Analysis of Top Restaurants and Auto Thefts in Toronto, Canada

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February 23 2021

1.0 Introduction

When travelling to new cities it is helpful to know where the good restaurants are located. In addition, it can be useful to have an understanding of the crime in the area, so as to avoid parking in those neighbourhoods.

The goal of this assignment is to find a top-rated restaurant in a Toronto neighbourhood with a low number of auto thefts. Neighbourhoods will be divided into three clusters based on common auto theft characteristics. Then each restaurant will be scanned within a 1/2 KM radius for auto thefts in the area. This will ensure to consider the surrounding neighbourhood in case there is a need to park slightly further away.

This problem would be of interest to tourists who are new to the city and would like to find a good place to eat while avoiding high crime areas. Tourist sites may also be interested as they can generate recommendations to indicate crime levels. Finally, potential restaurant owners may also want to find low crime neighbourhoods when researching where to open a new restaurant.

2.0 Data

A list of Toronto boroughs, neighbourhoods and postal codes will be web scrapped from Wikipedia. These postal codes will then be converted into geographical information (latitude and longitude). This process is called geocoding, which is the computational process of transforming a physical address description to a location on the earth's surface. Geocoder will be the python library used to do this. It is a simple and consistent geocoding library that can deal with multiple different geocoding providers. The provider will be ArcGIS World Geocoding Service. It finds addresses and places in all supported countries from a single endpoint. The geographical information returned from the Wikipedia postal codes will then be compared with the centroids and neighbourhood boundaries made available by the City of Toronto[1].

Foursquare City Guide, commonly known as Foursquare, will be used to determine the locations of all the top-rated restaurants in Toronto. Foursquare is a technology company that has built a large dataset of location data that is currently the most comprehensive available. Many popular services like Apple Maps, Uber, Snapchat, Twitter and many others, including over 100,000 developers, use it for its accuracy.

Two datasets made available by the Toronto Police Services containing auto theft locations and information on neighbourhood crime rates will be examined. The first dataset is called the Auto Theft dataset[2], which is a subset of the Major Crime Indicators (MCI) dataset. The dataset contains the closest intersection to where each auto theft occurred, between 2014 and 2019, as well as the neighbourhood, the time and date of the theft occurrence and many other attributes. The second dataset that will be used is the Neighbourhood Crime Rates Boundary File[3]. This dataset contains various crime statistics for each neighbourhood in Toronto.

3.0 Methodology

The following section will outline the steps taken in processing the data. The first part discusses how the neighbourhood locations are determined, then it reviews the auto theft datasets and neighbourhood clustering, then filters for all restaurants in the venue dataset.

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[1] https://open.toronto.ca/dataset/neighbourhoods/

[2] https://data.torontopolice.on.ca/datasets/auto-theft-2014-to-2019

[3] https://data.torontopolice.on.ca/datasets/neighbourhood-crime-rates-boundary-file-

The last part explains how the top restaurants in low-risk neighbourhoods are determined.

3.1 Neighbourhood Locations

A list of Toronto postal codes has been web scrapped from Wikipedia, parsing the HTML using BeautifulSoup. This returned 180 unique rows of postal codes, however, Wikipedia has several boroughs and neighbourhoods that are unassigned.

Postal Code	Borough	Neighbourhood
M1A	Not assigned	Not assigned
M2A	Not assigned	Not assigned
M3A	North York	Parkwoods
M4A	North York	Victoria Village
M5A	Downtown Toronto	Regent Park, Harbourfront

Dropping the unassigned neighbourhoods and removing the Borough column leaves 103 rows of unique postal codes. The postal codes are then passed through ArcGIS using Geocoder and then merged back into the postal code data frame.

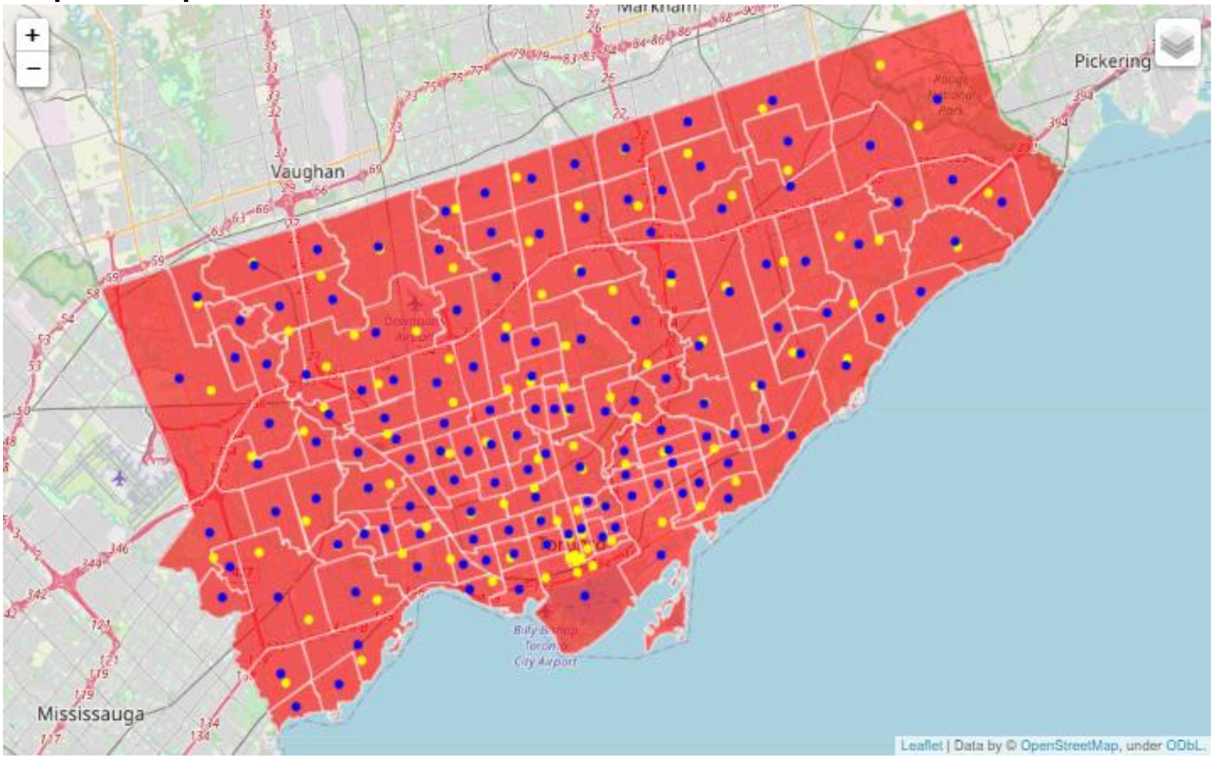
Postal Code	Neighbourhood	Latitude	Longitude
M3A	Parkwoods	43.75245	-79.32991
M4A	Victoria Village	43.73057	-79.31306
M5A	Regent Park, Harbourfront	43.65512	-79.36264
M6A	Lawrence Manor, Lawrence Heights	43.72327	-79.45042
M7A	Queen's Park, Ontario Provincial Government	43.66253	-79.39188

