ASSESSMENT OF TORONTO CRIME DATA THROUGH EXPLORATORY DATA ANALYSIS AND CLASSIFICATION METHODS

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1. INTRODUCTION

While the concept of crime forecasting can be traced back a century, it was through the adoption of geographic information systems (GIS) to map crime data during the 1990s which led researchers to recognize the potential for predictive analytics to forecast crime (Hvistendahl, 2016). The use of machine learning methods in the field of crime analysis to identify crime patterns and predict criminal activity is of considerable interest to law enforcement agencies with the results used to support evidence-based decisions in addition to informing choices regarding resource allocation, deployment, divisional staffing, and patrol plans (Lau, 2020).

Through exploration and analysis of the recently released Toronto Major Crime Indicators (MCI) dataset (Toronto Police Service, 2022), several research questions will be investigated through the application of various analytical tools and machine learning methods. Research questions include, but are not limited to:

- Can crime type(s) be predicted based on neighbourhood attributes (e.g., population density, unemployment rate, average income, average education level)?
- Which neighborhoods are the most violent and which the least violent?
- Which neighborhood has the highest incidence of crime and which neighbourhood the lowest?
- Applying the crime severity index weights (StatCan, 2021) to incidents, which neighbourhood has the highest overall crime weighting and which the lowest?
- What are the general crime trends within the City of Toronto?
- Are there recognizable temporal trends?
- Are specific crime types concentrated within certain geographical areas?

The data used for this project includes the Toronto MCI dataset noted above, in addition to Crime Severity Index weights for Canada (Statcan, 2021), geographic feature files (shapefiles) of Toronto Police patrol zones and Toronto neighbourhoods, and Toronto neighbourhood profiles (all from open.Toronto.ca, 2022).

The techniques employed will be data cleaning and exploratory data analysis of the Toronto MCI and Toronto neighbourhood datasets, merging of datasets, identification of relevant factors associated with crime, and application of k-NN, Naïve Bayes and logistic regression classification algorithms for crime prediction; all methods to be conducted using R.

The source code for this project can be found on GitHub:

https://github.com/kmault/CIND820_Capstone.

2. LITERATURE REVIEW

The literature search and review focused on studies where machine learning methods, preferably comparative studies, were applied to crime data to determine their effectiveness in crime pattern recognition and crime prediction. While several papers were found where clustering and classification methods were carried out through machine learning methods, they often simply described the application of the techniques(s) and failed to provide outcomes in terms of model performance or qualitative comparisons and subsequently were not included in the literature summaries.

The prediction of crime in San Francisco using k-NN, support vector machines, random forest and Naïve Bayes models was completed by Palanivinayagam et al., (2021). The authors generated 3 models for each algorithm with Naïve Bayes typically outperforming each method for every

iteration with average accuracies of 94.8%, 93.8%, 93.7% and 93.7% for Naïve Bayes, random forest, k-NN, and SVM, respectively.

Wibowo and Oesman (2020) carried out a comparative analysis of the k-NN, Naïve Bayes, and decision tree algorithms to detect and predict crime within the Sleman Regency of Indonesia. The data focused on the crimes of theft, fraud, and embezzlement over a three-year period with the dataset containing a total of 1,735 incidents and 15 variables (i.e., day, time, season, victim gender, occupation, location etc.). Using accuracy to evaluate the comparative performance of the algorithms, Naïve Bayes achieved the highest level of accuracy (65.6%), followed by the k-NN model with accuracies ranging from 57.9% to 61.6%, and the decision tree model with an accuracy of 60.3%.

Zhang et al., (2020) compared several machine learning algorithms to predict property crime hotspots within a large coastal city in Southeast China using 2015 to 2018 public crime data. Through the application and comparison of 6 algorithms in predicting crime hotspots, the long-short term memory (LSTM) neural network model consistently outperformed those generated by k-NN, random forest, support vector machine, Naïve Bayes, and convolutional neural networks.

Alves et al., (2018) proposed that statistical learning methods were the best way to predict crime in relation to urban factors and applied a random forest algorithm to forecast crime and evaluate the importance of various urban indicators (e.g., literacy rates, employment etc.). Using the number of homicides as the dependent variable, the authors were able to obtain a 97% accuracy on the prediction of homicides in Brazilian cities. The authors also observed that factors such as employment rate and literacy influenced crime.

The use of k-means, decision tree, and tree-based algorithms to analyze and predict crimes were applied to the 2011 to 2012 UK crime data by Akila and Mohana (2017). The attributes of crime type, month, year, and location were assessed and predicted with the results showing that the k-means model provided higher accuracies compared to the decision tree and tree-based algorithms; 90.3% compared to 80.8% and 88.7%, respectively.

Classification of crime data from the Nigerian Prisons Services was carried out using decision tree (J48), Naïve Bayes, and ZeroR rule induction algorithms by Obuandike et al., (2015). Comparison of the 3 techniques revealed that the decision tree classifier returned the highest accuracy; 59.15% compared to 56.78% from Naïve Bayes and 56.78% from ZeroR.

Multivariate linear regression was used to predict crime counts using historical crime data from Chicago by Sengupta et al., (2014). The authors thoroughly described the process from data extraction to modeling and performance evaluation. The model was considered useful for predicting the probability of crime counts as the p-value was less than 0.05.

Shojaee et al., (2013) compared the performance of 5 machine learning algorithms in the classification of crime using the American Communities and Crime Unnormalized dataset. Utilizing crime status as the dependent variable, the authors determined that the k-NN algorithm returned the highest accuracy (87.5%) compared to Naïve Bayes (84.6%), neural network (85.3%), support vector machine (85.6%), and J48 decision tree (84.9%) models. The authors also noted that model performance was enhanced through feature selection. Iqbal et al., (2013), classified the dataset used by Shojaee et al., (2013) by implementing Naïve Bayes and decision tree algorithms using 10-fold cross validation to predict crime category. The performance measures of accuracy, precision and recall for the decision tree classifier consistently exceeded those for Naïve

Bayes by at least 10% for each measure; 83.9%, 83.5% and 84% for decision tree compared to 70.8%, 66.4% and 70.8% for Naïve Bayes.

Using a dataset comprised of a combination of publicly available datasets from various American cities, Yu et al., (2011) assessed the performance of support vector machine (SVM), decision tree (J48), neural network and k-NN (k=1) classification models on crime forecasting. The authors attempted to predict residential burglaries using the attributes such as the number of arrests, commercial burglaries, foreclosure, street robberies etc. The model results indicated that the k-NN method consistently underperformed compared to, from highest to lowest, neural network, decision tree, and SVM algorithms.

Kim et al., (2018), using 15 years of Vancouver crime data, generated predictive models by KNN and boosted decision tree methods. Both models returned low accuracies, 39% for KNN and 44% for boosted decision tree and the authors noted that while the predictive accuracy was poor, they could be used as a framework for developing and executing future models.

Several studies were found that specifically investigated Toronto crime data (e.g., Oliveira, 2021., Stodulka, 2021., Sundar, 2020., Uwoghiren, 2020., Li, 2017., Vempala, 2016., Taneja et al., n.d.). Oliveira (2021) carried out an analysis of 2019 Toronto major crime indicator data to identify neighbourhoods with the highest and lowest number of crimes as well as any spatial and temporal trend in crimes. Based on his analysis, the Church-Yonge, and Bay Steet Corridors were identified as the most dangerous neighbourhoods and that crimes were most likely to occur at noon and between the 11 pm and 3 am. Stodulka (2021) analysed Toronto major crime indicators between 2014 and 2018 to determine neighbourhoods with the most crime in addition to evaluating the different assault types. The results of his study showed that most of the crime in Toronto was comprised of assaults which represented over 50% of incidents in the dataset and that the Church-

Yonge Corridor was the most dangerous. Sundar (2020) applied decision tree (J48), k-NN, Naïve Bayes, and random forest classifiers to predict Toronto crime categories (i.e., assault, auto theft, B&E, robbery, and theft over $5000). Following feature selection and applying the SMOTE technique to rectify the imbalanced nature of the dataset, the author found that while none of the algorithms had particularly good precision and recall values for the theft over category, the random forest model outperformed the other methods, returning the highest precision and recall values for all crime categories, 52% compared to 40%, 49% and 43% for Naïve Bayes, KNN, and decision tree models, respectively. Review of incident data revealed that the Waterfront, Bay Street Corridor, and the Yonge-Church neighbourhoods were the most dangerous while Lambton Baby Point, Woodbine Lumsden, and Maple Leaf were the safest. Uwoghiren (2020) sought to group Toronto neighbourhoods via k-means clustering in order of desirability based on factors such as location of venues, crime rate, employment rate etc. The most desirable neighbourhoods were identified as Mount Pleasant West, Church-Yonge Corridor, Yonge-St Clair, and Bay Street Corridor with most neighbourhoods in the north-west region of the city (e.g., Etobicoke) considered least desirable. Using the 2008 to 2011 Toronto crime data, Vempala (2016) determined via linear regression and random forest models that the percentage of males, number of businesses and social assistance recipients were the most important crime predictors for 2011 although neither model was considered to perform particularly well, and the author noted that the features did not allow for the generation of a model that could make practical predictions. Li (2017) explored the 2016 Toronto MCI crime dataset, mapped crimes, and applied k-means clustering to group neighbourhoods based on crime categories. The results of her data exploration, mapping, and clustering indicated that the Waterfront was the most dangerous neighbourhood followed by the Church-Yonge Corridor (based on incident counts) with the safest neighbourhoods

identified as Richmond Hill and Leaside Bennington. Cluster analysis indicated that 2 clusters were sufficient to group neighbourhoods: one cluster representing neighbourhoods with low crime (all categories) and a second cluster for those neighbourhoods with high crime (all categories). Taneja et al., (n.d.) applied, post PCA feature selection, the cluster techniques of k-means, agglomerative and DBSCAN to the 2000 to 2017 Toronto MCI dataset to identify violent versus non-violent neighbourhoods. Using internal validation measures such as silhouette, Dunn Index, C-H score, and D-B score to evaluate performance, agglomerative clustering provided the most suitable result followed by DBSCAN and k-means.

