Comparison of Toronto Neighbourhoods as Rental Locations

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Researching city neighbourhoods is important to recent arrivals

* Discovering rental value proposition of city neighbourhoods is important to newly arrived people
* Key considerations are average rent for the type and size of housing they want, distance/ commute time from their work location
* Other important factors would be neighbourhood amenities for shopping, healthcare, recreation, education, etc.

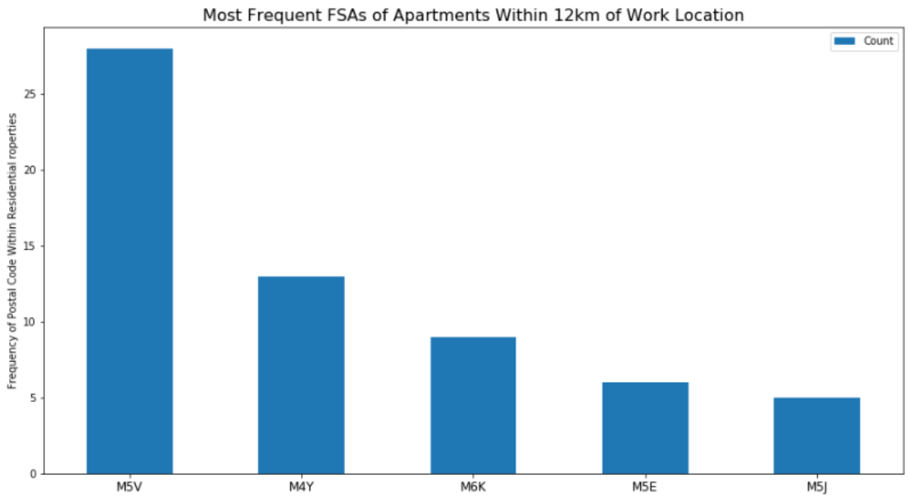
Data acquisition and cleaning

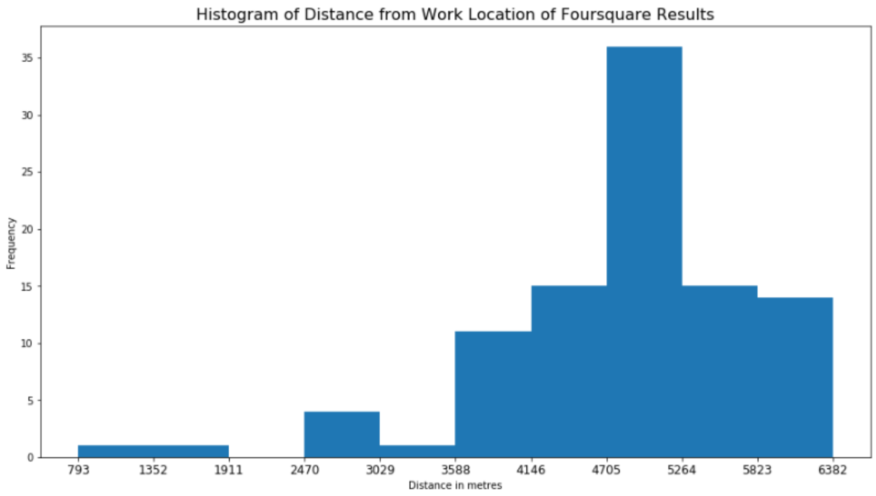
- Name, address, location coordinates, distance and postal code of residential apartments within '*x*' km of work location, from Foursquare location database (100 rows and 8 features)
- Average rent for apartments of different configurations by Toronto neighbourhood, from CMHC, Canada's national housing agency (134 rows and 11 features)
  - Irrelevant rows and columns were dropped
  - Compound neighbourhood names were separated, cleaned up
- Forward Sortation Areas (FSA) (initial 3 characters of postal codes), were extracted
- Final dataset for clustering had 21 unique FSAs, average rent for a 2BR apartment by FSA, average distance from work location, number of apartment buildings by FSA, and FSA location coordinates

Key Data Preparation Challenge

* Toronto FSAs and official neighbourhoods are not the same and do not map one-on-one. They are useful proxies for one another, however
  * An FSA may overlap adjacent neighbourhoods and vice-versa
  * Rent statistics maintained by CMHC are aligned with neighbourhoods
  * Location data providers like Foursquare and OpenStreetMap provide postal codes (FSAs)
    * 45 of the 100 residential buildings within 12km of work location, provided by Foursquare, did not have any postal code (FSA) tagged
    * Missing FSAs had to be fetched by providing name and address information to OpenStreetMap database through Nominatim geocoder
  * Neighbourhood names in CMHC table are often aggregates of adjacent neighbourhoods and do not line up squarely with official neighbourhood names
    * Parsed neighbourhood name components were passed on to OpenStreetMap geocoder service to retrieve associated postal codes
  * FSAs are the key to linking rent data table and residential properties data table