There are 103 postal codes in 99 neighbourhoods available on Wikipedia. However, according to the City of Toronto, there are 140 neighbourhoods[4]. Due to this discrepancy, a comparison is made using the geo-coordinates from Wikipedia and the centroids available from the actual boundary file provided by the City of Toronto.

[4] https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/neighbourhood-profiles/

The map below indicates that the Wikipedia points, marked in yellow, do not appear to be accurate when compared with the centroids, marked in blue. The centroids will instead be used to mark the neighbourhoods going forward.

Map 1. Wikipedia versus centroids



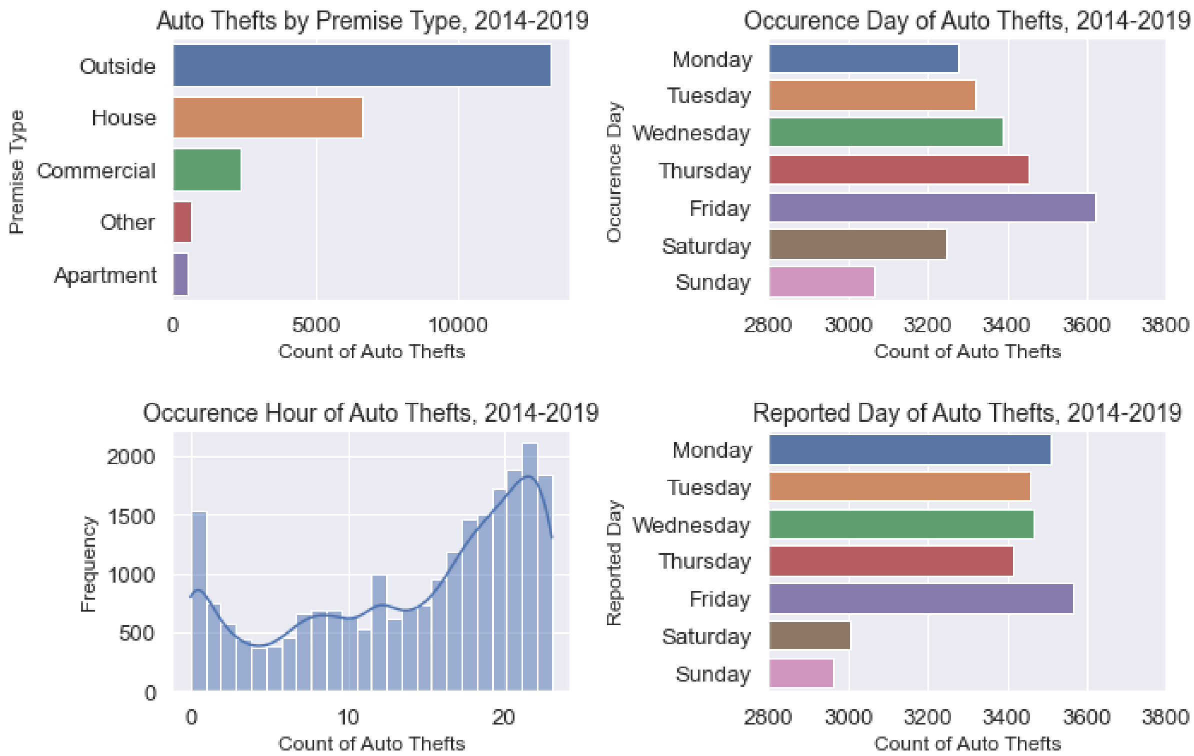
3.2 Auto Thefts

The next step is to load the auto theft data that is made publicly available by the Toronto Police. A total auto theft count per location is calculated based on the number of unique longitude and latitude codes. There are a total of 23,380 auto thefts that occurred from 2014 to 2019 across 9,016 unique locations.

On inspection, there are 315 unique auto theft locations that have multiple neighbourhoods assigned to them. This could be possible as the auto theft locations reported may fall on the neighbourhood boundaries. For this analysis, the duplicates will be reclassified to be based on the highest frequency of the neighbourhoods reported for each location. Where there are duplicate neighbourhoods reported with only single cases, then the first neighbourhood in the list will be chosen. This process will ensure to assign a single neighbourhood to each auto theft location. There are also three cases where the occurrence day is missing. The highest frequency day is used as an estimate.

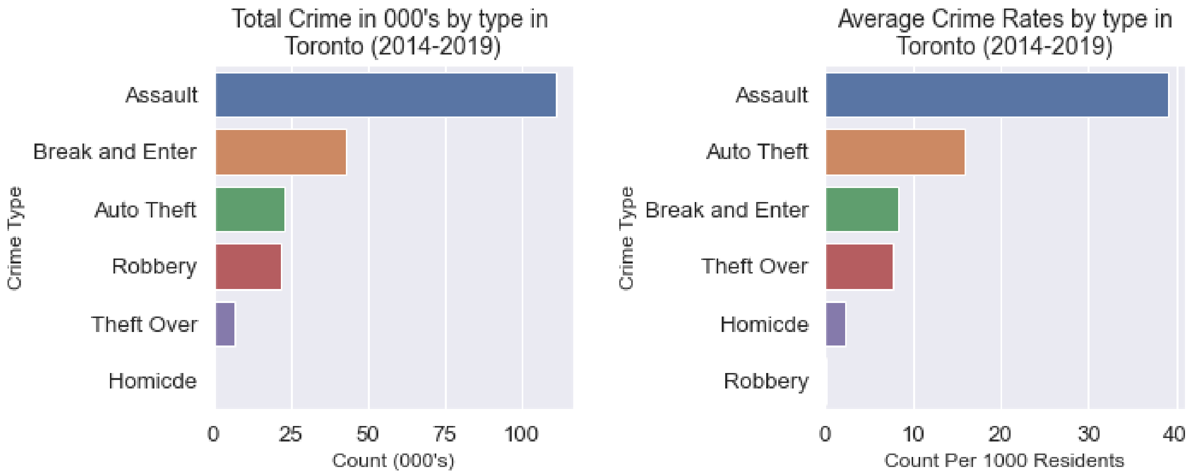
The majority of auto thefts in Toronto occur on Friday evenings, peaking at around 10:00 PM, and occur away from a person's place of residence. It is interesting to see a steady increase in auto thefts as the evening progresses and then starts to decline in the early mornings.