Following review of available literature pertinent to classification of crime data, the decision was taken to use the k-NN, Naïve Bayes and logistic regression algorithms to classify crime in Toronto. Several research questions were answered during review of previous studies involving crime data including:

- *Which Toronto neighborhoods are the most violent and which the least violent (generally assessed as high crime versus low crime)?* The most and least dangerous neighbourhoods were consistently identified as the Waterfront, Yonge-Church and Bays Street Corridors, and Lambton Baby Point
- What are the general crime trends within the City of Toronto?
- *Are there recognizable temporal trends?* Most incidents were noted to occur between May and October, on Friday and Saturday, at noon and between 11 pm and 3 am.
- *Are specific crime types concentrated within certain geographical areas?* While assaults were the main crime type for each neighbourhood, Waterfront and the Yonge-Church Corridor had the most break and enters while the most vehicle thefts occurred in West Humber-Clairville.

The current project comprises several similar elements to that of Sundar (2020); however, this study will use a more expansive and up to date dataset (2014 to 2021, compared to 2014 to 2019) and a few different predictive algorithms will also be executed. The outcome and performance measures will then be evaluated and compared.

This project will build upon the knowledge and framework produced during previous predictive studies of crime data, both for Toronto and other regions. Given that crime is, and likely will always be, an ongoing societal issue, studies that seek to provide any sort of predictive capability would be of great value to law enforcement agencies.

3. DATA & DATA DESCRIPTION

3.1 Data, Data Cleaning

3.1.1 Toronto MCI Dataset

The primary dataset used for this project was the 2014 to 2021 Toronto Major Crime Indicator (MCI) data released by the Toronto Police Service and available through the Toronto Police Service Public Safety Data Portal (data.torontopolice.on.ca). The dataset contains a summary of founded incidents that fall within the categories of assault, break and enter, auto theft, robbery, and theft over $5000. Initial assessment of the MCI dataset showed that it contained 281,692 observations and 30 variables; variable data types were comprised of character (14), integer (12), and numeric (4). The dataset contained no NA values, 20,233 duplicated rows (based on event ID and offense), and 1372 entries for occurrences prior to 2014. Several redundant columns were identified during the initial evaluation based on the similarity of information: columns X, Y and Long, Lat both listed geographic coordinates, the dates of interest were for occurrences between

2014 and 2021 and not reports generated between those dates, and premises type and location type were quite similar with preference given to the premises type which contained a higher-level categorization of physical location.

Following preliminary review of the Toronto MCI dataset, initial feature reduction could be carried out by removing the following columns: X, Y, index, reported date, location type, reported year, reported month, reported day, reported day of year, reported day of week, reported hour and object ID. All rows with duplicated incident IDs and offence types, and those with an occurrence date prior to 2014 were removed. Two new columns were added: weight based on the Crime Severity Index weights for Canada dataset and a season column based on the occurrence month. Additionally, several of the variable columns (e.g., day, month, crime time, premises type) were converted to factors to avoid potential complications during subsequent analysis.

The cleaned Toronto MCI dataset contained 260175 observations and 17 variables (Figure 1).

```
'data.frame':   260175 obs. of  17 variables:
 $ event_unique_id    : chr  "GO-20141625305" "GO-20141297201" "GO-20141302953" "GO-20141304312" ...
 $ Division           : Factor w/ 17 levels "D11","D12","D13",..: 6 6 6 6 6 6 6 6 6 6 ...
 $ occurrencedate     : chr  "2014/03/02 05:00:00+00" "2014/01/03 05:00:00+00" "2014/01/08 05:00:00+00" "2014/01/08 05:00:00+00" ...
 $ premises_type      : Factor w/ 7 levels "Apartment","Commercial",..: 4 2 2 4 2 4 5 1 6 1 ...
 $ ucr_code           : int  1430 2120 2130 2120 2130 2120 1430 1430 1450 1430 ...
 $ weight             : num  26.4 211 144.4 211 144.4 ...
 $ offence            : Factor w/ 50 levels "Administering Noxious Thing",..: 6 13 43 13 43 13 6 6 21 6 ...
 $ occurrenceyear     : int  2014 2014 2014 2014 2014 2014 2014 2014 2014 2014 ...
 $ occurrencemonth    : Factor w/ 12 levels "April","August",..: 8 5 5 5 5 5 5 5 5 5 ...
 $ occurrencedayofweek: Factor w/ 7 levels "Friday    ","Monday    ",..: 4 1 7 7 2 1 4 4 4 2 ...
 $ occurrencehour     : int  8 10 2 11 0 18 10 21 22 9 ...
 $ MCI                : Factor w/ 5 levels "Assault","Auto Theft",..: 1 3 5 3 5 3 1 1 1 1 ...
 $ Hood_ID            : chr  "1" "1" "1" "1" ...
 $ Neighbourhood      : Factor w/ 141 levels "Agincourt North",..: 126 126 126 126 126 126 126 126 126 126 ...
 $ Long               : num  -79.6 -79.6 -79.6 -79.6 -79.6 ...
 $ Lat                : num  43.7 43.7 43.7 43.7 43.7 ...
 $ season             : Factor w/ 4 levels "Autumn","Spring",..: 2 4 4 4 4 4 4 4 4 4 ...
```

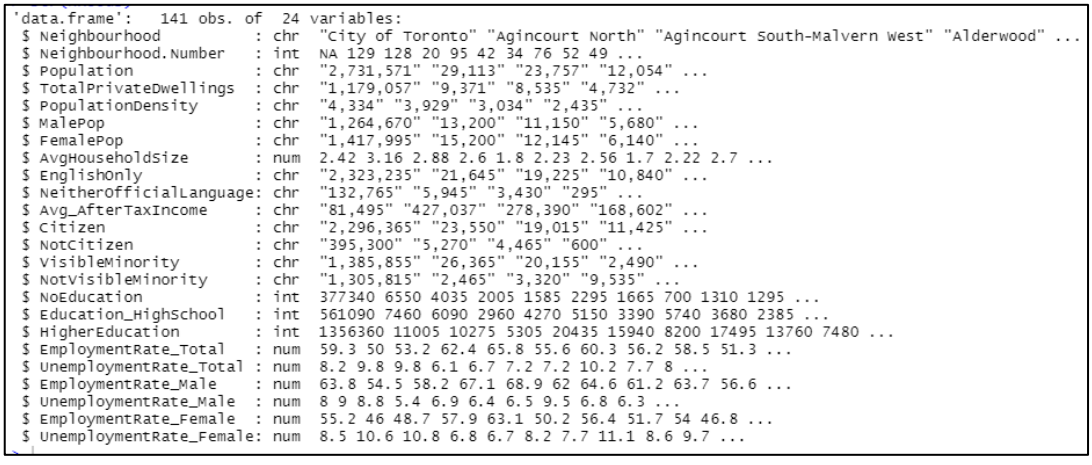
Figure 1. Structure of the cleaned Toronto MCI dataset.

3.1.2 Neighbourhood Profile Dataset

The second dataset reviewed was the Toronto Neighbourhood Profiles data released by the Division of Social Development, Finance & Administration and available from the City of Toronto Open Data Portal (https://open.toronto.ca/dataset/neighbourhood-profiles/). The neighbourhood profiles dataset contained 2,383 entries and 146 attribute columns; variable datatypes were integer (1) and character (145). The data frame was structured in such a way that individual neighbourhoods comprised the columns while each row contained information obtained primarily from 2016 census profile data; preliminary review revealed the dataset contained several redundant attribute columns. The dataset contained 7847 NA values and no duplicated rows. The dataset was transposed resulting in each row representing a unique neighbourhood and each column the various census-derived attributes.

Following the cursory examination of the Neighbourhood Profiles dataset, initial feature reduction could be carried out through the removal of rows such as: X_id, Category, Data.Source, and Characteristic as well as those with information pertaining to the 2011 population, population change 2011-2016, private dwellings occupied by usual residents, languages spoken, income statistics other than average income, mobility status, and anything that did not pertain to general neighbourhood details (e.g., detailed population breakdown rather than general population for the area).

The cleaned Neighbourhood dataset contained 141 observations and 24 variables (Figure 2).



```
'data.frame':   141 obs. of  24 variables:
 $ Neighbourhood          : chr  "City of Toronto" "Agincourt North" "Agincourt South-Malvern West" "Alderwood" ...
 $ Neighbourhood.Number   : int  NA 129 128 20 95 42 34 76 52 49 ...
 $ Population             : chr  "2,731,571" "29,113" "23,757" "12,054" ...
 $ TotalPrivateDwellings  : chr  "1,179,057" "9,371" "8,535" "4,732" ...
 $ PopulationDensity      : chr  "4,334" "3,929" "3,034" "2,435" ...
 $ MalePop                : chr  "1,264,670" "13,200" "11,150" "5,680" ...
 $ FemalePop              : chr  "1,417,995" "15,200" "12,145" "6,140" ...
 $ AvgHouseholdSize       : num  2.42 3.16 2.88 2.6 1.8 2.23 2.56 1.7 2.22 2.7 ...
 $ EnglishOnly            : chr  "2,323,235" "21,645" "19,225" "10,840" ...
 $ NeitherOfficialLanguage: chr  "132,765" "5,945" "3,430" "295" ...
 $ Avg_AfterTaxIncome     : chr  "81,495" "427,037" "278,390" "168,602" ...
 $ Citizen                : chr  "2,296,365" "23,550" "19,015" "11,425" ...
 $ NotCitizen             : chr  "395,300" "5,270" "4,465" "600" ...
 $ VisibleMinority        : chr  "1,385,855" "26,365" "20,155" "2,490" ...
 $ NotVisibleMinority     : chr  "1,305,815" "2,465" "3,320" "9,535" ...
 $ NoEducation            : int  377340 6550 4035 2005 1585 2295 1665 700 1310 1295 ...
 $ Education_HighSchool   : int  561090 7460 6090 2960 4270 5150 3390 5740 3680 2385 ...
 $ HigherEducation        : int  1356360 11005 10275 5305 20435 15940 8200 17495 13760 7480 ...
 $ EmploymentRate_Total   : num  59.3 50 53.2 62.4 65.8 55.6 60.3 56.2 58.5 51.3 ...
 $ UnemploymentRate_Total : num  8.2 9.8 9.8 6.1 6.7 7.2 7.2 10.2 7.7 8 ...
 $ EmploymentRate_Male    : num  63.8 54.5 58.2 67.1 68.9 62 64.6 61.2 63.7 56.6 ...
 $ UnemploymentRate_Male  : num  8 9 8.8 5.4 6.9 6.4 6.5 9.5 6.8 6.3 ...
 $ EmploymentRate_Female  : num  55.2 46 48.7 57.9 63.1 50.2 56.4 51.7 54 46.8 ...
 $ UnemploymentRate_Female: num  8.5 10.6 10.8 6.8 6.7 8.2 7.7 11.1 8.6 9.7 ...
```

Figure 2. Structure of the cleaned Neighbourhood dataset.

