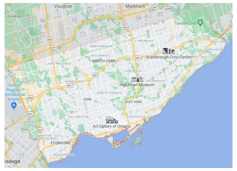
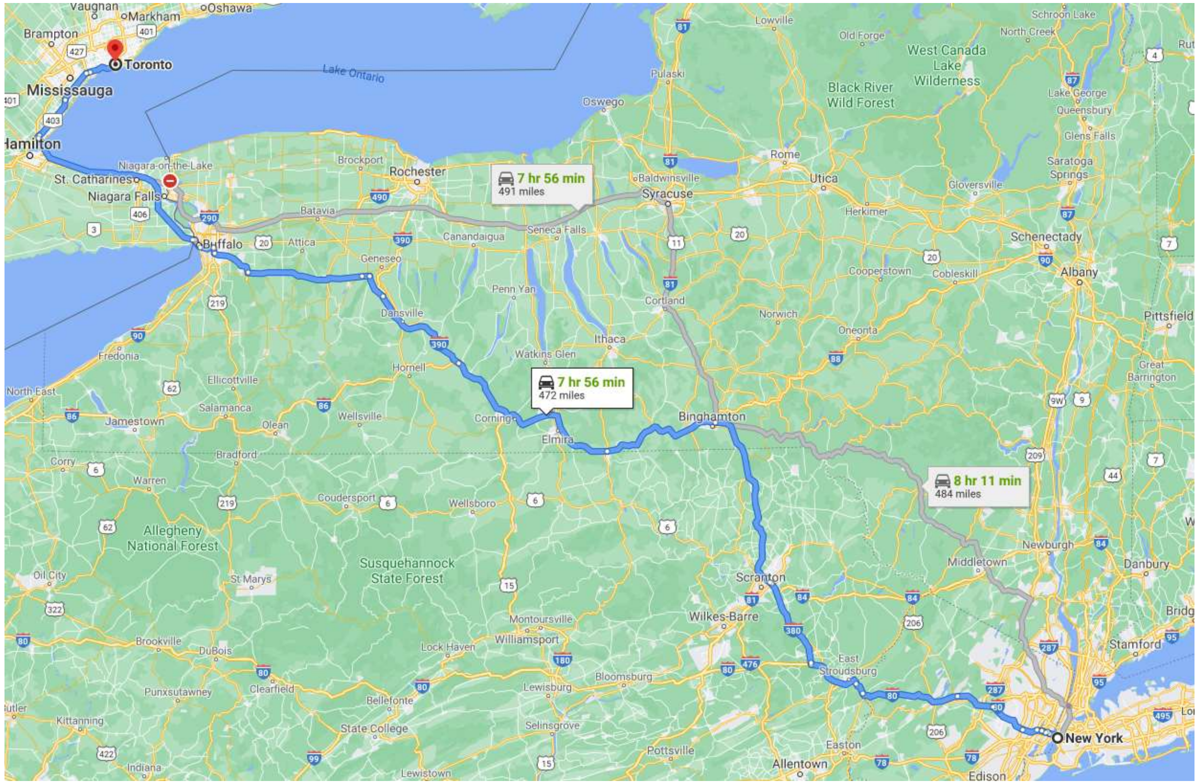
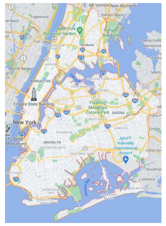
Background and business problem to solve







ABC is a successful house construction company in New York, wants to establish its busines in Toronto.

ABC employs a data scientist for 2 question:

- Are the Toronto neighborhoods similar as New York?
- What kind of houses the potential clients in Toronto most want?

Data Source for analysis

New York neighborhood data: https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DS0701EN-SkillsNetwork/labs/newyork_data.json

Toronto post code data: https://en.wikipedia.org/wiki/List_of_postal_codes_of_Canada:_M

Toronto Geospatial_data: http://cocl.us/Geospatial_data

Four Square geolocation data: FOURSQUARE

The Statistic Canada Census data: https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/download-telecharger/comp/page_dl-tc.cfm?Lang=E

This data is the 2016 census data. For each Post Code, there are 2247 lines of data to cover different aspects:

0. General (8 lines)
1. Population age distribution (26 lines)
2. Dwelling structure (28 lines)
3. Family structure (41 lines)
4. Knowledge on languages (561 lines)
5. Income (211 lines)
6. Language (263 lines)
7. Citizenship and migration status (482 line)