Figure 1. Total Auto Thefts in Toronto between 2014 to 2019



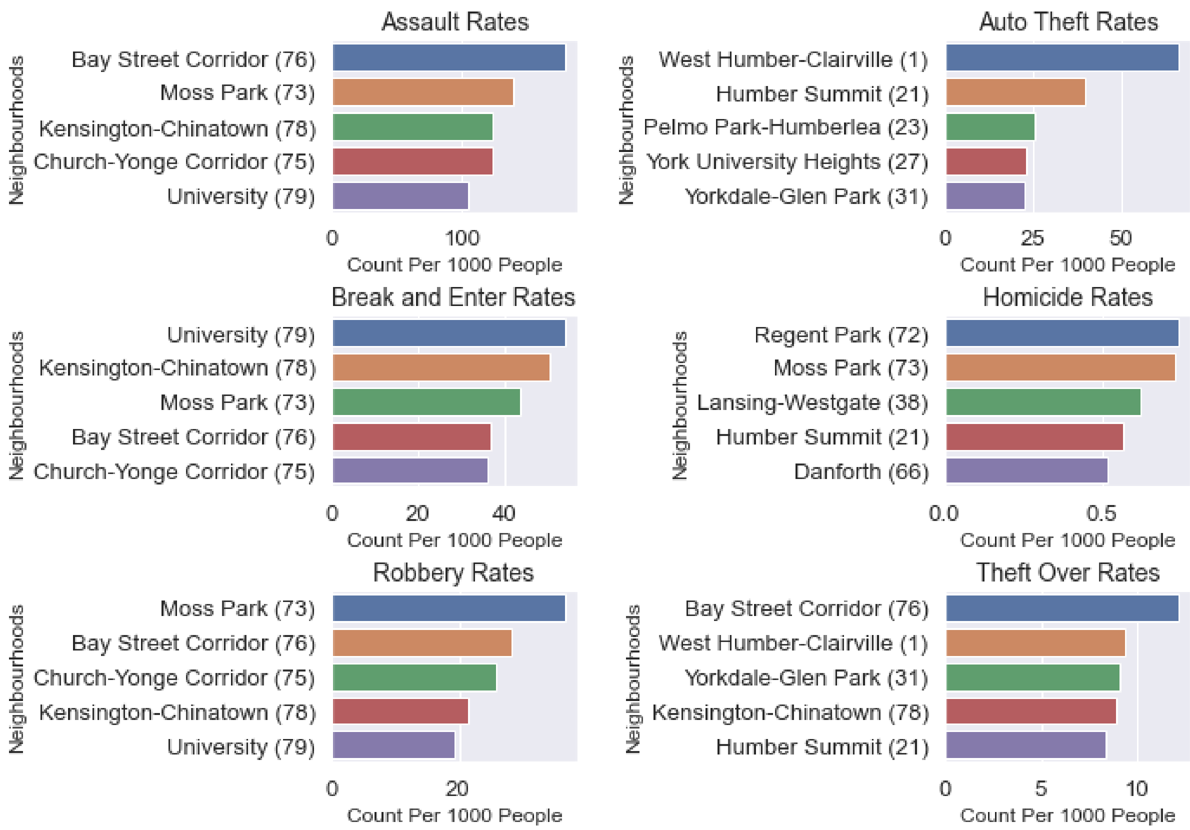
The second dataset provides neighbourhood crime statistics for each year between 2014 and 2019. The total number of crimes for each type are aggregated over all years. Assault is the most common crime in Toronto. When looking at the average crime rates per 1000 residents, then auto thefts come up to the second-highest.

Figure 2. Total Crime and Crime Rates in Toronto between 2014 to 2019



The below figure provides the crime rates per 1000 residents in each neighbourhood. The total number of crimes by category are aggregated across all years. West Humber-Clairville neighbourhood has the highest rate of auto thefts. Bay Street Corridor has the highest assault and theft rates, University and Kensington-Chinatown are high on break and enter rates, Regent Park and Moss Park are top for homicide rates, and Moss Park has high robbery rates.

Figure 3. Total Crime Crime Rates by Neighbourhood between 2014 to 2019



3.3 Clustering

Using selected features of auto thefts for each neighbourhood, the neighbourhoods will be clustered into three groups using K-Means clustering, an unsupervised machine learning algorithm. K-Means is a type of partitioning clustering that divides the data into “k” non-overlapping subsets based on common characteristics. The best “k” is determined using the elbow method.

The first step is to build the data frame in a way that is required for clustering. The following features are selected, based on each auto theft location and grouped by neighbourhood: the premise type, occurrence day, and occurrence hour. The occurrence hour is converted into four ranges: early morning, morning, afternoon and evening. All categorical features are converted into indicator variables and then the counts are aggregated by neighbourhood, giving the number of auto thefts by feature. The total number of auto thefts by neighbourhood is also added to the data frame. A sample of the features is shown below.

	Agincourt North (129)	Agincourt South-Malvern West (128)	Alderwood (20)	Annex (95)	Banbury-Don Mills (42)
Apartment	3	3	0	2	3
Commercial	6	45	14	22	18
House	94	42	22	14	38
Other	5	9	3	1	5
Outside	59	110	58	88	65
Monday	27	36	12	18	19
Tuesday	21	41	13	16	15
Wednesday	25	34	10	23	25
Thursday	28	30	13	23	19
Friday	25	27	13	15	18
Saturday	20	26	21	16	23

The features are then centred and scaled based on their mean and standard deviation. Standardization is a common requirement for many machine learning estimators.

```
# feature scaling
X = df_rest_crime_final.values[:,1:-2] # excludes neighbourhoods & locations
X = np.nan_to_num(X)
scaled_features = StandardScaler().fit_transform(X)
scaled_features
```

```
array([[-0.18727774, -0.18341701,  0.92849548, ...,  0.19157175,
        -0.11062765,  0.05249939],
       [-0.18727774,  0.73931743, -0.10950315, ..., -0.09666087,
         0.78204502,  0.25295162],
       [-0.97384425, -0.07796164, -0.5087334 , ..., -0.42812838,
        -0.28916218, -0.33408704],
```

