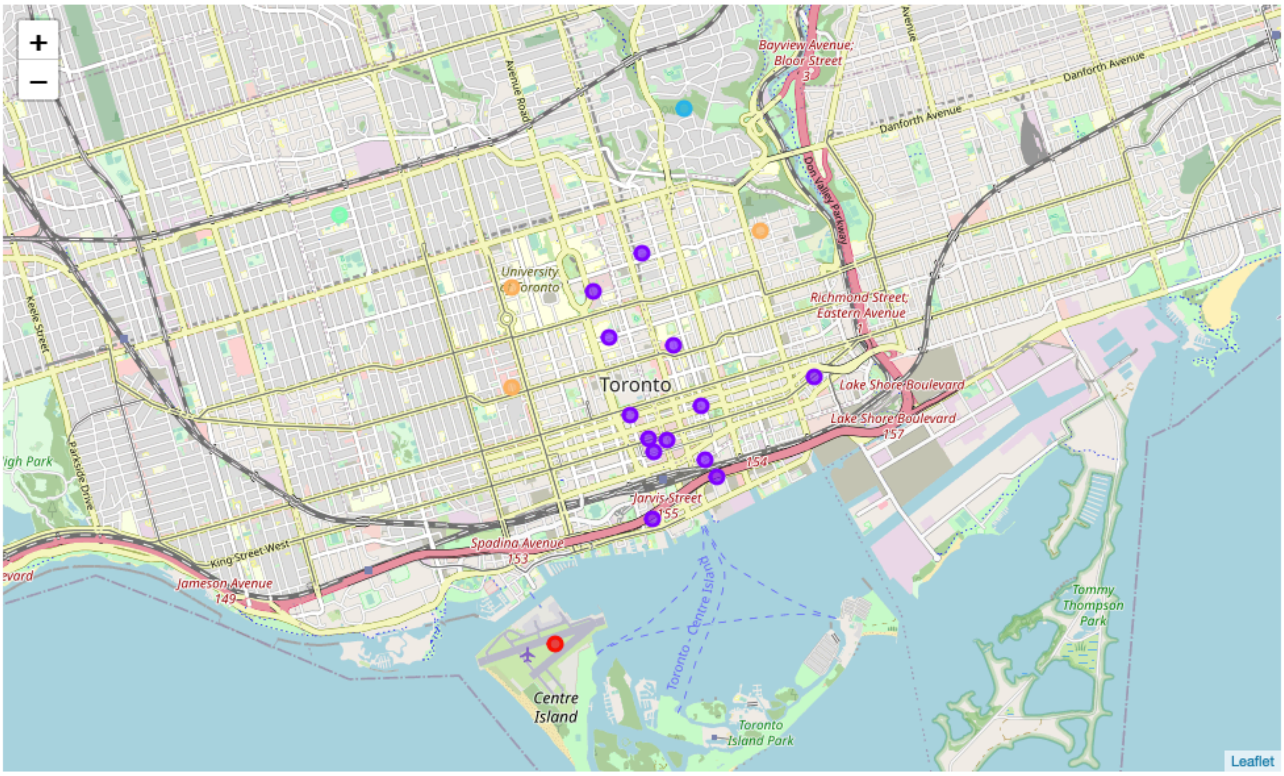
	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Berczy Park	Coffee Shop	Bakery	Beer Bar	Cocktail Bar	Cheese Shop	Farmers Market	Shopping Mall	Hotel	Basketball Stadium	Beach
1	CN Tower, King and Spadina, Railway Lands, Har...	Airport Lounge	Airport Service	Sculpture Garden	Harbor / Marina	Plane	Rental Car Location	Boutique	Boat or Ferry	Bar	Coffee Shop
2	Central Bay Street	Coffee Shop	Café	Sandwich Place	Salad Place	Bubble Tea Shop	Burger Joint	Department Store	Comic Shop	Bookstore	Poke Place
3	Christie	Grocery Store	Café	Park	Athletics & Sports	Candy Store	Nightclub	Baby Store	Coffee Shop	Fried Chicken Joint	Deli / Bodega
4	Church and Wellesley	Coffee Shop	Gay Bar	Yoga Studio	Pub	Hotel	Men's Store	Bubble Tea Shop	Café	Diner	Theater

3.6.1 Run KMean Cluster

Same as before neighbours are clustered by venues, this time excluding any restaurants and steakhouse, into 5 clusters.