3.1.3 CSI Weights Dataset

The Crime Severity Index weights for Canada dataset, provided via email request to StatCan, contained 284 entries and 3 attributes. The attributes were comprised of the Uniform Crime Reporting (UCR) violation codes (e.g., 1110), description of violation (e.g., Murder 1st Degree) and violation weighting (e.g., UCR 1110 has an associated weight of 7656.16). The dataset contained no duplicates or NA values. No changes were made to the file.

3.1.4 Shape Files

3.1.4.1 TPS Patrol Zones.

The shapefile for the Toronto Police Patrol Zones was provided by the Toronto Police Service and available from the City of Toronto Open Data Portal (https://open.toronto.ca/dataset/patrol-zones/). The file contained information such as the number of polygon features representing each patrol zone (n=17), divisional address, geographic coordinate system, zone, and datum (i.e., UTM zone 17N/NAD27), and extent of each patrol zone. No changes were made to the patrol zones file. Plots showing the extent of police patrol zones are shown on Figure 3.

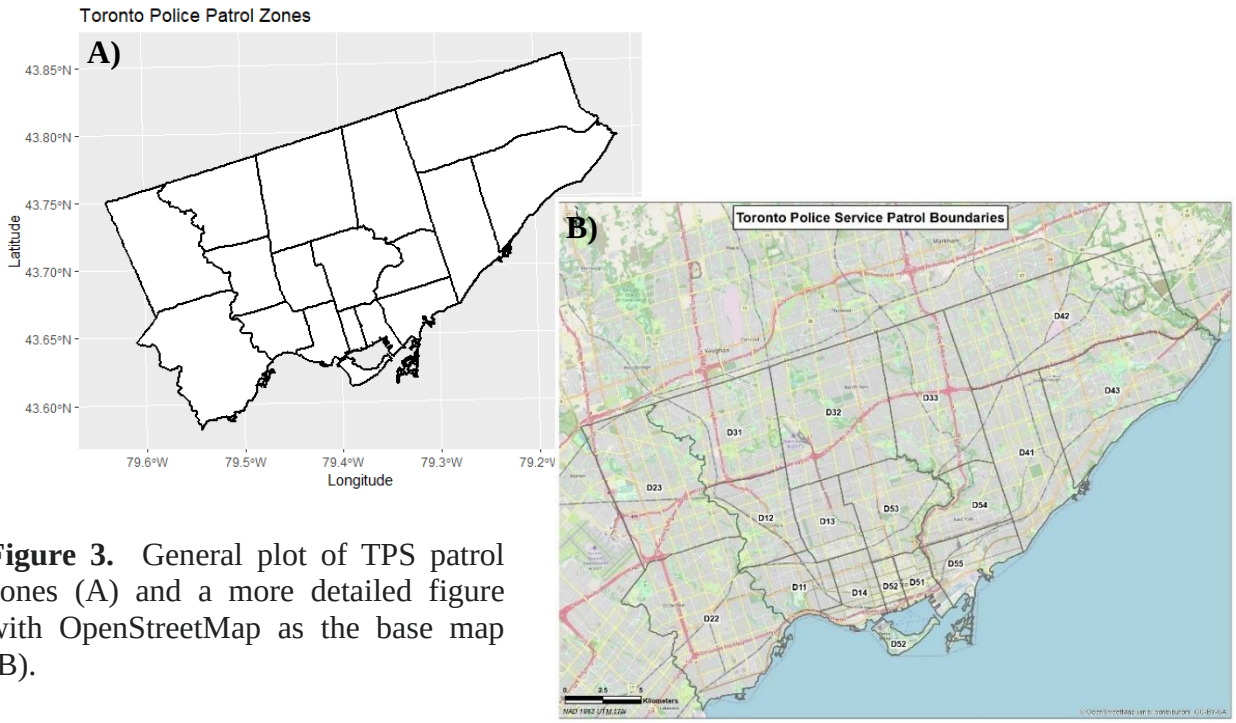


Figure 3. General plot of TPS patrol zones (A) and a more detailed figure with OpenStreetMap as the base map (B).

3.1.4.2 Neighbourhoods.

The Neighbourhoods shapefile was provided by the Division of Social Development, Finance & Administration and available from the City of Toronto Open Data Portal (https://open.toronto.ca/dataset/neighbourhoods/). The file contained information such as the number of polygon features representing each neighbourhood, the neighbourhood designation (e.g., neighbourhood improvement area - NIA), geographic bounds as well as geographic coordinate system, zone, and datum (i.e., Lat/Long, WGS84), and neighbourhood name and number (e.g., West Humber-Clairville: 1). This file was not changed, and a simple plot of Toronto neighbourhoods is presented in Figure 4.

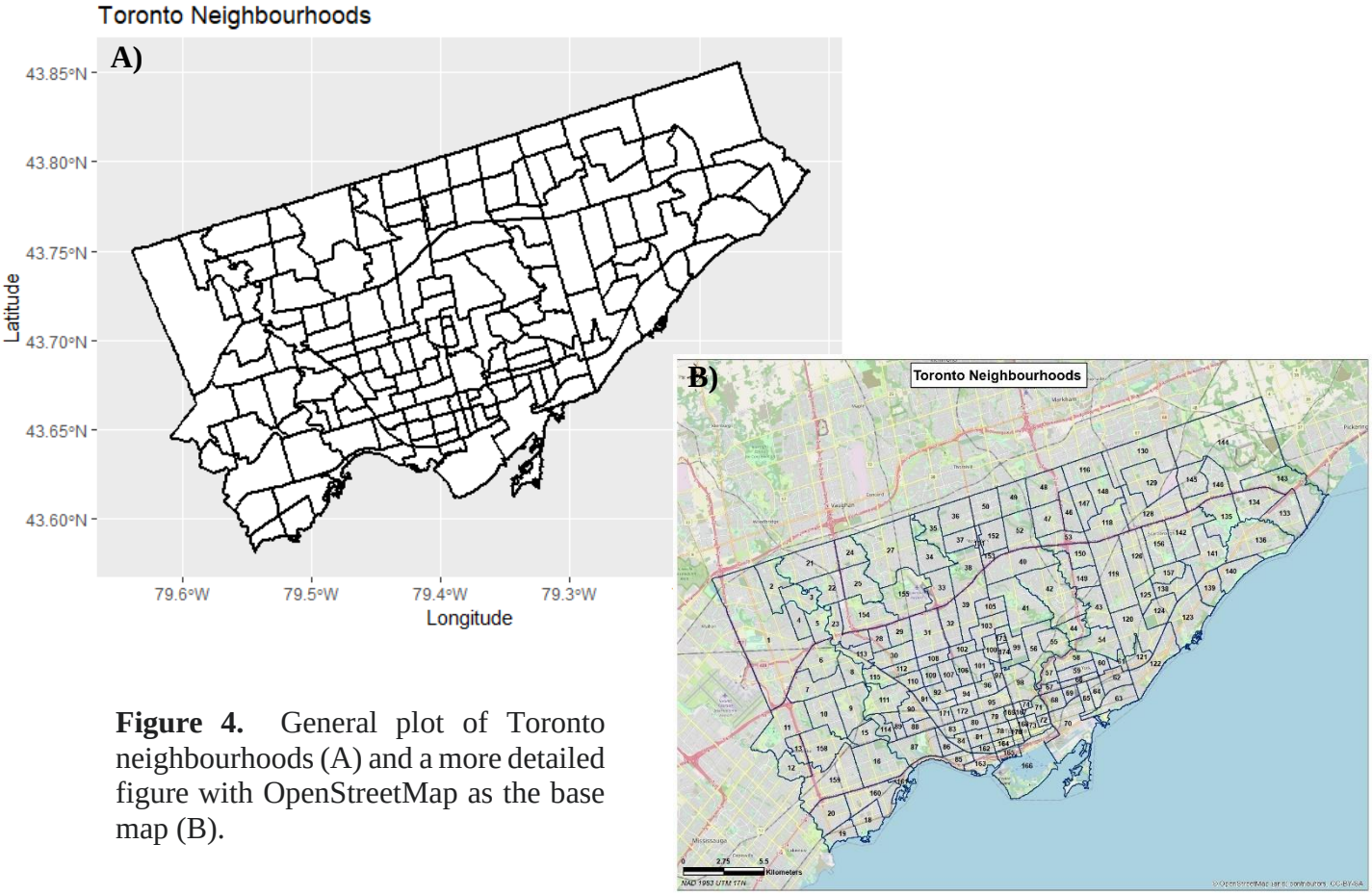


Figure 4. General plot of Toronto neighbourhoods (A) and a more detailed figure with OpenStreetMap as the base map (B).