Exploratory Data Analysis - I





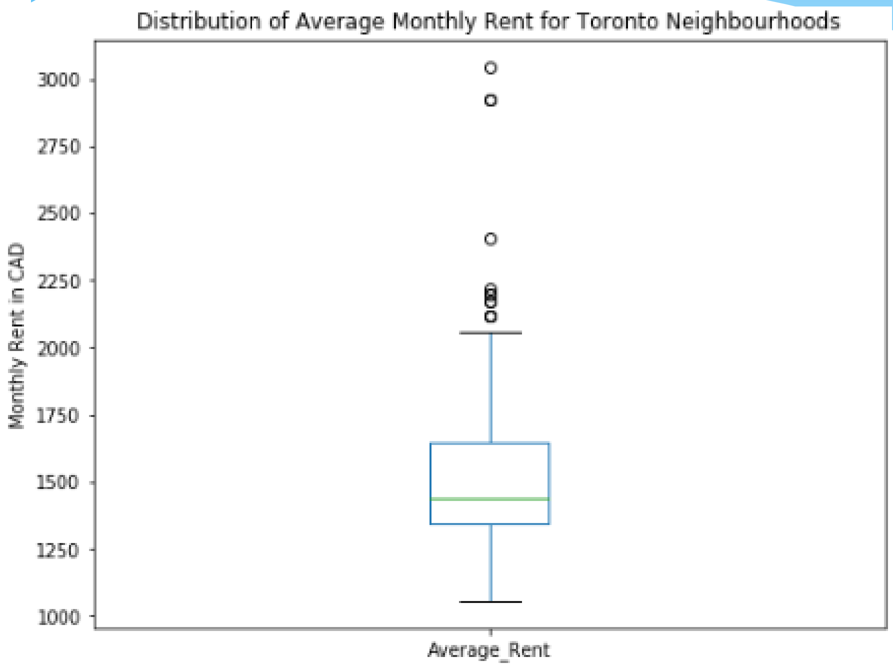
Of 26 FSAs associated with 98 residential buildings,

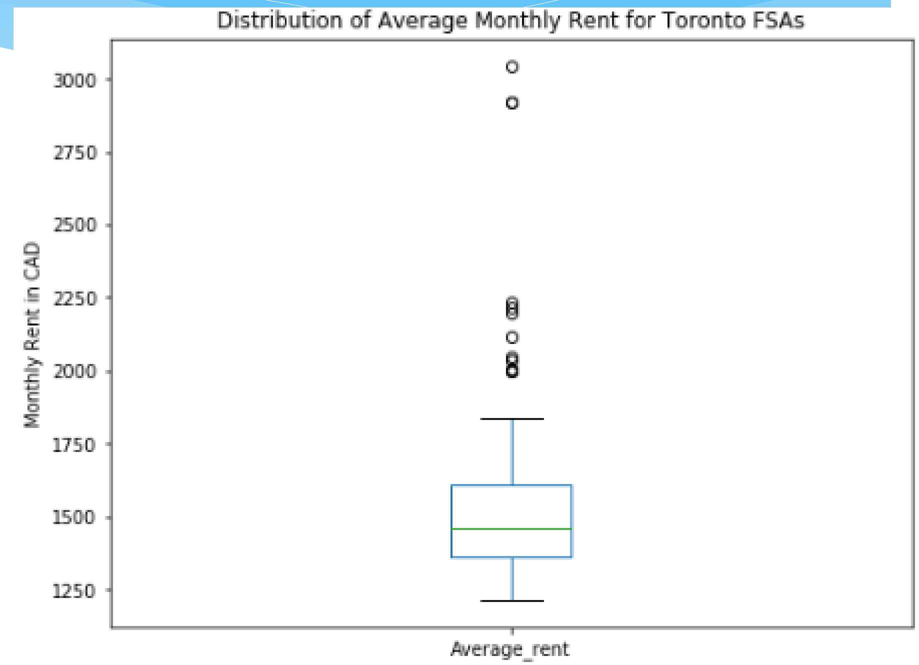
- M5V is heavily represented (28 times)
- 10 FSAs occur only once, 8 occur twice

Foursquare returns maximum 100 venues:

- 100 residential buildings were found within a radius of 6382 metres

Exploratory Data Analysis - II





Rent figures as they exist in CMHC table for 168 neighbourhood names

- Range is from CAD 1,055 to CAD 3,047
- Median = CAD 1,437, Mean = CAD 1,555

Rent figures for 90 FSAs: FSA average rent is mean of rent of neighbourhoods tagged to an FSA