K-Means clustering is an iterative process. The elbow method is used to help determine the best “k”. This is done by running a range of different “k” values and storing the inertia. The inertia is the sum of squared errors (SSE) of each data point to its closest cluster centre. If all data points are tightly congregated around their allocated centroid, then the SSE will be low — otherwise, it will be high.

```
kmeans_kwargs = {
                  "init": "random",
                  "n_init": 10,
                  "max_iter": 300,
                  "random_state": 42,
                    }

# A list holds the SSE values for each k
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
    kmeans.fit(scaled_features)
    sse.append(kmeans.inertia_)
```

The best “k” is selected at the “elbow” point, after which the inertia starts decreasing in a linear fashion. The below graph provides a visual of the generated SSE and the cluster number. The best “k” is determined to be based on three clusters.

Figure 4. The Elbow Method using Inertia

This can also be verified using the KneeLocator function in Python.

In [170]:

```python
# Auto detect best number of clusters
kl = KneeLocator(
 range(1, 11), sse, curve="convex", direction="decreasing"
)

kclusters = kl.elbow
kclusters
```

Out[170]: 3

The cluster labels are then inserted back into the original data frame and the average number of auto thefts are generated by feature.

Table 1. Statistics of crimes by cluster and feature

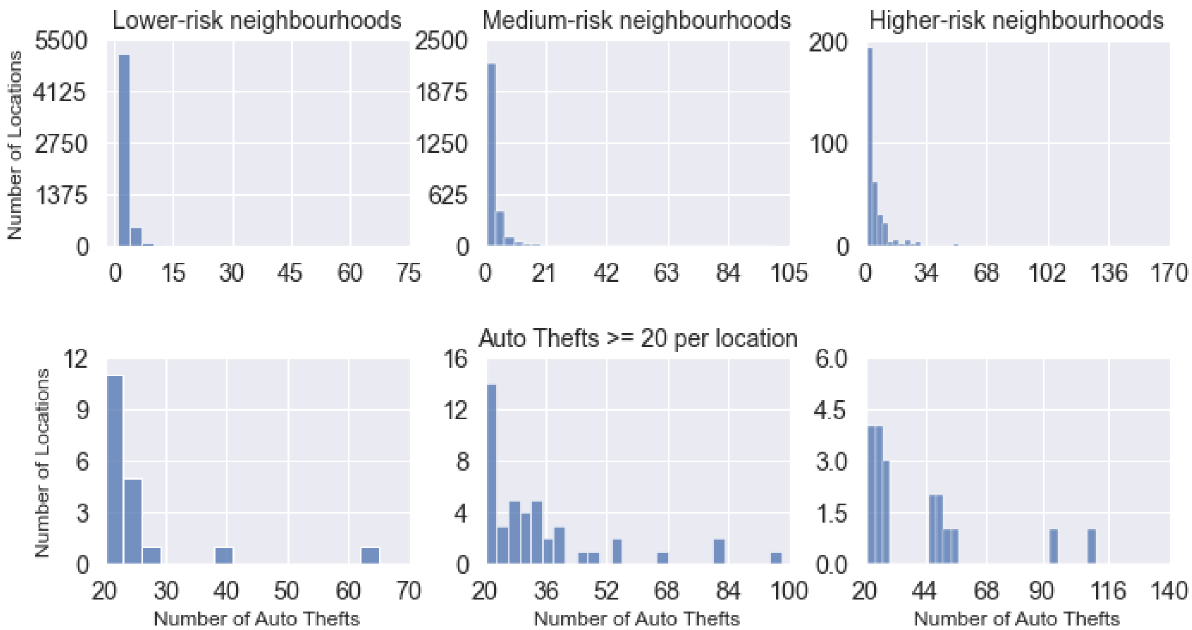
	Low-Risk	Medium-Risk	High-Risk
Apartment	3	8	12
Commercial	7	45	362
House	34	92	405
Other	3	9	50
Outside	59	197	1415
Friday	16	55	375
Monday	15	48	300
Saturday	14	50	352
Sunday	14	46	265
Thursday	16	50	305
Tuesday	15	51	309
Wednesday	15	51	338
Afternoon	25	87	551
Early Morning	20	67	503
Evening	44	130	725
Morning	18	67	465
Auto Thefts	106	351	2244
Neighbourhoods (#)	113	26	1
Total Thefts (#)	12010	9126	2244
Unique Locations (#)	5815	2863	338
Auto-theft Density	2	3	7

It is clear from the above table that the first cluster, containing 113 neighbourhoods, has a lower number of auto thefts on average across the various features than the other clusters. The clusters are appropriately renamed as low-, medium- and high-risk clusters accordingly. The high-risk cluster is based on a single neighbourhood and will be looked at closer on its own later.

There are a total of 12,010 auto thefts in low-risk neighbourhoods, across 5,815 unique auto theft locations, with an auto theft density of 2.1 thefts per location. The medium-risk neighbourhoods have a total of 9,126 auto thefts across 2,863 unique locations, with an auto theft density of 3.2 thefts per location. Finally, the high-risk cluster has 2,244 auto thefts in 338 locations, with an auto theft density of 6.6 thefts per location.