1619	8. Dwelling situation	Total - Private households by tenure - 25% sample data
1620		Owner
1621		Renter
1622		Band housing
1623		Total - Occupied private dwellings by condominium status - 25% sample data
1624		Condominium
1625		Not condominium
1626		Total - Occupied private dwellings by number of bedrooms - 25% sample data
1627		No bedrooms
1628		1 bedroom
1629		2 bedrooms
1630		3 bedrooms
1631		4 or more bedrooms
1632		Total - Occupied private dwellings by number of rooms - 25% sample data
1633		1 to 4 rooms
1634		5 rooms
1635		6 rooms
1636		7 rooms
1637		8 or more rooms
1638		Average number of rooms per dwelling
1639		Total - Private households by number of persons per room - 25% sample data
1640		One person or fewer per room
1641		More than 1 person per room
1642		Total - Private households by housing suitability - 25% sample data

The Toronto geojson data: Not used

Analysis Steps - I

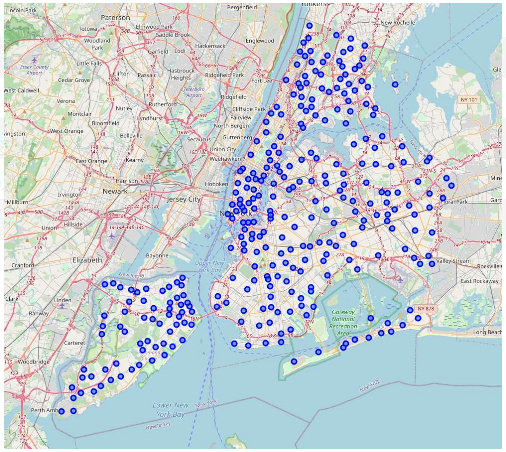
	Borough	Neighborhood	Latitude	Longitude
0	Bronx	Wakefield	40.894705	-73.847201
1	Bronx	Co-op City	40.874294	-73.829939
2	Bronx	Eastchester	40.887556	-73.827806
3	Bronx	Fieldston	40.895437	-73.905643
4	Bronx	Riverdale	40.890834	-73.912585

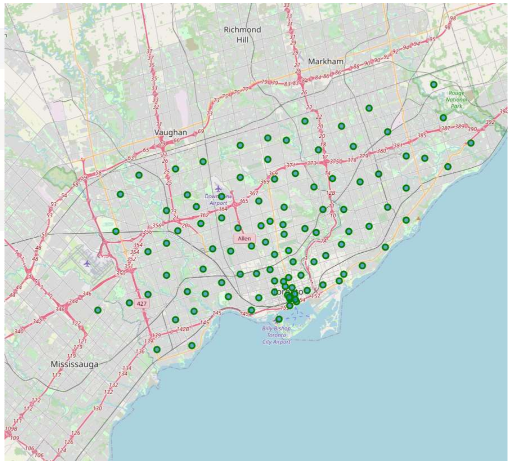
Postal Code	Borough	Neighbourhood
M3A	North York	Parkwoods
M4A	North York	Victoria Village
M5A	Downtown Toronto	Regent Park, Harbourfront
M6A	North York	Lawrence Manor, Lawrence Heights
M7A	Downtown Toronto	Queen's Park, Ontario Provincial Government

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

Retrieve and combined the data from different tables
Eventually link the key information in one table: Neighborhood – Latitude- Longitude

	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
...		...	...	...			
2113		43.628841	-79.520999	Islington Florist & Nursery			
2114		43.628841	-79.520999	Koala Tan Tanning Salon & Sunless Spa			
2115		43.628841	-79.520999	Once Upon A Child			
2116		43.628841	-79.520999	Kingsway Boxing Club			
2117		43.628841	-79.520999	Burrito Boyz			





Analysis Steps - II

New York

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Wakefield	40.894705	-73.847201	Lollipops Gelato	40.894123	-73.845892	Dessert Shop
1	Wakefield	40.894705	-73.847201	Rite Aid	40.896649	-73.844846	Pharmacy
2	Wakefield	40.894705	-73.847201	Walgreens	40.896528	-73.844700	Pharmacy
3	Wakefield	40.894705	-73.847201	Carvel Ice Cream	40.890487	-73.848568	Ice Cream Shop
4	Wakefield	40.894705	-73.847201	Dunkin'	40.890459	-73.849089	Donut Shop

(10045, 7)
There are 440 uniques categories.