3.62 Visualising Clusters

Here's a map of each cluster is shown:



Here are the 5 clusters after named:

Cluster: 1 (Airport)

Neighbourhood	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
CN Tower, King and Spadina, Railway Lands, Har...	0	Airport Lounge	Airport Service	Sculpture Garden	Harbor / Marina	Plane	Rental Car Location	Boutique	Boat or Ferry	Bar	Coffee Shop

Cluster: 2 (Commerce)

Neighbourhood	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
Regent Park, Harbourfront	1	Coffee Shop	Park	Pub	Bakery	Café	Theater	Breakfast Spot	Performing Arts Venue	Brewery	Event Space
Queen's Park, Ontario Provincial Government	1	Coffee Shop	Yoga Studio	College Auditorium	Bar	Sandwich Place	Beer Bar	Café	Music Venue	College Cafeteria	Smoothie Shop
Garden District, Ryerson	1	Clothing Store	Coffee Shop	Café	Bubble Tea Shop	Cosmetics Shop	Hotel	Theater	Bookstore	Lingerie Store	Pizza Place
St. James Town	1	Coffee Shop	Café	Cocktail Bar	Beer Bar	Gastropub	Lingerie Store	Hotel	Department Store	Clothing Store	Farmers Market
Berczy Park	1	Coffee Shop	Bakery	Beer Bar	Cocktail Bar	Cheese Shop	Farmers Market	Shopping Mall	Hotel	Basketball Stadium	Beach
Central Bay Street	1	Coffee Shop	Café	Sandwich Place	Salad Place	Bubble Tea Shop	Burger Joint	Department Store	Comic Shop	Bookstore	Poke Place
Richmond, Adelaide, King	1	Coffee Shop	Café	Gym	Bar	Hotel	Clothing Store	Salad Place	Deli / Bodega	Pizza Place	Office
Harbourfront East, Union Station, Toronto Islands	1	Coffee Shop	Aquarium	Café	Hotel	Brewery	Scenic Lookout	Fried Chicken Joint	Music Venue	History Museum	Pizza Place
Toronto Dominion Centre, Design Exchange	1	Coffee Shop	Hotel	Café	Salad Place	Bar	Beer Bar	Sporting Goods Shop	Gastropub	Bakery	Deli / Bodega
Commerce Court, Victoria Hotel	1	Coffee Shop	Café	Hotel	Gym	Deli / Bodega	Cocktail Bar	Beer Bar	Gastropub	Breakfast Spot	Bakery
Stn A PO Boxes	1	Coffee Shop	Café	Hotel	Beer Bar	Pub	Park	Farmers Market	Gym	Creperie	Cocktail Bar
First Canadian Place, Underground city	1	Coffee Shop	Café	Hotel	Gym	Salad Place	Deli / Bodega	Pizza Place	Beer Bar	Concert Hall	Gastropub
Church and Wellesley	1	Coffee Shop	Gay Bar	Yoga Studio	Pub	Hotel	Men's Store	Bubble Tea Shop	Café	Diner	Theater

Cluster: 3 (Parks)

Neighbourhood	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
Rosedale	2	Park	Trail	Playground	College Rec Center	Deli / Bodega	Dance Studio	Cupcake Shop	Creperie	Cosmetics Shop	Convenience Store

Cluster: 4 (Residential)