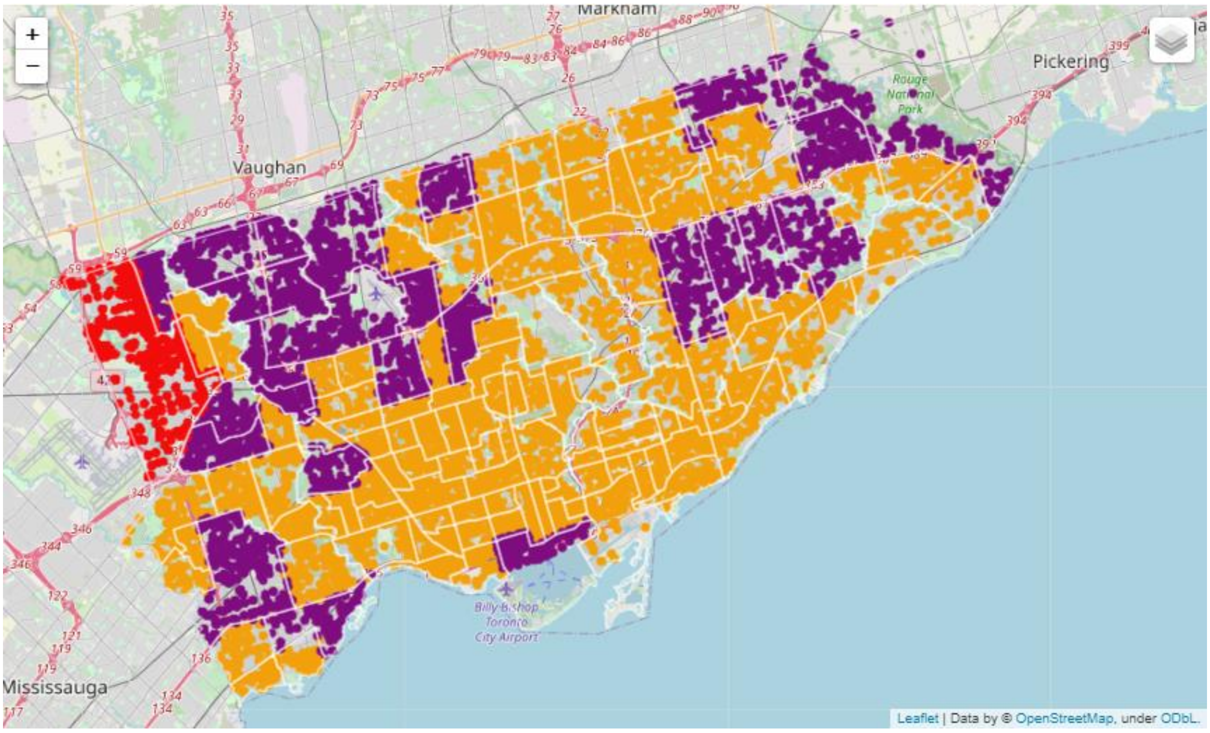
The majority of locations contained only a small number of auto thefts across the different risk categories (Figure 4). Filtering for the locations containing 20 or more auto thefts, there is evidence of auto theft “hot zones” within the various risk groups. A hot zone would be locations that are more frequently targeted. For example, within the medium-risk neighbourhoods, there are around 15 different locations with each having approximately 20 auto thefts and many other locations containing well above 20 or more.

Figure 5. Frequency of Auto Thefts by Neighbourhood Risk



The following is a map showing the auto theft locations based on the clustering results. Auto thefts in low-risk neighbourhoods are in yellow, medium-risk is in purple and high-risk is in red.

Map 2. Neighbourhood Clusters based on Auto Theft Characteristics



From the clustering above, only the low-risk neighbourhoods will be used to filter for restaurants in Toronto.

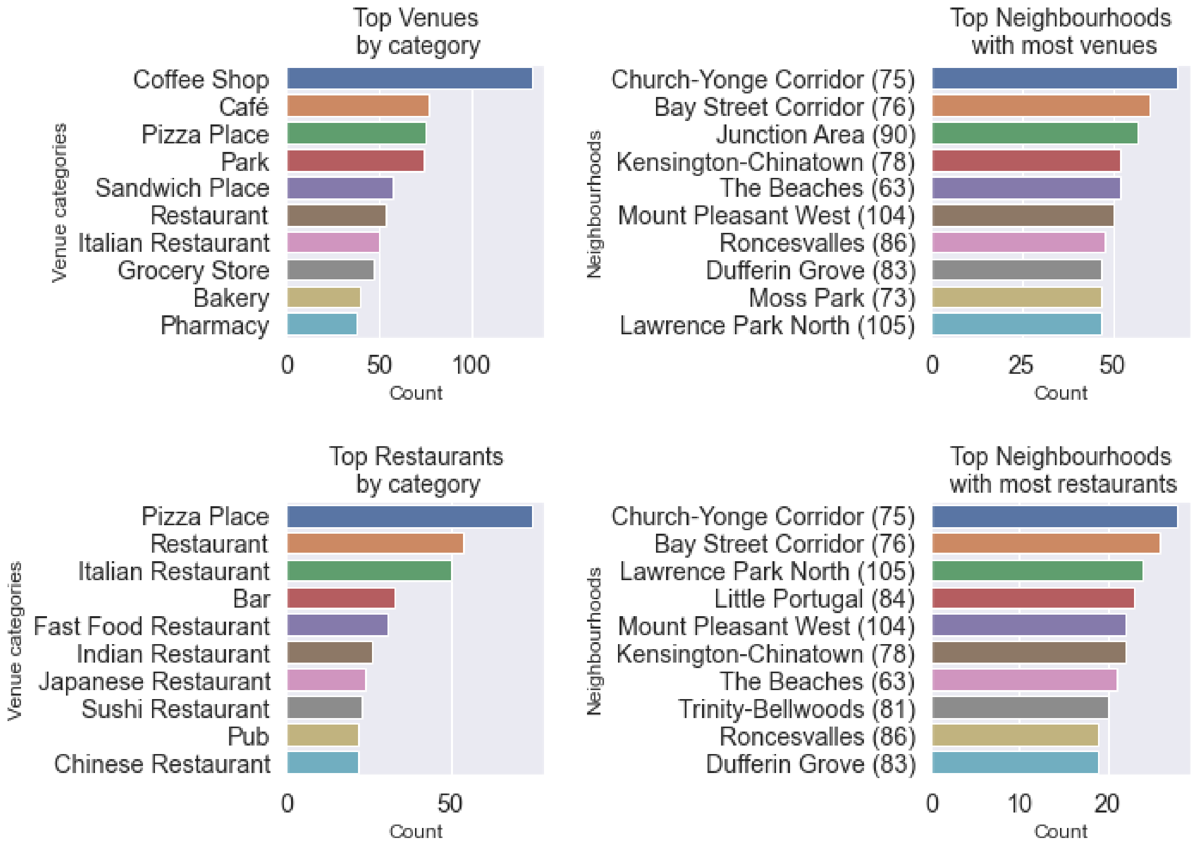
The next step is to determine the top-rated venues and find the number of restaurants located in the lower risk neighbourhoods.

3.4 Top-rated venues and restaurants

The neighbourhood locations are used to return the top 100 highly rated venues within a 500 radius around each neighbourhood in Toronto. This was done by using a Foursquare API connection, and returned a total of 1,536 unique venues across 1,923 different locations in Toronto.