Toronto

	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

(2112, 7)
There are 265 uniques categories.

Made Four Square queries

Check the most frequent venue categories in each neighborhood

----Allerton----

	venue	freq
0	Pizza Place	0.12
1	Deli / Bodega	0.08
2	Supermarket	0.08
3	Chinese Restaurant	0.08
4	Department Store	0.04

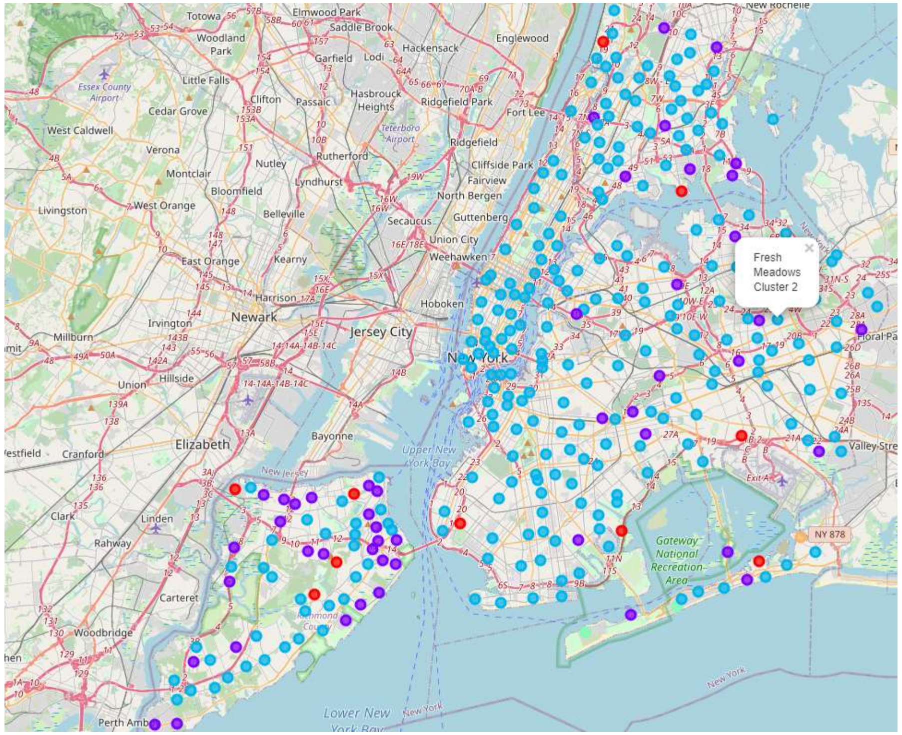
----Annadale----

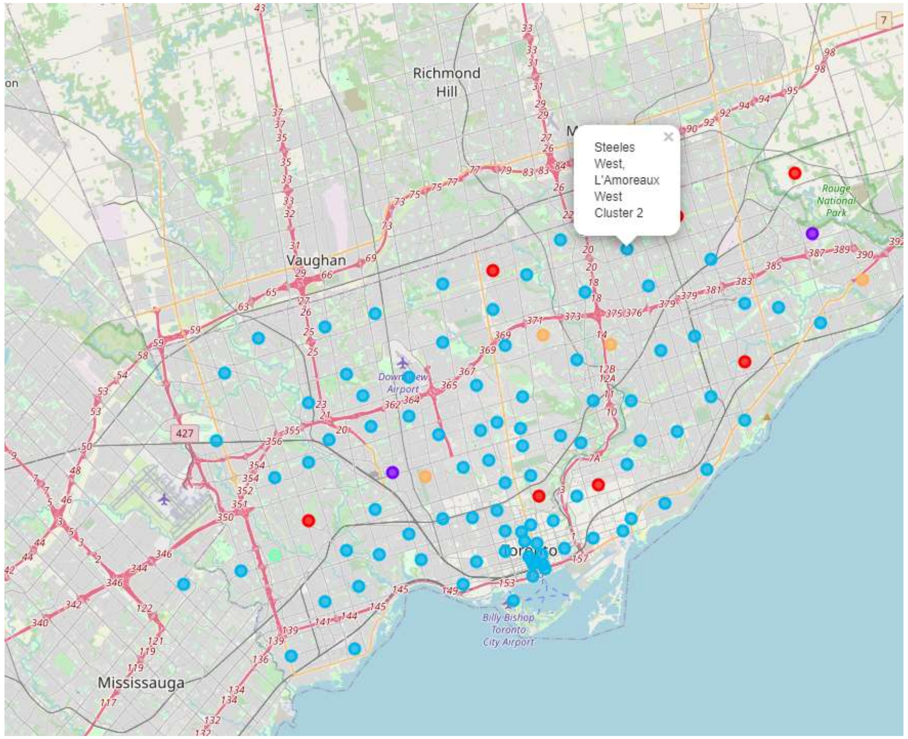
	venue	freq
0	Liquor Store	0.11
1	Diner	0.11
2	Train Station	0.11
3	Park	0.11
4	Pizza Place	0.11