4. EXPLORATORY DATA ANALYSIS & DESCRIPTIVE STATISTICS

The Toronto MCI dataset is the primary dataset under review, as such it is the only data that underwent EDA. The number of founded criminal incidents in Toronto exhibited a gradual increase from 2014 to 2019 after which time incident numbers started to decrease (Figure 5); annual crime counts ranged from 30197 to 37024 and a median value of 31849 (Figure 6). The monthly trend in crime counts showed minor variation, with higher values observed between May and October (Figure 7); the number of incidents ranged from 18736 to 23248 with a median value of 22180 (Figure 8). The number of incidents per day was relatively consistent (Figure 9) with the highest counts noted over the weekend (Friday to Sunday); the number of daily incidents ranged from 35569 to 39552 and exhibited a median value of 36734 (Figure 10) MCT. There was minor variation in the number of crimes committed per season (Figure 11) with a gradual increase from winter to summer; seasonal numbers ranged from 60783 (Winter) to 68512 (Summer). The number of incidents per premises type ranged from 6607 for educational to 67550 for outside (Table 1, Figure 12).

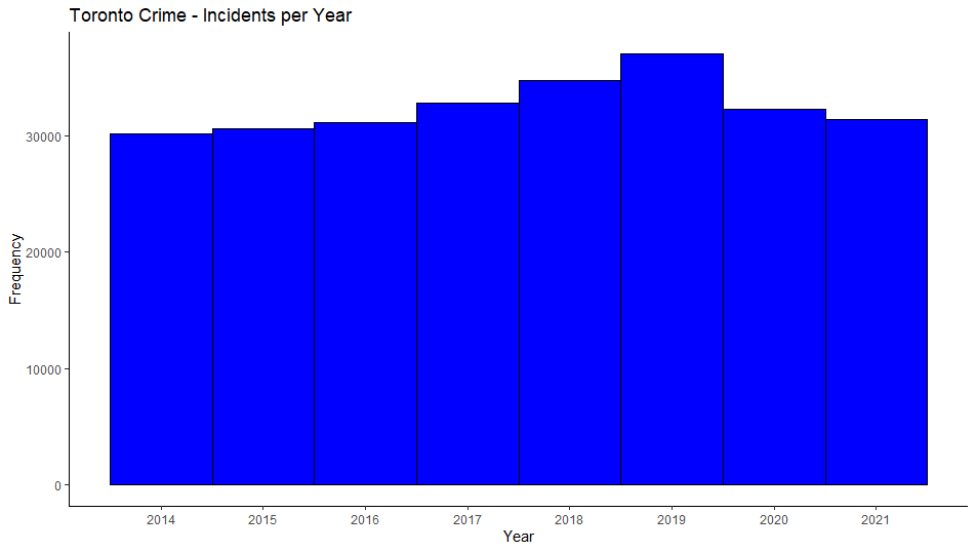


Figure 5. Trend in Toronto crime counts per year.

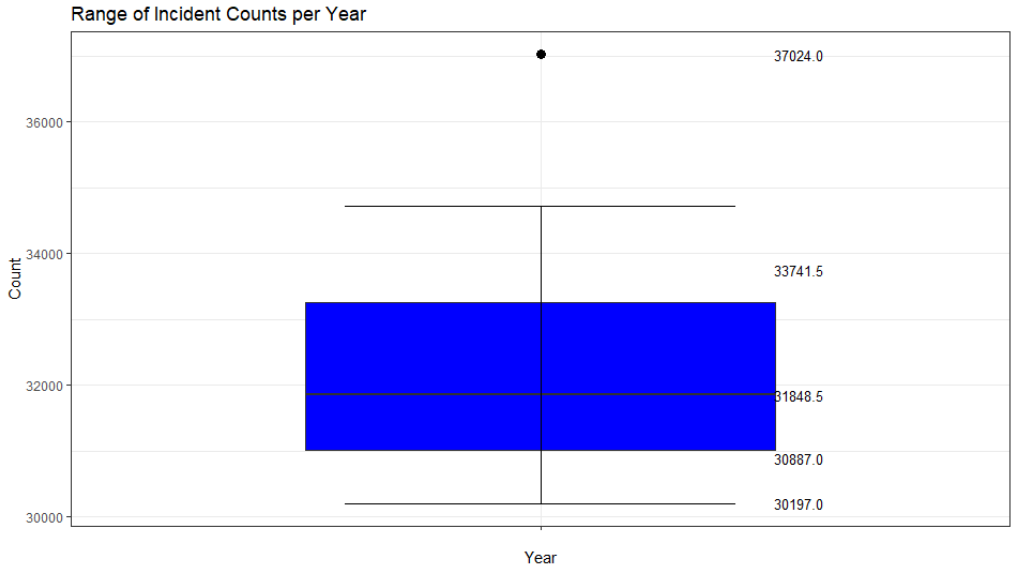


Figure 6. Range in Toronto crime counts per year.

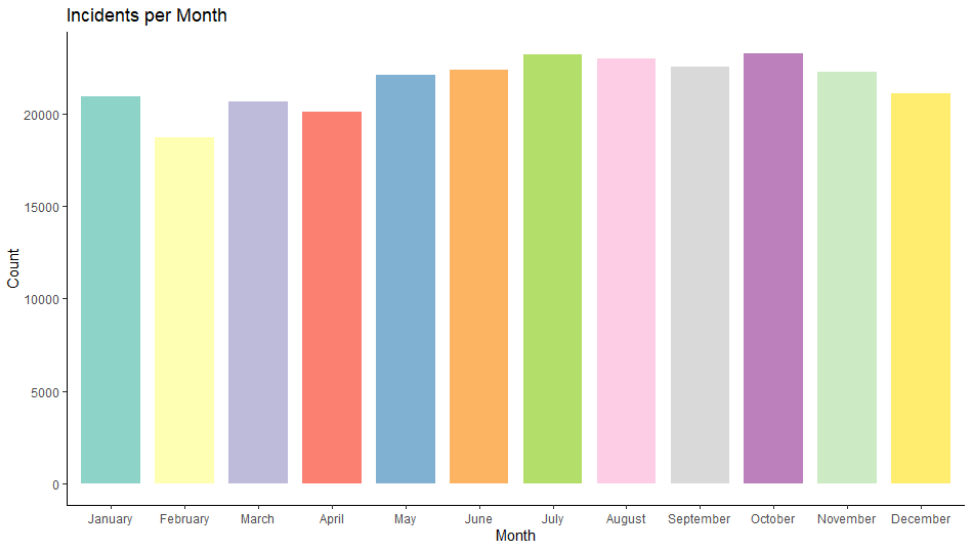


Figure 7. Trend in Toronto crime counts per month.

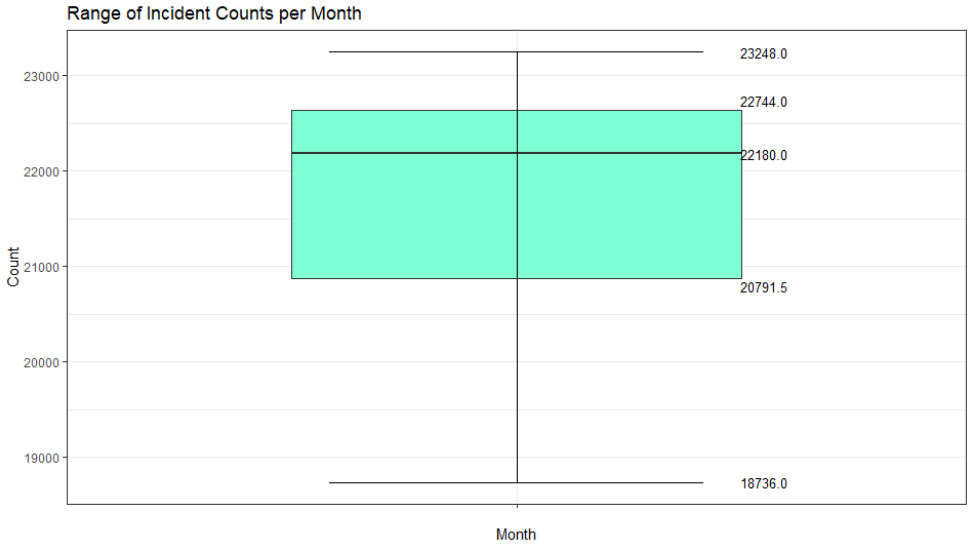


Figure 8. Range in Toronto crime counts per month.

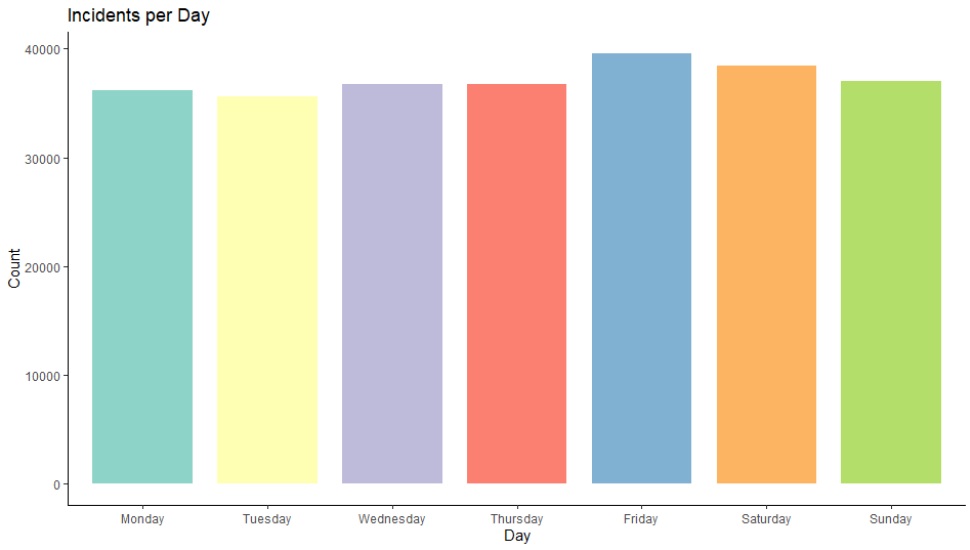


Figure 9. Trend in Toronto crime counts per day of week.