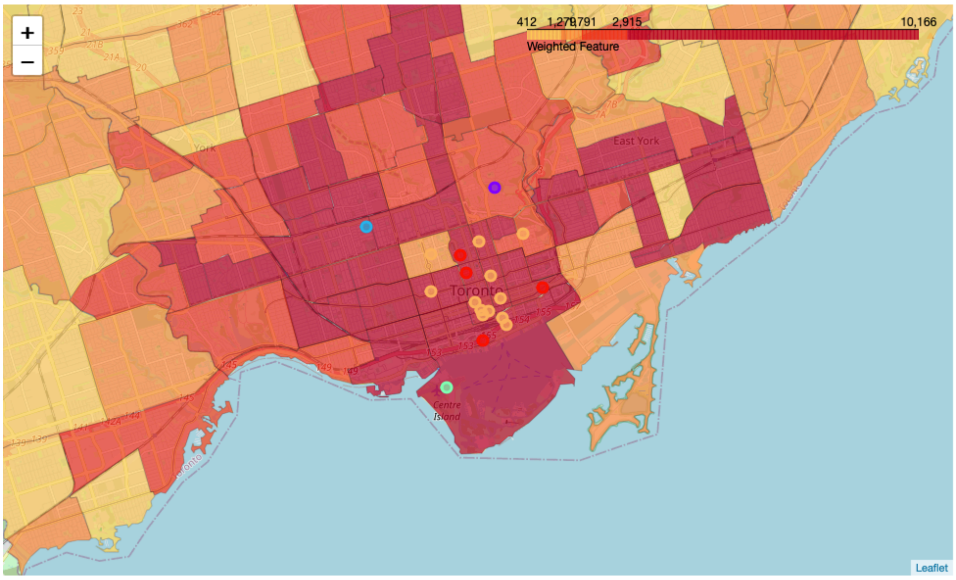
Neighbourhood	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
Christie	3	Grocery Store	Café	Park	Athletics & Sports	Candy Store	Nightclub	Baby Store	Coffee Shop	Fried Chicken Joint	Deli / Bodega

Cluster: 5 (Entertainment)

Neighbourhood	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
University of Toronto, Harbord	4	Café	Bookstore	Bakery	Sandwich Place	Bar	Yoga Studio	Coffee Shop	College Arts Building	College Gym	Pub
Kensington Market, Chinatown, Grange Park	4	Café	Coffee Shop	Bar	Bakery	Gaming Cafe	Dessert Shop	Park	Burger Joint	Pizza Place	Grocery Store
St. James Town, Cabbagetown	4	Coffee Shop	Café	Pizza Place	Pub	Bakery	Market	Park	Plaza	Playground	Pharmacy

4. Results

Lets's merge our finding into a choropleth map. Here is a map of neighbourhood clustered by venues:



My aim was search for best place to open a steakhouse with the following features:

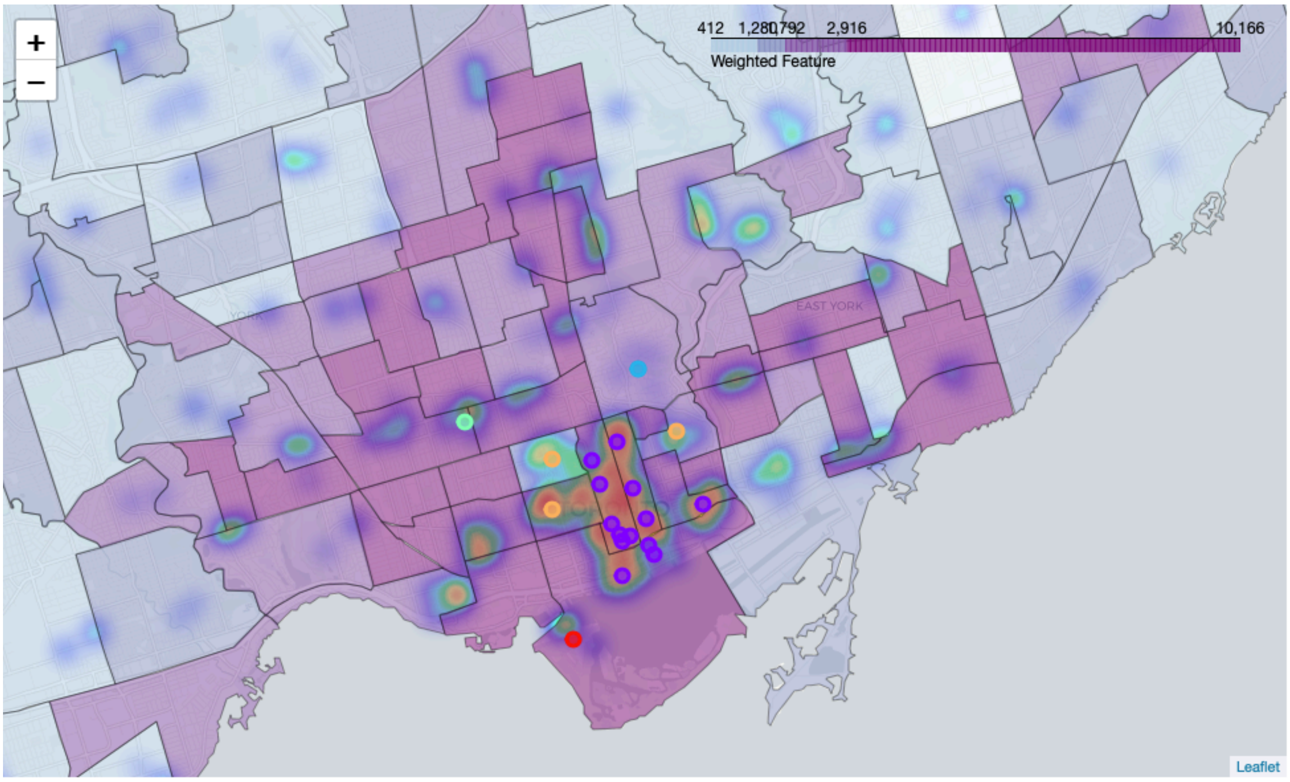
- Higher population density
- Higher concentration of working age group
- Higher median household income