----Arden Heights----

	venue	freq
0	Pharmacy	0.25
1	Coffee Shop	0.25
2	Bus Stop	0.25
3	Pizza Place	0.25
4	Outlet Store	0.00

Analysis Steps - III





Did K-Means clustering for New York and Toronto separately

Analysis Steps - IV

```
newyork_merged['Cluster Labels'].value_counts()
```

```
]:  2    245
    1     48
    0     10
    3      2
    4      1
    Name: Cluster Labels, dtype: int64
```

```
[44]: df_cluster = newyork_merged[(newyork_merged['Cluster Labels'] ==1)]
      df_cluster['1st Most Common Venue'].value_counts()
```

```
Out[44]: Pizza Place          37
         Italian Restaurant   23
         Deli / Bodega        22
         Coffee Shop          18
         Chinese Restaurant   13
                              ..
         Other Nightlife       1
         Mobile Phone Shop     1
         Dessert Shop          1
         Market                1
         Baseball Field        1
         Name: 1st Most Common Venue, Length: 79, dtype: int64
```

```
[42]: toronto_merged['Cluster Labels'].value_counts()
```

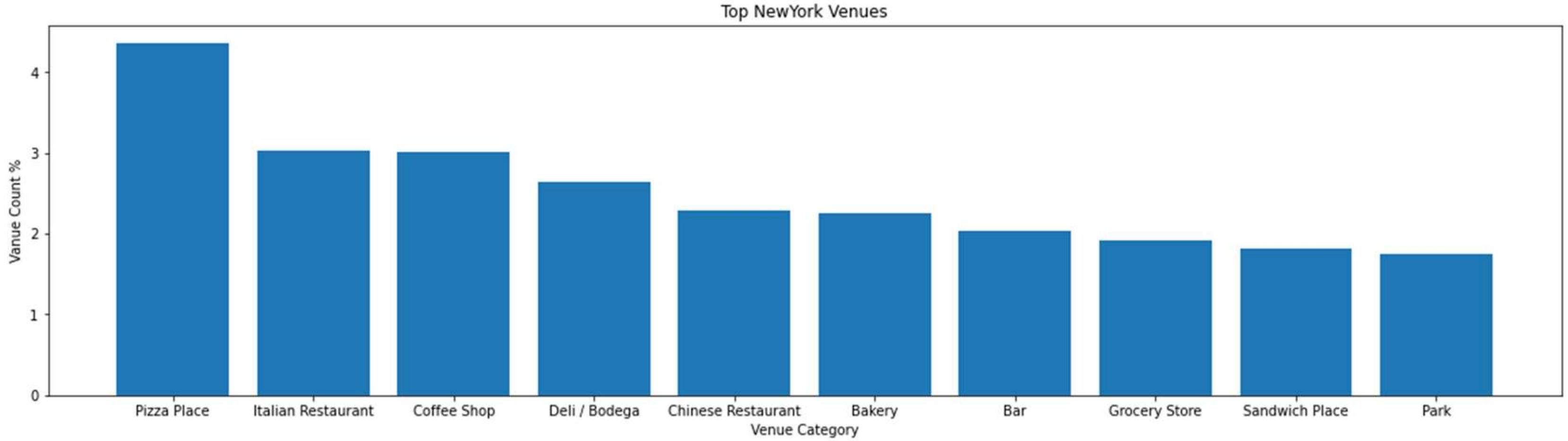
```
Out[42]: 1    87
         0    12
         2     2
         4     1
         3     1
         Name: Cluster Labels, dtype: int64
```

```
[45]: df_cluster = toronto_merged[(toronto_merged['Cluster Labels'] ==1)]
      df_cluster['1st Most Common Venue'].value_counts()
```

```
Out[45]: Coffee Shop                21
         Pizza Place                12
         Café                        7
         Grocery Store               6
         Pharmacy                    3
         Clothing Store              3
         Gym                         2

         Furniture / Home Store      2
         Bakery                      1
         Yoga Studio                 1
         Vietnamese Restaurant       1
         Airport Service             1
         Name: 1st Most Common Venue, dtype: int64
```