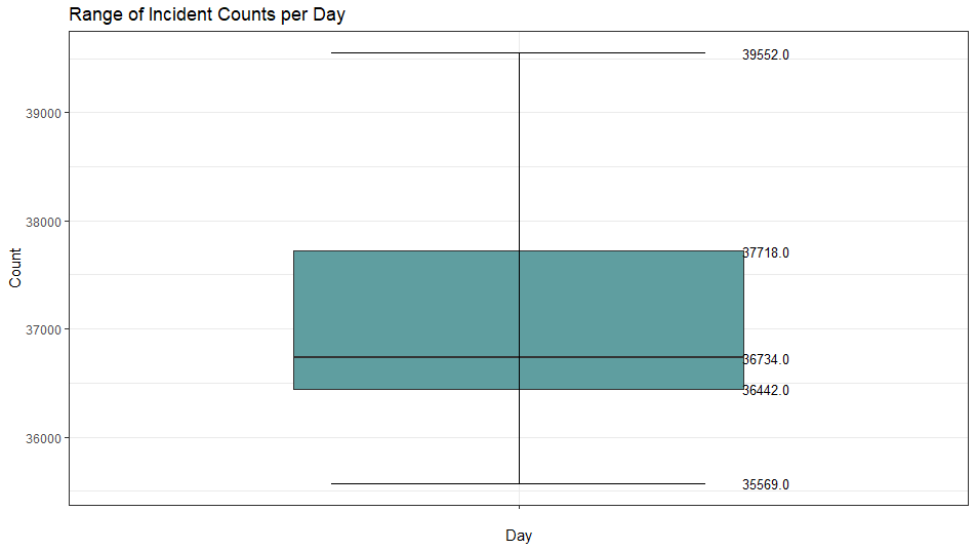


Figure 10. Range in Toronto crime counts per day of week.

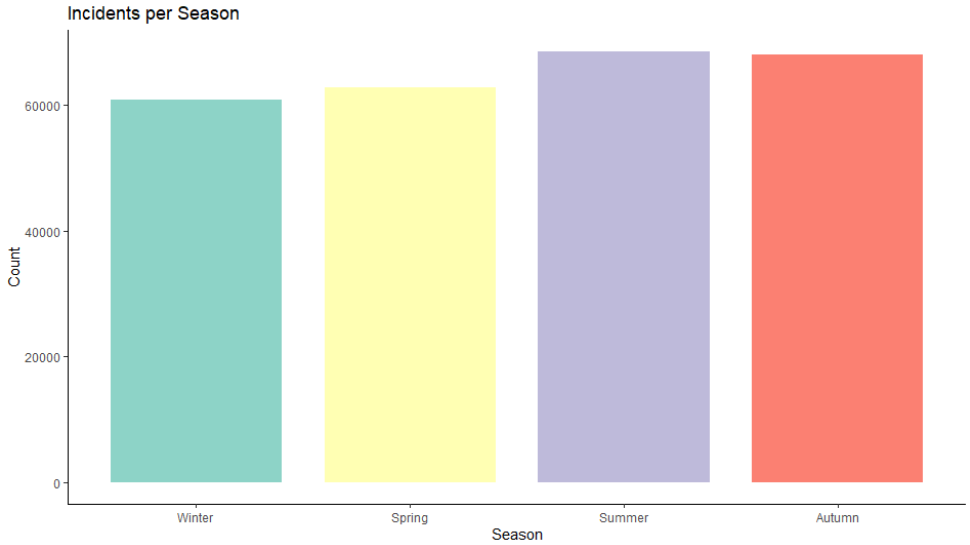


Figure 11. Trend in Toronto crime counts per season.

Premises	Incident Count
Apartment	63513
Commercial	52657
Educational	6607
House	47694
Other	14920
Outside	67550
Transit	7234

Table 1. Incident count per premises type.

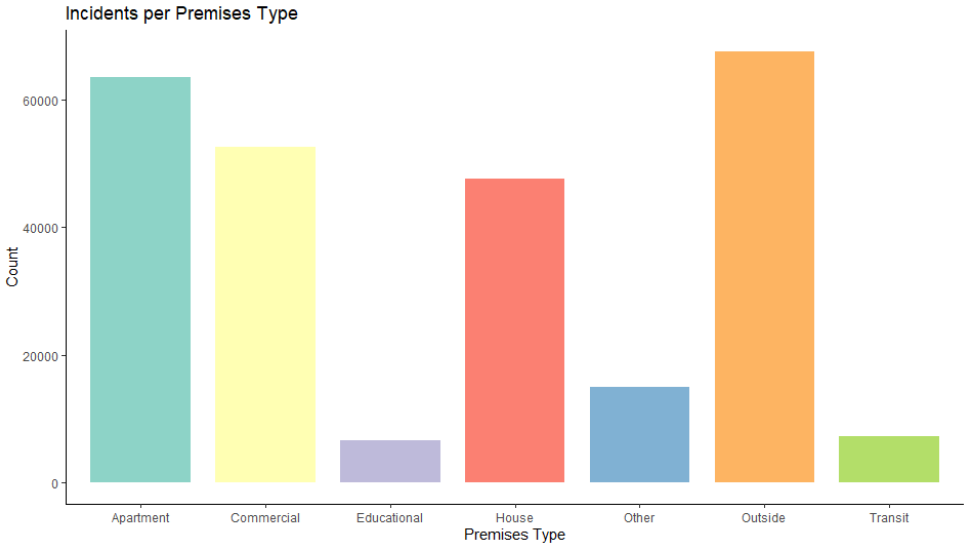


Figure 12. Trend in Toronto crime counts per premises type.

The was a progressive decrease in the number of incidents per hour from midnight to 7 am, after which incident counts increased with a significant peak between the hours of noon and 1 pm (Figure 13). A day-time analysis of crime indicated that most incidents occurred between midnight and 1 am on Saturday and Sunday, and the lowest crime numbers were noted for every weekday between the hours of 3 am and 11 am (Figure 14).

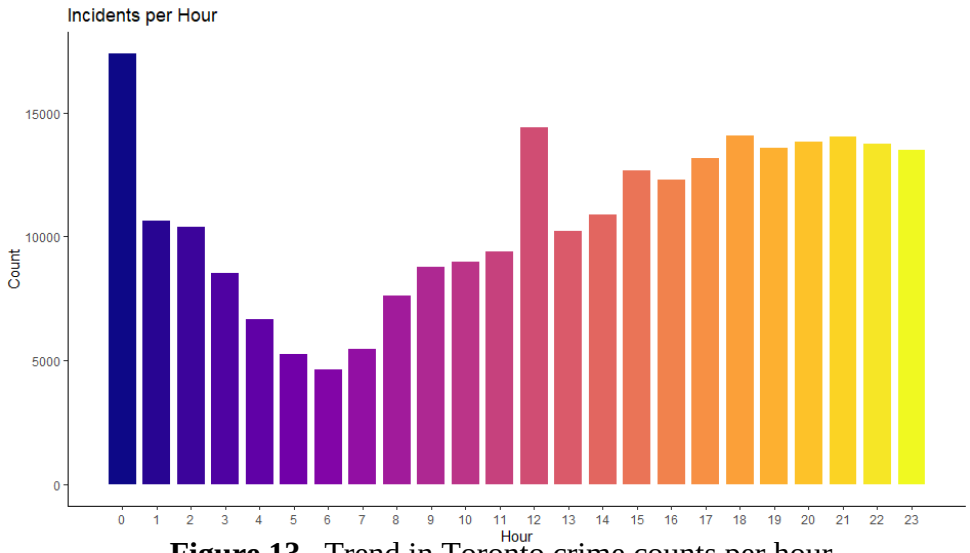


Figure 13. Trend in Toronto crime counts per hour.

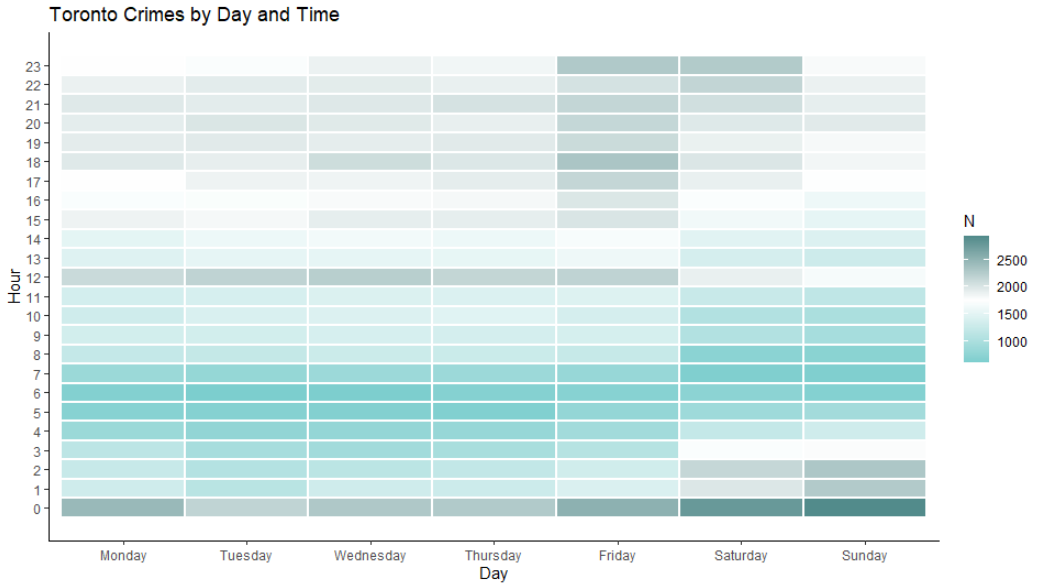


Figure 14. Day/Time trends in Toronto crime counts.

Incidents per neighbourhood ranged from 388 for Lambton Baby Point to 9622 for the Waterfront Communities, with a median value of 1371.5 (Figure 15). Outlier values were observed for the neighbourhoods of Waterfront Communities (9622), Church-Yonge Corridor (8606), Bay Street Corridor (7300), West Humber-Clairville (6874), Moss Par (6479), York University Heights (5056), Kensington-Chinatown (4960), Downsview-Roding-CFB (4931), Woburn (4547), and West Hill (4143). The outlier values were retained as neighbourhood-specific analysis related to crime counts were carried out; it is anticipated that rebalancing of the dataset will minimize the effect of the outliers. The top 10 neighbourhoods with the highest and lowest crime counts are shown on Figures 16 and 17.