- Range is from CAD 1,213 to CAD 3,047
- Median = CAD 1,460, Mean = CAD 1,573

Final Dataset for Unsupervised ML Modeling

	Postal Code	Neigh_Latitude	Neigh_Longitude	Number of Properties	Average_rent	DistanceFromOffice_y
0	M6P	43.661608	-79.464763	2	2005.000000	1202.000000
1	M6K	43.636847	-79.428191	9	1509.428571	3754.444444
2	M5T	43.653206	-79.400049	2	2004.000000	3837.500000
3	M5V	43.636039	-79.397400	28	2920.000000	4749.392857

- 21 FSAs representing 90 apartment buildings within 12 km of work location, for which average distance and average monthly rent could be mapped
- Average rent for an FSA is the mean of monthly rent figures of all CMHC neighbourhoods partially or fully tagged to that FSA
- Average distance is the mean of distances of all residential apartment buildings tagged to an FSA
- Average rent and average distance from work will be the two features to be used for cluster modeling of FSAs

K-Means clustering for Toronto FSAs

- K-means is an efficient clustering algorithm and quickly converges to a local optimum
- Optimum number of clusters '*k*' can be determined by examining elbow point of a plot of inertia (sum of squared distances of samples to their closest cluster centre) vs. '*k*'
- Setting number of iterations with random centroid initializations to high (>20) mitigates inherent variance in results generated by k-means algorithm
- Both features - Average rent and Distance from work – are standardized
- Our modeling penalizes average rent values more compared to distance from work. Two ways to model this:
  - Assign 80:20 weights to values of average rent and distance from work ✓
  - Derive a composite score as:

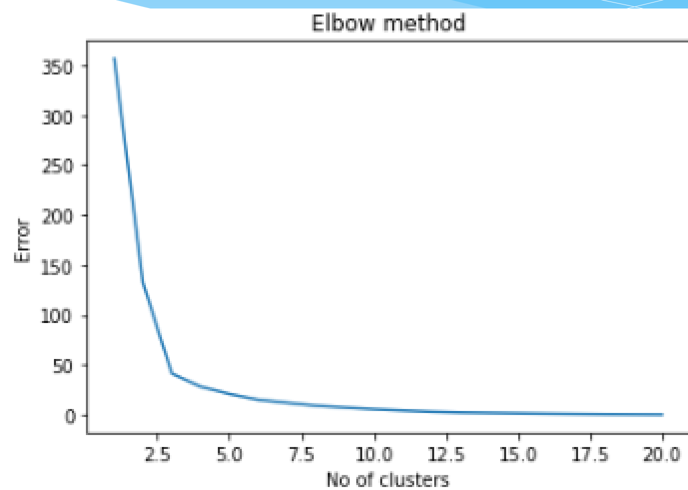
*Composite Score = 0.8 * Standardized Rent Value + 0.2 * Standardized Distance*

and then use a univariate grouping algorithm like Jenks optimization

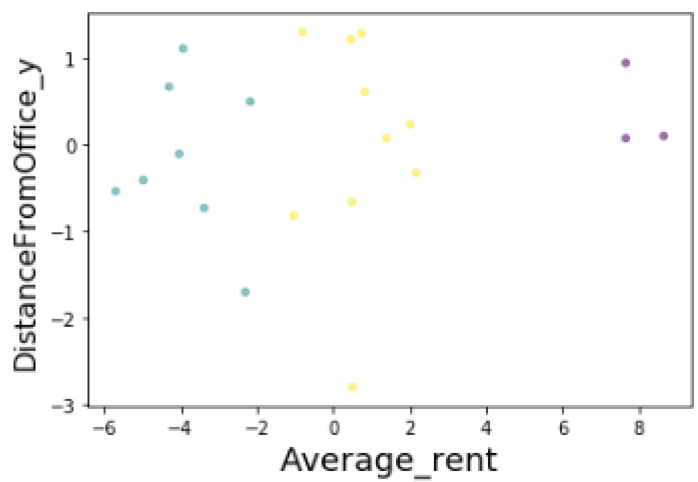
K-Means Results

	Postal Code	Average_rent	DistanceFromOffice_y	Cluster Labels
0	M6P	2005.000000	1202.000000	0
1	M6K	1509.428571	3754.444444	1
2	M5T	2004.000000	3837.500000	0
3	M5V	2920.000000	4749.392857	2
4	M4W	2118.000000	4751.000000	0
5	M5S	3047.000000	4782.000000	2
6	M4Y	1664.000000	5272.076923	1
7	M5G	2198.000000	4946.500000	0
8	M5B	2046.500000	5413.000000	0
9	M5J	2920.000000	5824.800000	2
10	M5E	1439.000000	6030.666667	1
11	M4S	2035.000000	6245.000000	0
12	M5A	1838.000000	6265.500000	0
13	M6R	1647.500000	2560.000000	1
14	M5P	1809.500000	3644.000000	0
15	M8V	1213.000000	3992.000000	1
16	M6L	1305.666667	4151.000000	1