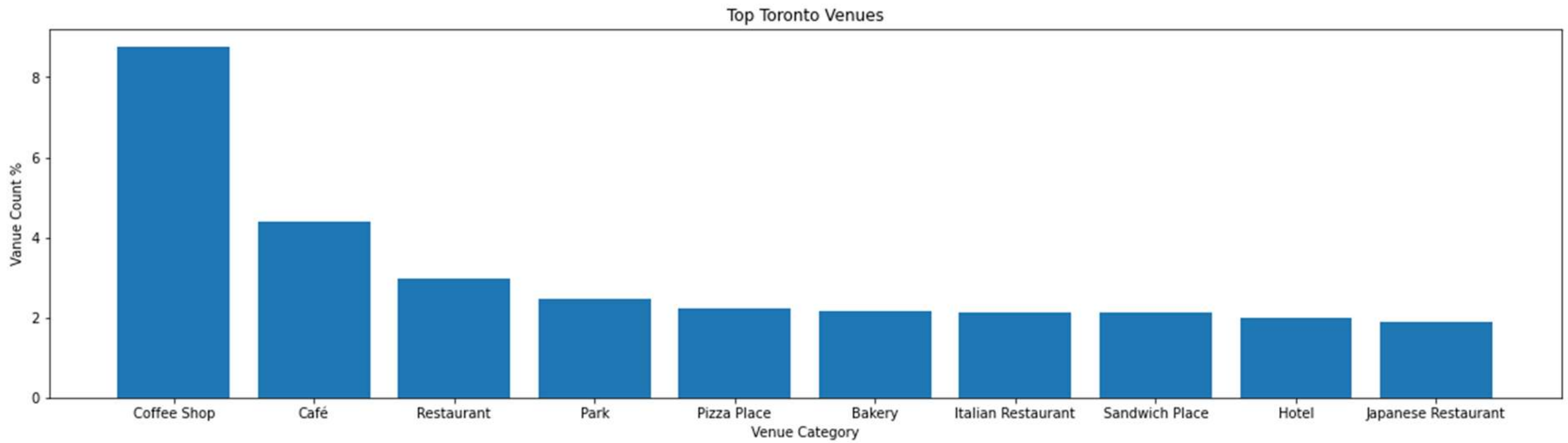
Checked the most popular clusters in New York and Toronto
Check the most popular venue categories in top1 cluster

Analysis Steps - V



Listed the top 10 most frequent venue types in New York and Toronto

This tells what venues are more common in New York, what venues are more common in Toronto



Analysis Steps - VI

Combined the Post Code – Neighborhood – Latitude – Longitude data with Statistics Canada data