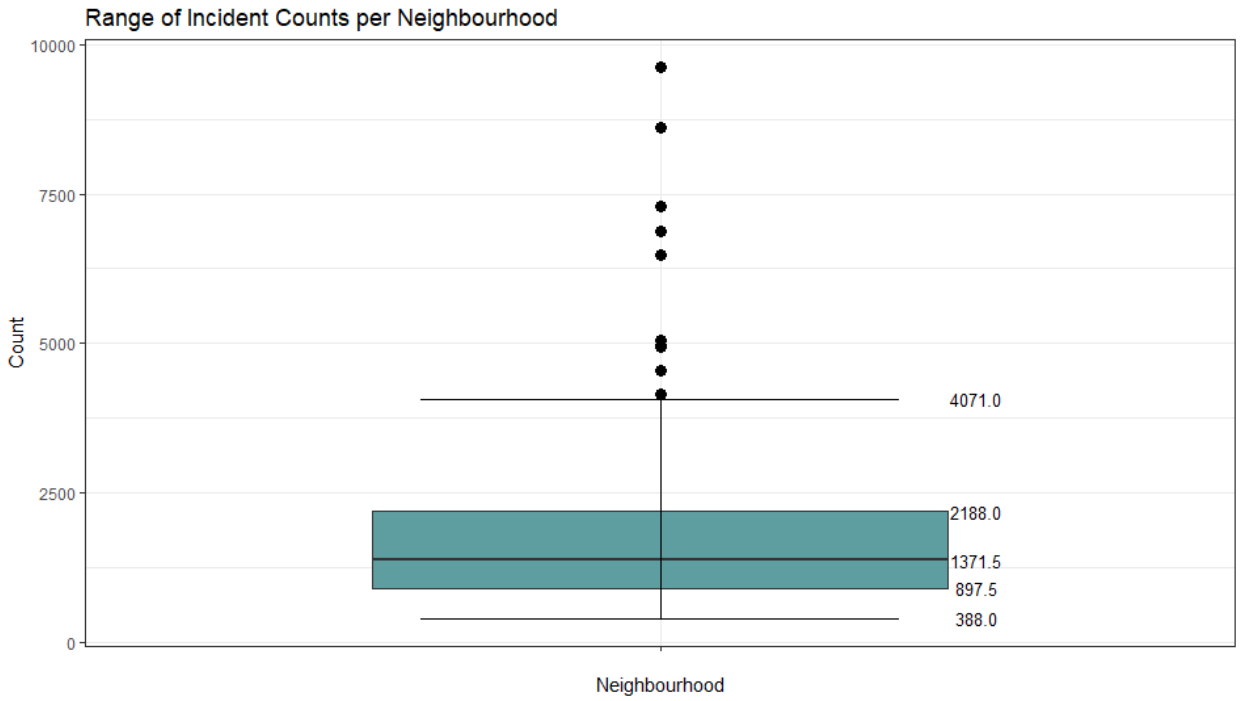


Figure 15: Box plot of incident counts per neighbourhood.

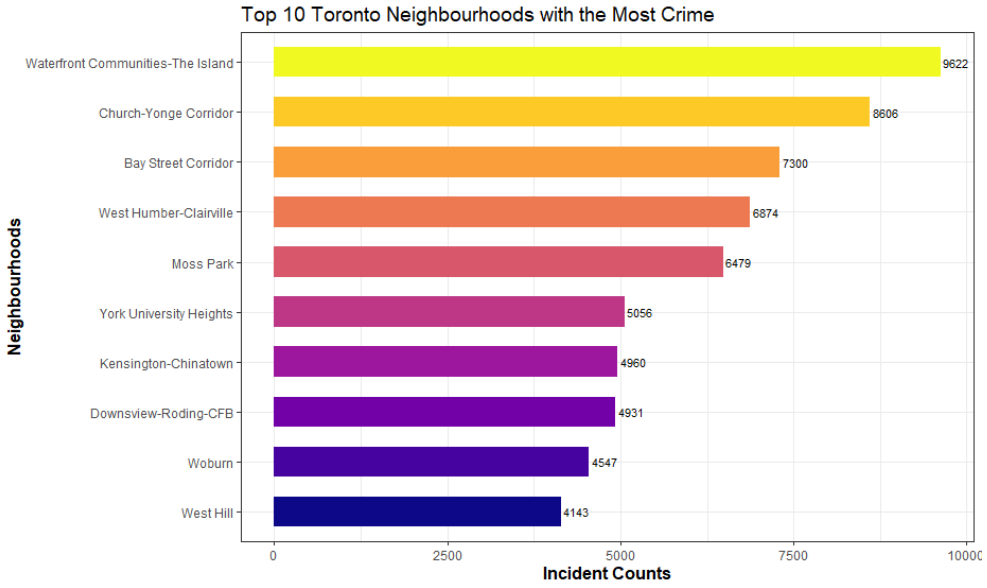


Figure 16: Toronto neighbourhoods with the highest crime counts – Top 10.

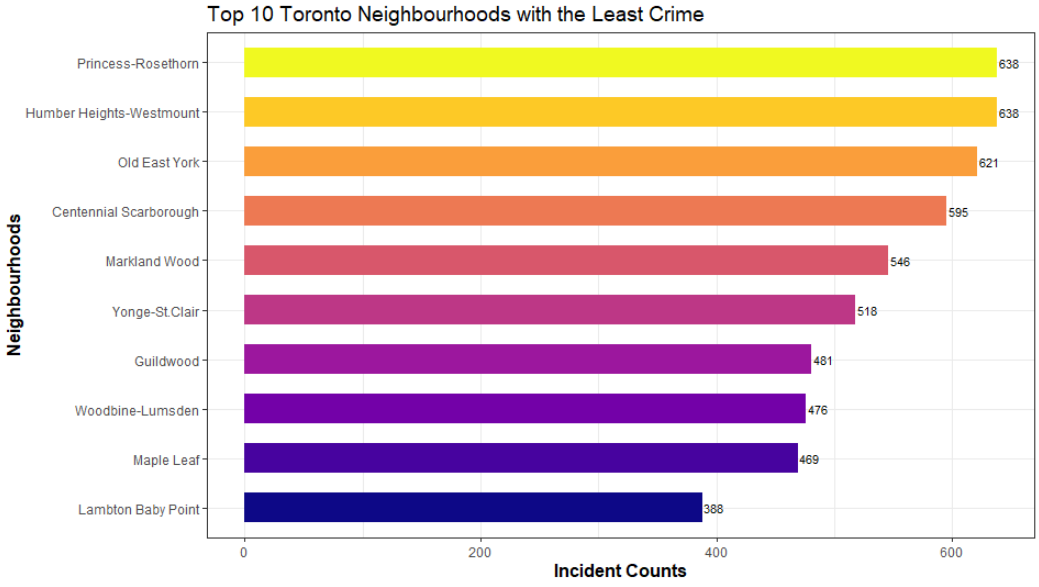


Figure 17: Toronto neighbourhoods with the lowest crime counts – Top 10.

Following the broad review of the crime dataset, the MCI data was examined in more detail to observe whether there were variations in the crime types in terms of time and location. There is a notable imbalance in the dataset with assaults clearly outnumbering the other MCI types (Figure 18) indicating that the data will be balanced prior to classification. A more detailed view of the offense types also shows assault as the primary offence type followed by break and enter, theft of motor vehicle and assault with a weapon (Figure 19). Assault was also the top MCI type per neighbourhood (Figure 20). The type of MCI shows some variation with respect to premises type with assault occurring primarily at apartments and outside, robberies were outside, break and enters were committed mainly at apartments, commercial properties, and houses, and theft over $5000 effectively the same across all types (Figure 21).

Assaults increased from 2014 to 2019 after which the number of incidents decreased. Break and enters exhibited minor variation between 2014 and 2018 with incidents increasing between 2019 and 2021. Similarly, auto theft increased between 2014 and 2017 and increased between 2018 and 2021. Theft over $5000 and robbery showed little annual variation (Figure 22). Apart from assaults, which occurred primarily between May and October, MCI categories showed little monthly variation (Figure 23). The was little variation in the MCI type per day; break and enters exhibited a subtle increase on Friday and assaults a slight increase on Saturday and Sunday (Figure 24). Assaults peaked between the hours of midnight and 1 am, and noon and 1 pm, with a distinct low between 3 am and 8 am. Break and enters showed a similar trend to assaults with maximums between midnight and 1 am and noon and 1 pm. Robbery and theft over $5000 exhibited little hourly variation while auto theft progressively increased from 7 pm to midnight (Figure 26).

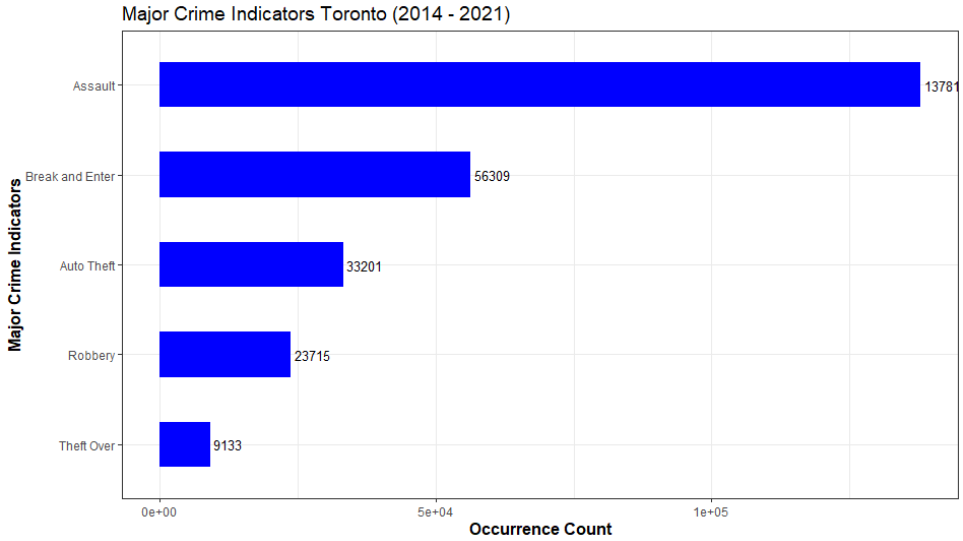


Figure 18: Trend in MCI categories.