Sample observations with 3 cluster labels (unstandardized)



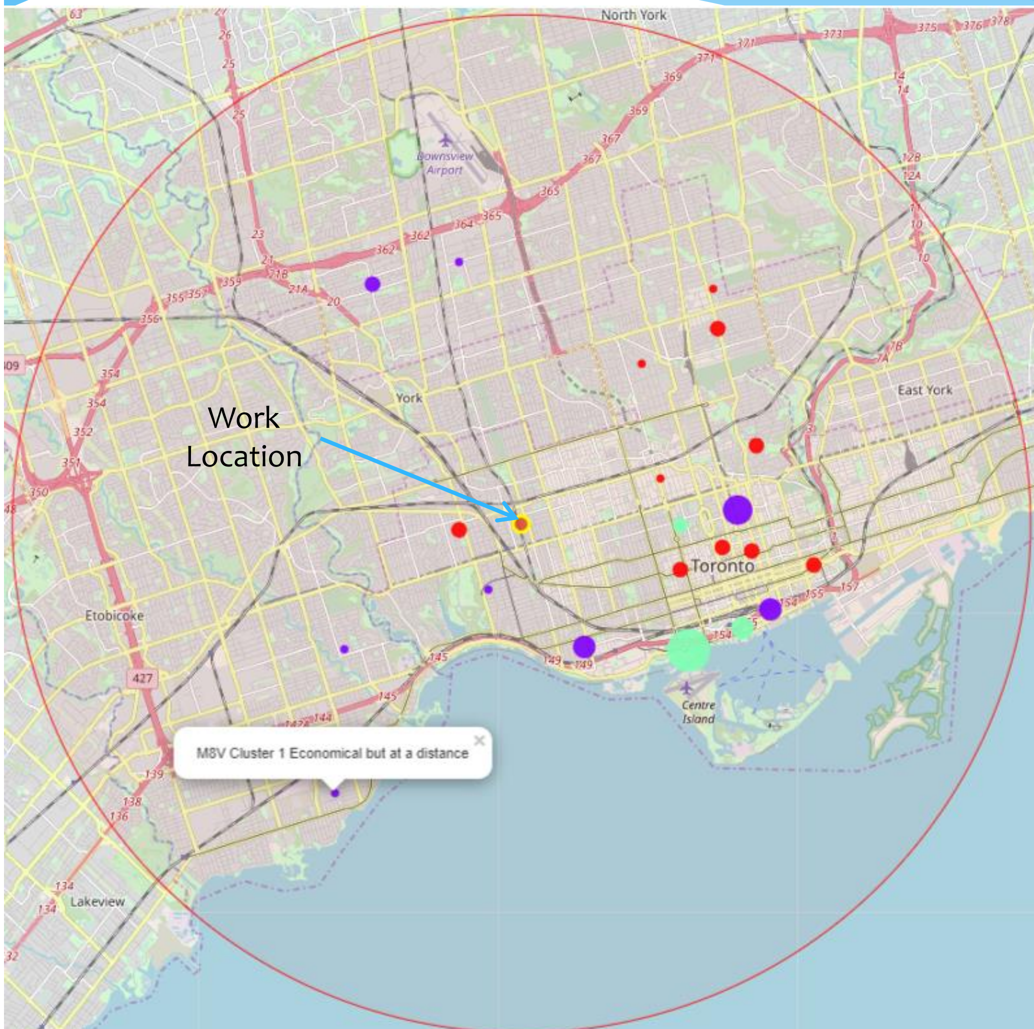
'Elbow' (sharp inflexion point) lies at a value of k=3



Clusters with standardized features:

- *Cluster 2*
- *Cluster 1*
- *Cluster 0*

Cluster Visualization on Toronto Map



Cluster Description	Circle Marker Colour
'Downtown Experience at a Steep Price' (2)	
'Mid-priced Experience in Popular Neighbourhoods' (0)	
'Economical but at some distance' (1)	

Conclusion

- **Aim:** to group Toronto neighbourhoods/ FSAs based on average rent for a 2BR apartment and distance from the target user's work location in Toronto
- **Modeling**: unsupervised learning through k-means clustering. Greater weightage assigned to average rent feature in forming clusters
- **Accuracy** of the clusters is heavily dependent upon the reliability of postal code mappings to venues in location data providers like Foursquare and OpenStreetMap
- **Improvement** avenues: include more data related to the attractiveness of a neighbourhood, e.g. easy neighbourhood amenities for shopping, recreation, etc., number of available residential units, etc.