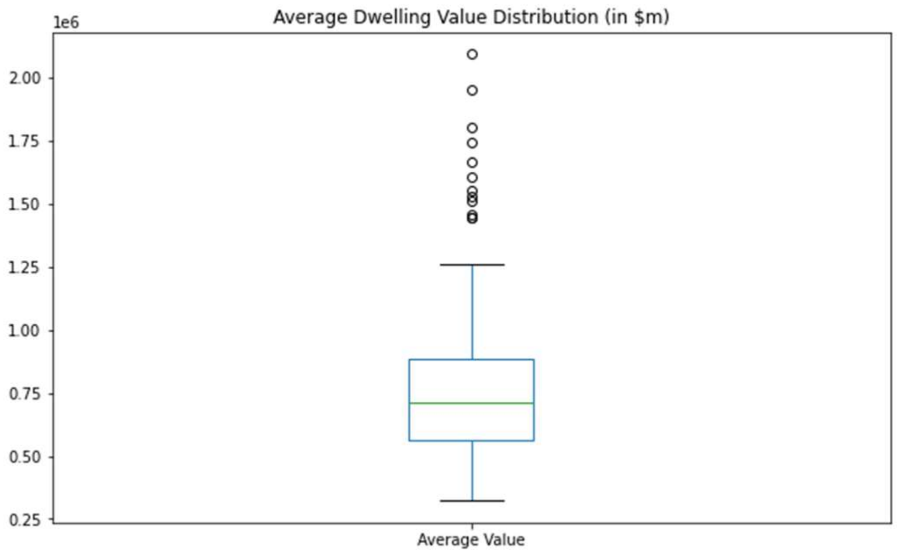
	Postal Code	Borough	Neighborhood	Latitude	Longitude	Average Rooms	Average Value
0	M3A	North York	Parkwoods	43.753259	-79.329656	5.3	786733.0
1	M4A	North York	Victoria Village	43.725882	-79.315572	4.7	560401.0
2	M5A	Downtown Toronto	Regent Park, Harbourfront	43.654260	-79.360636	3.5	573259.0
3	M6A	North York	Lawrence Manor, Lawrence Heights	43.718518	-79.464763	4.6	644259.0
4	M9A	Etobicoke	Islington Avenue, Humber Valley Village	43.667856	-79.532242	5.6	1089850.0
...	...	...	...	...	...	...	...
91	M4X	Downtown Toronto	St. James Town, Cabbagetown	43.667967	-79.367675	3.4	873003.0
92	M8X	Etobicoke	The Kingsway, Montgomery Road, Old Mill North	43.653654	-79.506944	6.4	1192475.0
93	M4Y	Downtown Toronto	Church and Wellesley	43.665860	-79.383160	3.2	501891.0
94	M8Y	Etobicoke	Old Mill South, King's Mill Park, Sunnylea, Hu...	43.636258	-79.498509	5.0	767225.0
95	M8Z	Etobicoke	Mimico NW, The Queensway West, South of Bloor,...	43.628841	-79.520999	6.2	762796.0

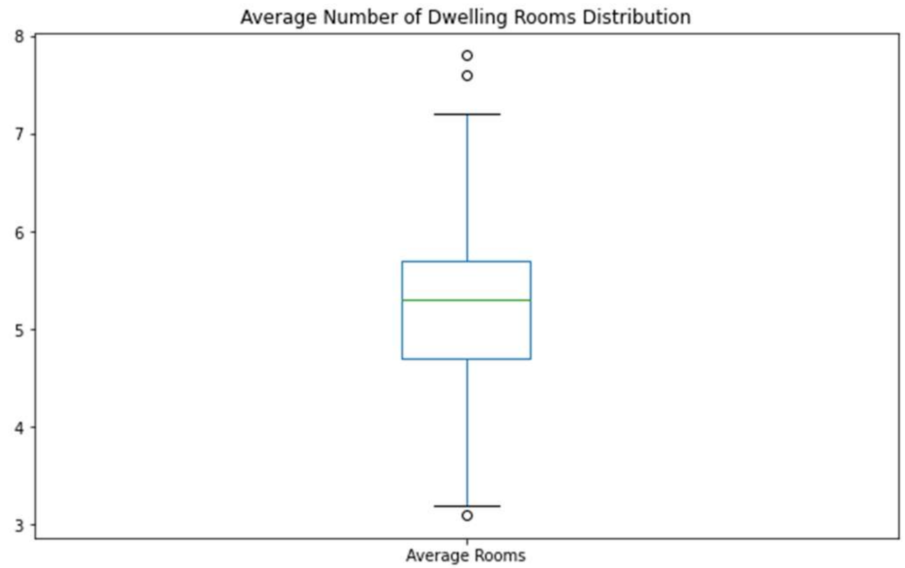
Analysis Steps - VII

```
[32]: tr_data['Average Value'].describe()

Out[32]: count    9.600000e+01
         mean     8.069142e+05
         std      3.701061e+05
         min      3.245700e+05
         25%      5.597500e+05
         50%      7.121075e+05
         75%      8.859228e+05
         max      2.090328e+06
         Name: Average Value, dtype: float64
```

```
[33]: tr_data['Average Rooms'].describe()

Out[33]: count    96.000000
         mean      5.167708
         std       1.001525
         min       3.100000
         25%       4.700000
         50%       5.300000
         75%       5.700000
         max       7.800000
         Name: Average Rooms, dtype: float64
```