The highest value of weighted feature has all three satisfied. Below is a list of top 10 neighbourhoods with highest weighted feature:

AREA_S_CD	AREA_NAME	POPULATION	DENSITY	CHILDREN	YOUTH	WORKING_AGE	PRE_RETIREMENT	SENIORS	MEDIAN_HOUSEHOLD_INCOME
74	North St.James Town (74)	18615	44321	12	12	56	10	9	41016
104	Mount Pleasant West (104)	29658	21969	8	9	59	10	13	61839
75	Church-Yonge Corridor (75)	31340	23044	4	15	61	10	10	56366
82	Niagara (82)	31180	10156	7	8	75	6	5	79441
84	Little Portugal (84)	15559	12859	9	11	62	8	10	66542
105	Lawrence Park North (105)	14607	6407	23	12	41	12	13	144963
97	Yonge-St.Clair (97)	12528	10708	10	8	48	12	23	80136
73	Moss Park (73)	20506	14753	8	11	62	11	9	52490
88	High Park North (88)	22162	11726	13	9	53	12	13	68116
95	Annex (95)	30526	10863	8	12	51	11	17	71053

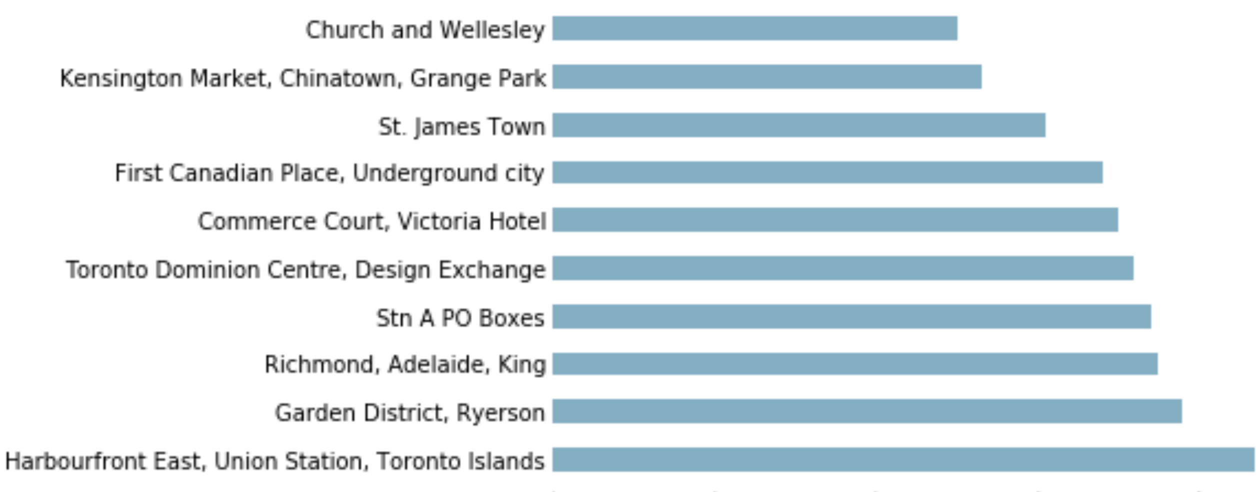
Also this project aimed to provide understanding on how popular venues are distributed in each neighbourhood. And to cluster the neighbourhood to understand where is best opportunity is for a newfound steakhouse to succeed.