There are over 288 unique venue categories that need to be further filtered in order to identify all restaurants in Toronto. The following keywords have been used to filter each venue’s category description: "Restaurant", "Pizza", "Burger", "Chicken", "BBQ", "Fish", "Steak", "Taco", "Burrito", "Bar", "Wings", "Buffet", and "Diner". This returned 698 unique restaurants.

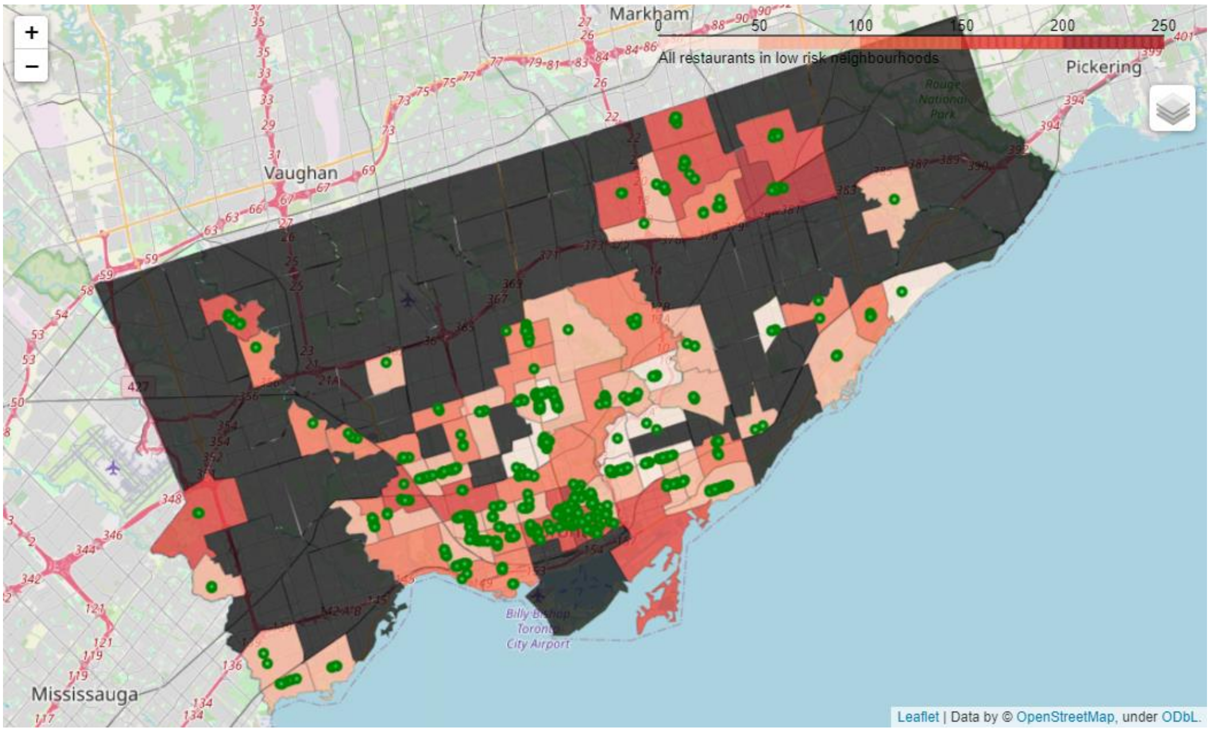
Graph 6. Top 10 Venues & Restaurants



The most common venues in Toronto are coffee shops and cafes, while the most common restaurants are pizza places. The Church-Young Corridor has the highest number of venues and restaurants.

The next step is to identify which restaurants are located in low risk neighbourhoods. This was done using geopandas to check if each venue's location falls within in each neighbourhood's geometric area. Based on this methodology there are 631 restaurants, shown in green, that fall into 80 low risk neighbourhoods.

Map 3. Restaurants located in low risk neighbourhoods



3.5 Calculating distance and determining low-risk restaurants

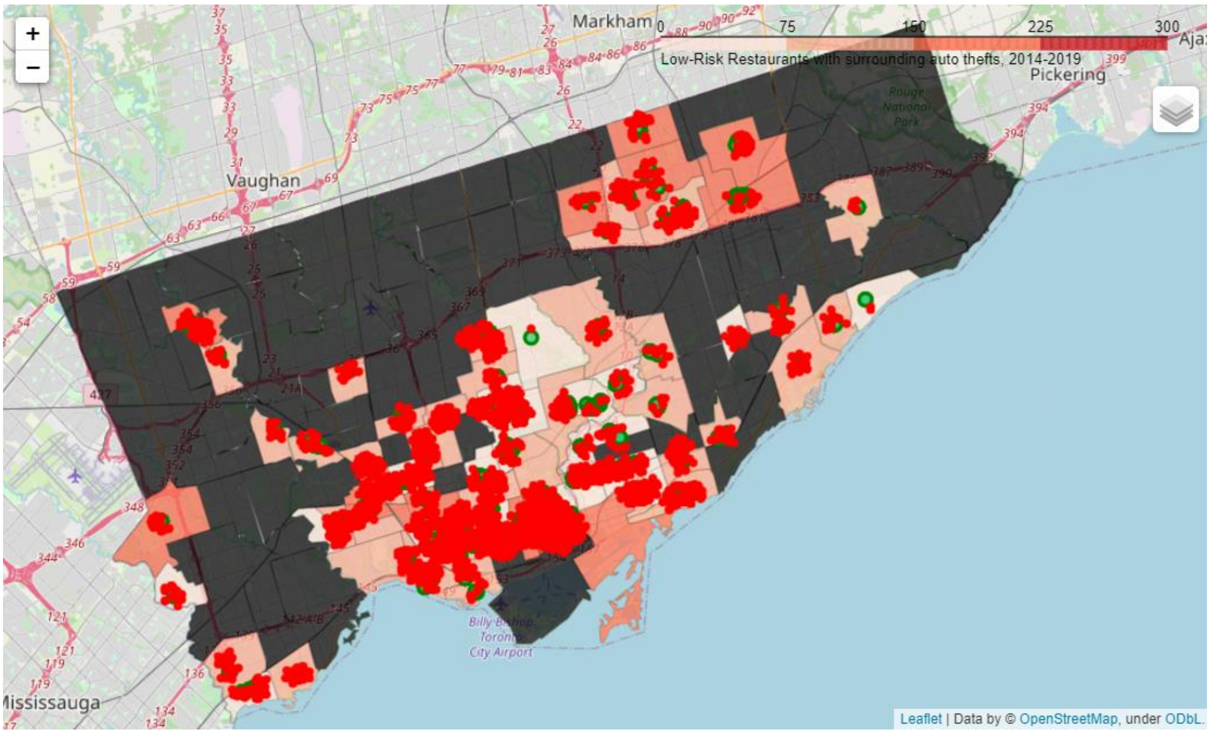
Now that we have the low-risk neighbourhoods and have identified all the restaurants then the next step is to determine how far each auto theft location is from each restaurant. The Haversine formula is used to calculate the distance as it is quite simple to set up and works well with geopandas. The Haversine formula calculates the shortest distance between two points on a sphere using their latitudes and longitudes measured along the surface. The formula is:

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)$$

After determining the distances between all restaurants that are located in low-risk neighbourhoods and all auto theft locations, then only the distances that are 1/2 KM or closer to the restaurant will be kept.