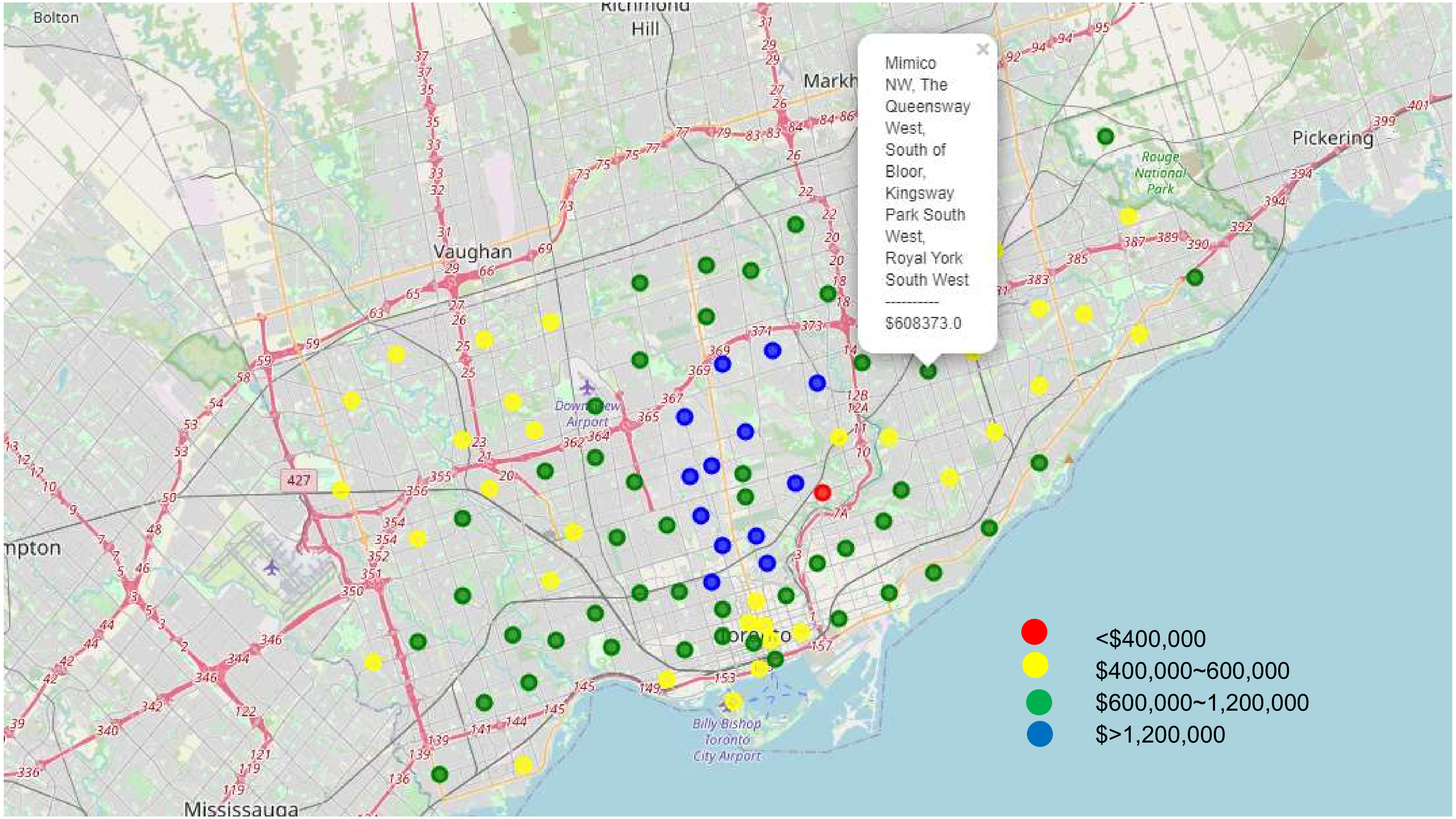
Get the statistics on "Average Dwelling Value" and "Average number of Rooms"





Analysis Steps - VIII

Illustrate “Average Value” on the map



Analysis Steps - IX

Illustrate “Average Rooms” on the map