Here is a map of all the neighbourhood clustered by venues (excluding restaurants) and superimposed onto choropleth map of Downtown Toronto. A heat-map of all venues are also added onto the map.



Choropleth shows neighbourhood with most weighted feature. And the heat-map shows popular venues excluding restaurants. This map suggests that the cluster in blue (Commerce) is best place to open a steakhouse.

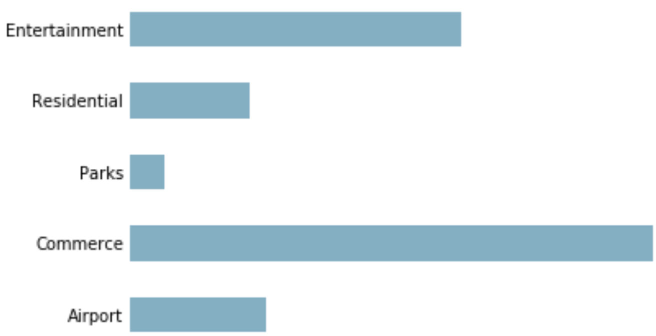
Here is top 10 neighbourhoods with most number of popular venues and a full list of all neighbourhood in downtown with venue count:



	Neighborhood	Venue_Count
0	Berczy Park	41
1	CN Tower, King and Spadina, Railway Lands, Har...	16
2	Central Bay Street	48
3	Christie	14
4	Church and Wellesley	50
5	Commerce Court, Victoria Hotel	70
6	First Canadian Place, Underground city	68
7	Garden District, Ryerson	78
8	Harbourfront East, Union Station, Toronto Islands	87
9	Kensington Market, Chinatown, Grange Park	53
10	Queen's Park, Ontario Provincial Government	27
11	Regent Park, Harbourfront	41
12	Richmond, Adelaide, King	75
13	Rosedale	4
14	St. James Town	61
15	St. James Town, Cabbagetown	36
16	Stn A PO Boxes	74
17	Toronto Dominion Centre, Design Exchange	72
18	University of Toronto, Harbord	27

According to cluster grouped Commerce cluster has the highest frequency of popular venues.

	Cluster Labels	venue per neighborhood	Cluster Names
0	0	16.000000	Airport
1	1	60.923077	Commerce
2	2	4.000000	Parks
3	3	14.000000	Residential
4	4	38.666667	Entertainment



5. Discussions

As mentioned before, Toronto is a big city with a population of 2.7 millions and a very high population density. The total number of measurements and population densities of the 140 borough in total can vary. As there is such a complexity, very different approaches can be tried in clustering and classification studies. Moreover, it is obvious that not every classification method can yield the same high quality results for this metropolitan.
I used the Kmeans algorithm as part of this clustering study. When I tested the Elbow method, I set the optimum k value to 5. For more detailed and accurate guidance, the data set can be expanded and the details of the neighbourhood or street can also be drilled.
I also performed data analysis through this information by adding the coordinates of districts and home sales price averages as static data on GitHub. In future studies, these data can also be accessed dynamically from specific platforms or packages.

I ended the study by visualising the data and clustering information on the Toronto map. In future studies, web or telephone applications can be carried out to direct investors.

6. Conclusion

Why choose open business in Toronto anyway?

- Capital of Ontario province and a major city in North America
- Toronto is sixth safest city
- Toronto along with Montreal are the top two best places to live in the world according to an index of city rankings compiled by The Economist
- Toronto has a population of 2.7M and monthly household income of CAD 65,829

As a result, people are turning to big cities to start a business or work. For this reason, people can achieve better outcomes through their access to the platforms where such information is provided. This project will help anyone who chooses to open a steakhouse tremendously. Not only for investors but also city managers can manage the city more regularly by using similar data analysis types or platforms.