It is important to distinguish that the auto theft locations are not exclusive to being located in low-risk neighbourhoods, but account for all auto thefts within the 1/2 KM surrounding area. This is to consider cases where a restaurant is located around a low-risk neighbourhood boundary. The following map provides the restaurants located in low-risk neighbourhoods and the surrounding auto thefts.

Map 4. Restaurants in low-risk neighbourhoods and surrounding auto thefts

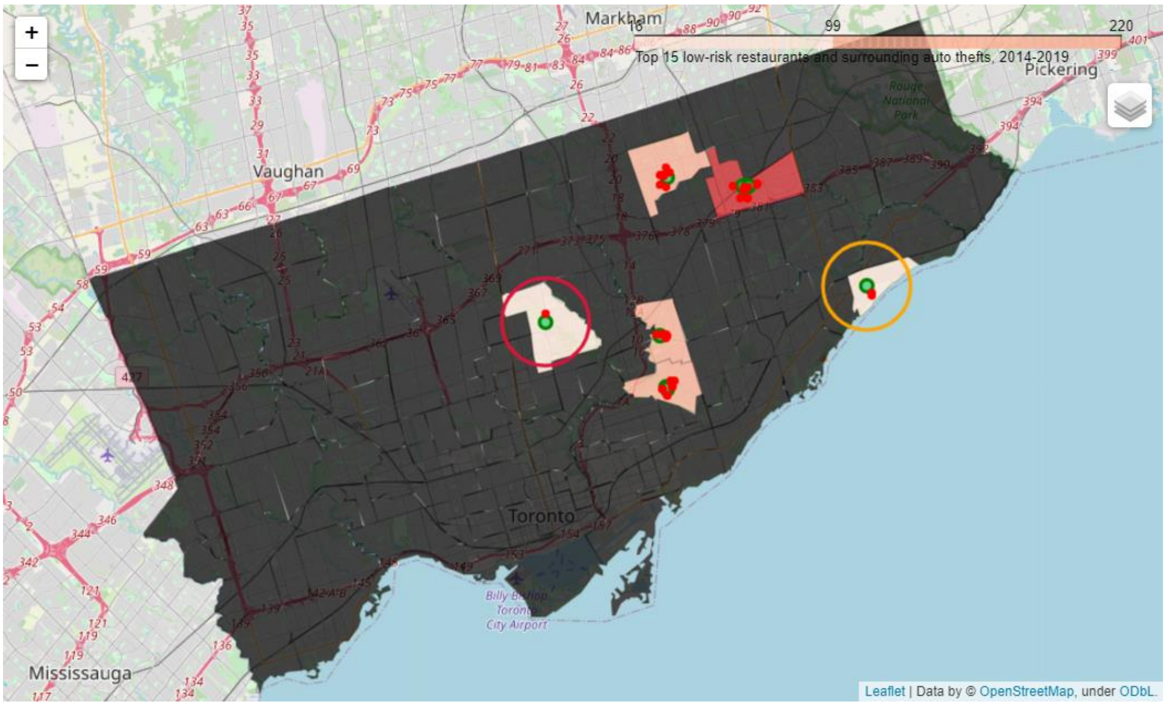


Now the top 15 restaurants with the lowest number of auto thefts will be selected.

4.0 Results

The top 15 restaurants are mapped below. The Granite Club Dining Room, located in the Bridle Path-Sunnybrook-York Mills neighbourhood, is the top restaurant with only one auto theft within a 1/2 KM radius (red circle). The Granite Club is a private social and athletic club, founded in 1875. The initial membership fee is $53,000 per couple!! It looks then like it will have to be pizza at the second top restaurant, Pizza Nova (yellow circle).