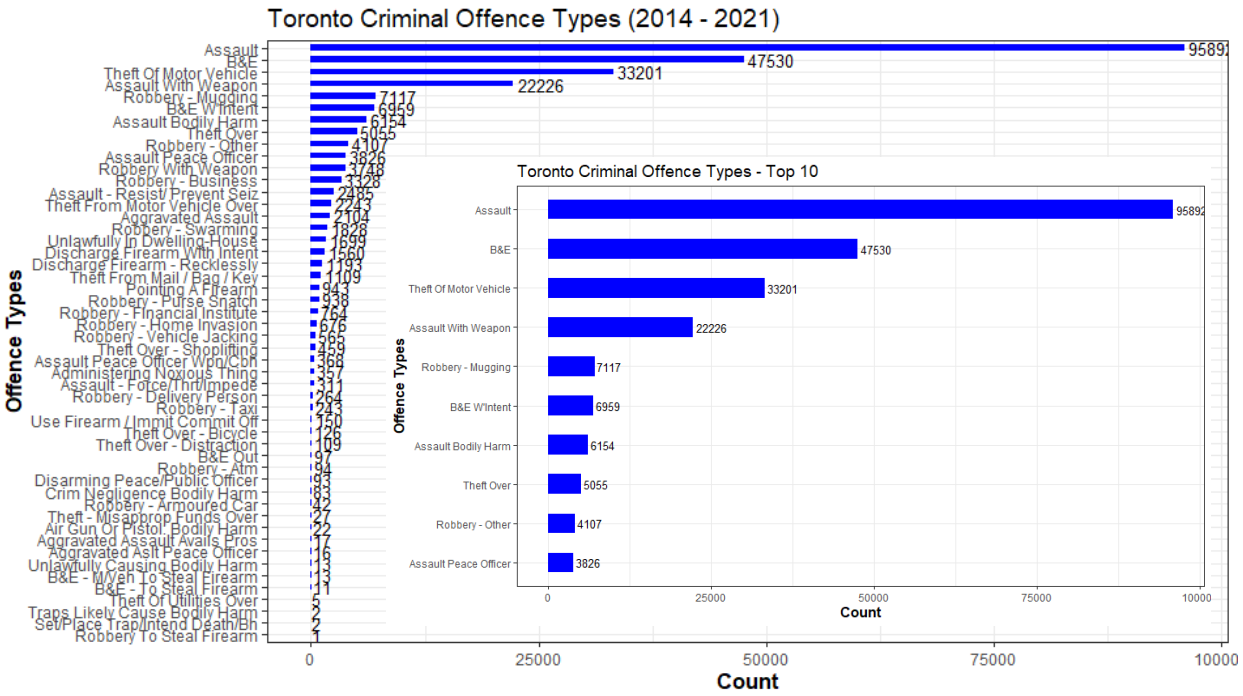


Figure 19: Toronto crime broken down by offence type with the top 10 shown in the inset plot.

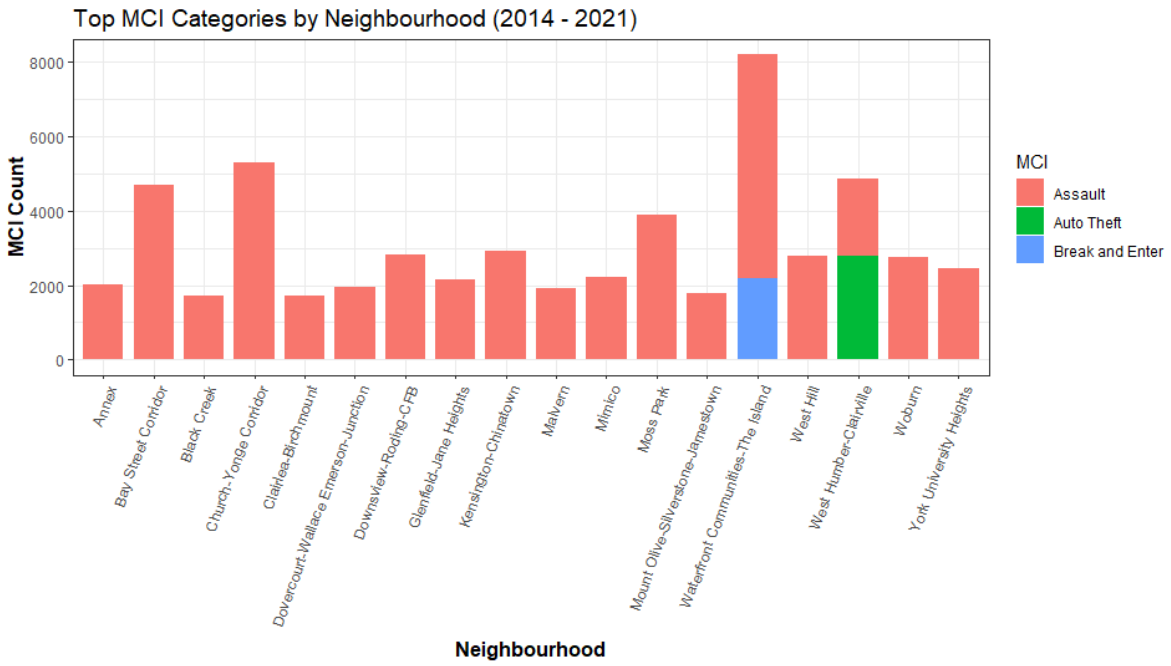


Figure 20: Primary MCI type per neighbourhood (first 20 neighbourhoods shown only).

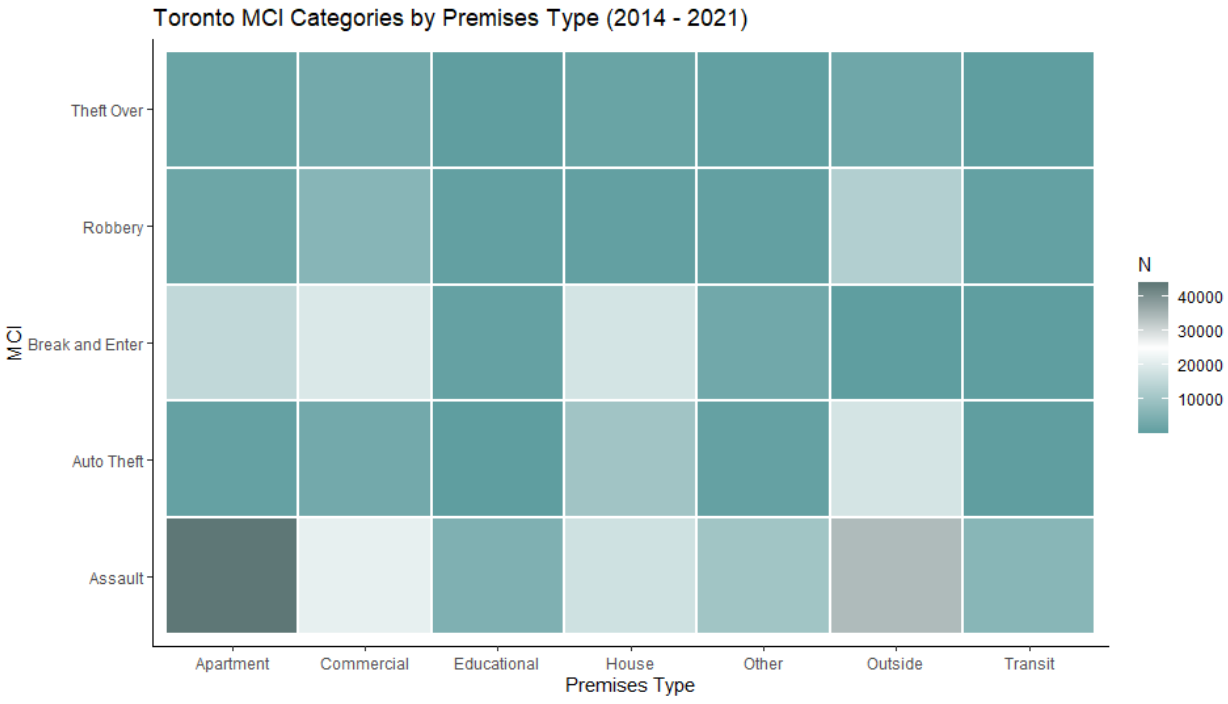


Figure 21: Variation in MCI category by premises type.