Map 5. Top 15 restaurants located in low risk neighbourhoods

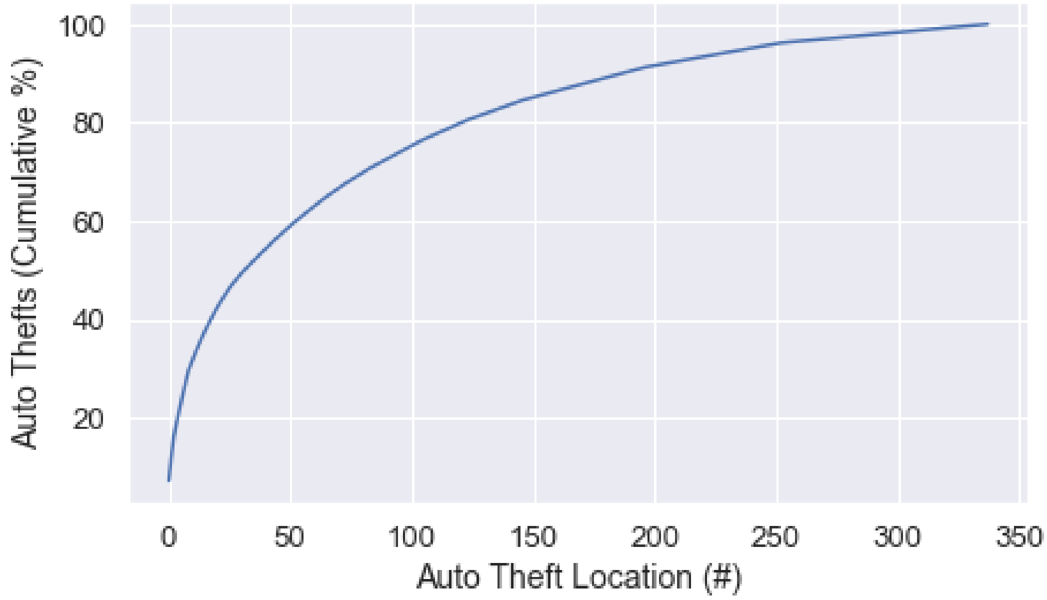


Name	Categories	Neighbourhood	Total Auto Thefts Around Restaurant	Number of Auto Theft Locations	Density	Average Distance	Minimum Distance
Granite Club Dining Room	Restaurant	Bridle Path-Sunnybrook-York Mills (41)	1	1	1.0	0.38	0.38
Pizza Nova	Pizza Place	Guildwood (140)	2	2	1.0	0.41	0.36
Yummy Cantonese Restaurant	Cantonese Restaurant	Agincourt South-Malvern West (128)	5	4	1.25	0.09	0.05
Wonton Chai Noodle	Noodle House	Agincourt South-Malvern West (128)	5	4	1.25	0.1	0.06
Mike's BBQ	BBQ Joint	Agincourt South-Malvern West (128)	5	4	1.25	0.11	0.07
Pizza Pizza	Pizza Place	O'Connor-Parkview (54)	6	5	1.2	0.3	0.23
Venice Pizza	Pizza Place	O'Connor-Parkview (54)	6	5	1.2	0.31	0.2
Jawny Bakers	Gastropub	O'Connor-Parkview (54)	7	6	1.17	0.32	0.24
Congee Me	Chinese Restaurant	Agincourt South-Malvern West (128)	8	5	1.6	0.17	0.04
Jesse Jr. (Filipino Foods & Restaurant)	Restaurant	Agincourt South-Malvern West (128)	8	5	1.6	0.17	0.02
Happy Lamb Hot Pot	Hotpot Restaurant	L'Amoreaux (117)	9	7	1.29	0.33	0.15
Shanghai Dim Sum	Chinese Restaurant	Agincourt South-Malvern West (128)	9	6	1.5	0.2	0.05
Perfect Chinese Restaurant	Chinese Restaurant	Agincourt South-Malvern West (128)	9	5	1.8	0.19	0.07
The Frig	French Restaurant	Victoria Village (43)	10	6	1.67	0.22	0.07
Asian Legend	Chinese Restaurant	Agincourt South-Malvern West (128)	11	6	1.83	0.28	0.11

High-Risk Neighbourhoods

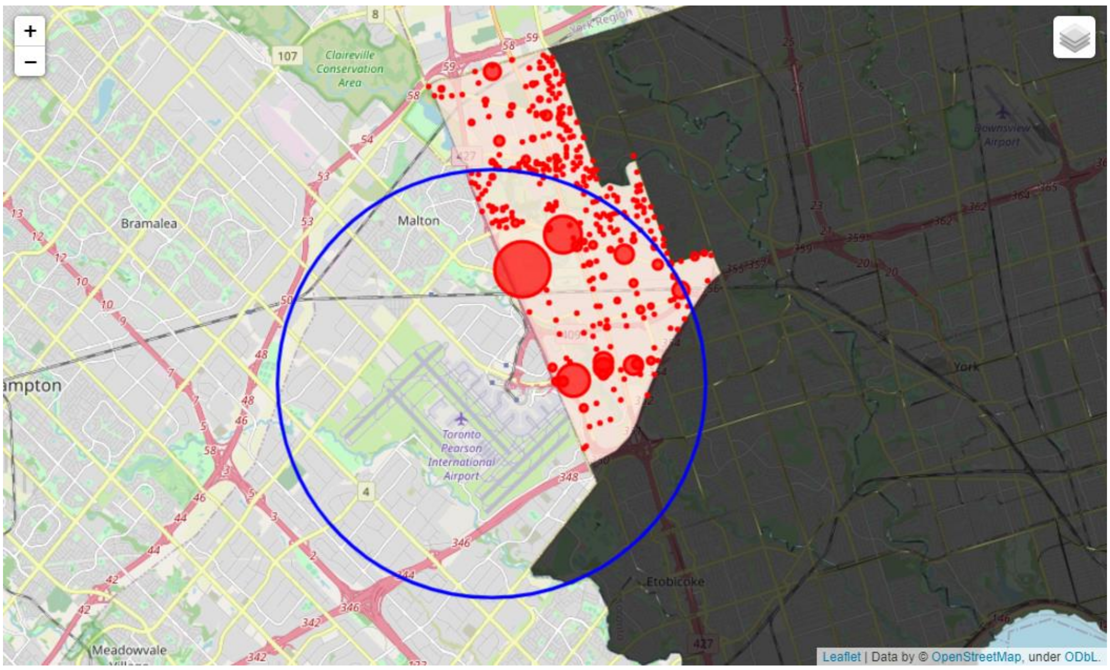
Returning briefly to the auto thefts located in the high-risk cluster. There are a total of 2,244 auto thefts located within a single neighbourhood, West Humber-Clairville. The auto thefts are spread across 338 locations and account for nearly 10% of the total auto thefts in Toronto between 2014 and 2019. There are only 18 locations that account for just over 40% of all auto thefts in high-risk neighbourhoods.

Figure 7. Cumulative Percent of High-Risk Auto Thefts



It is interesting to note that over 60% of the auto thefts in the high-risk neighbourhoods occur within 5KM from the departures gate of the Toronto Pearson International Airport. There is also evidence of "hot zones" near the airport, indicated by the larger circles (Map 6). This area has a high concentration of parking lots, suggesting that travellers commuting from outside of Toronto may be unaware of the risks of parking near the airport, making it an easy target for a career-minded criminal.

Map 6. Auto Thefts Around Toronto Pearson Airport



5.0 Conclusion

When travelling to Toronto it can be useful to have an idea of what areas have higher crime rates when looking to go out for dinner at a nice restaurant.

Utilising auto theft data it is possible to be able to determine restaurants that are located in neighbourhoods with a low number of auto thefts in the surrounding area.

K-means clustering is used to group the locations of auto thefts into three clusters based on common characteristics. In this analysis, it generated 113 low-risk neighbourhoods, with over 600 restaurants to choose from.

A final analysis of auto thefts in the high-risk cluster suggests that it may be better to take an airport shuttle or park your vehicle at a friend's place when flying from the Pearson International Airport.

These results offer visitors who are new to the city additional information on where they can go out for dinner at a highly rated restaurant located in neighbourhoods with low auto theft rates, as well as areas where to avoid parking all together.