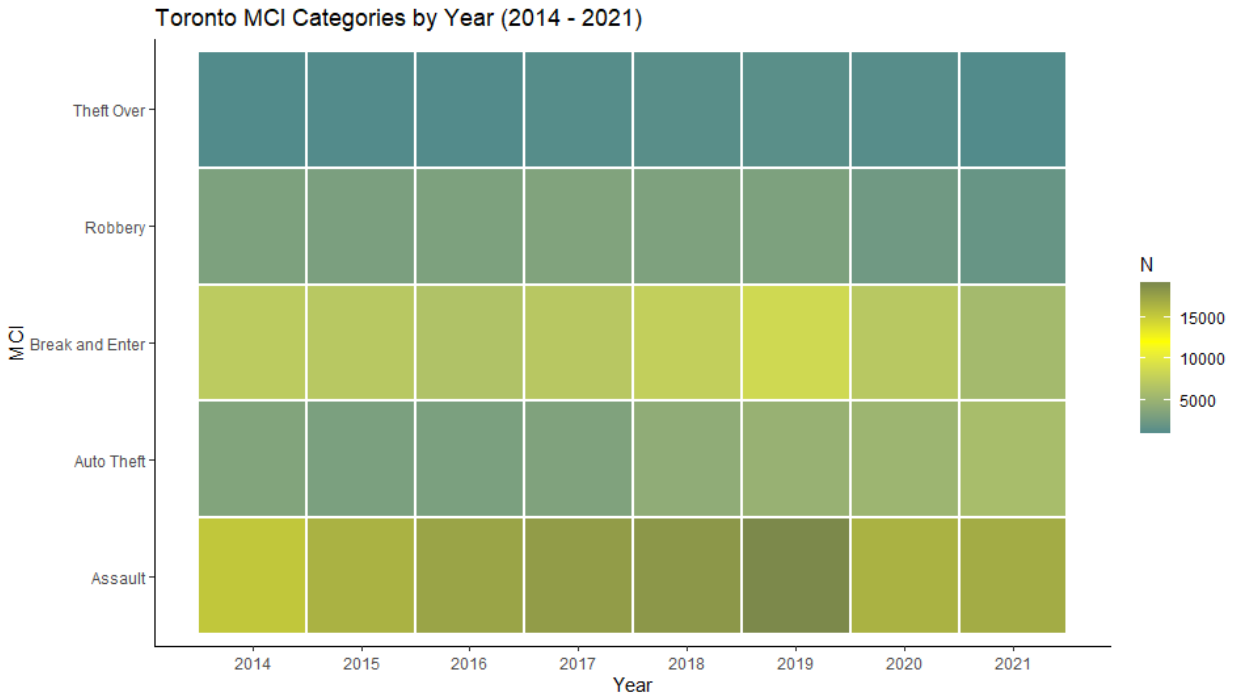


Figure 22: Variation in MCI categories per year.

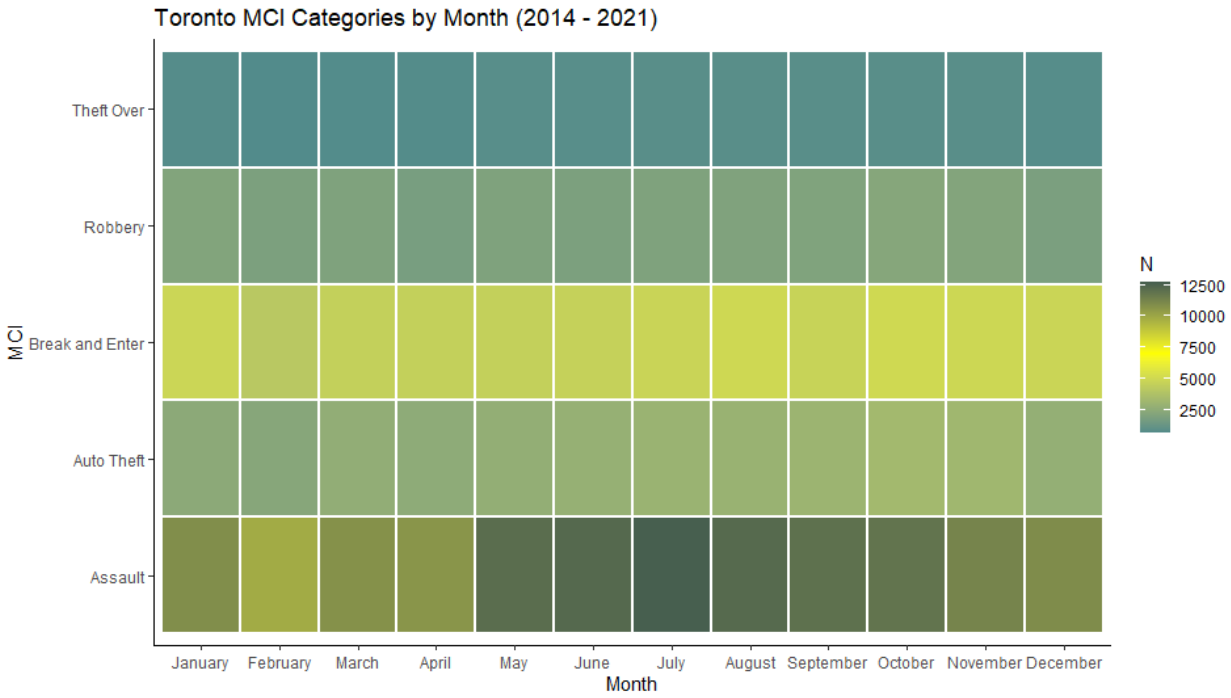


Figure 23: Variation in MCI categories per month.

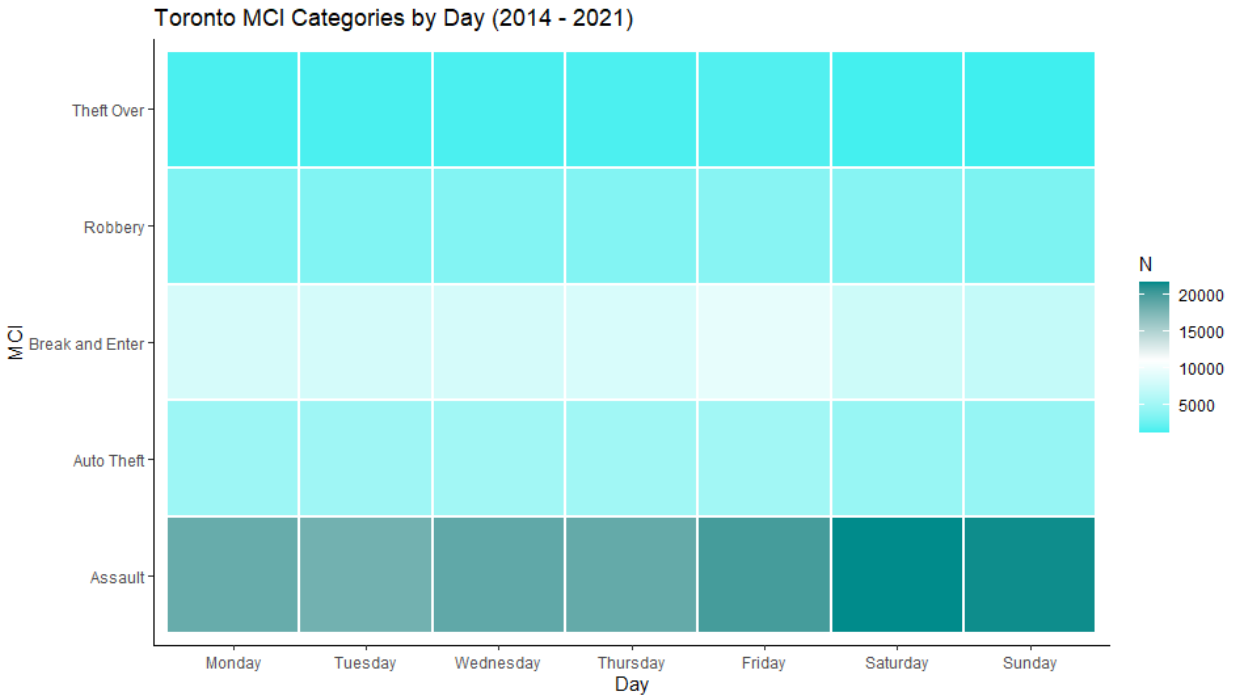


Figure 24: Variation in MCI categories per day.

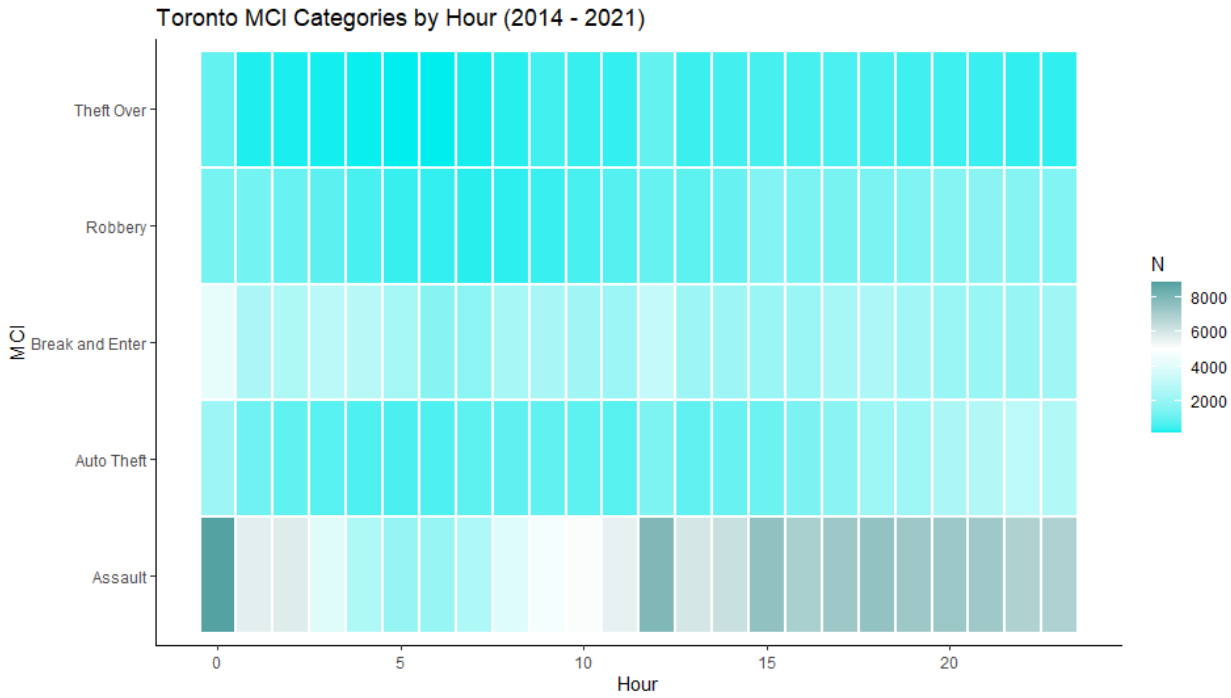


Figure 25: Variation in MCI categories per hour.

5. APPROACH

The project methodology is anticipated to follow the steps shown in Figure 26. Double arrows denote those project stages that could have some overlap.

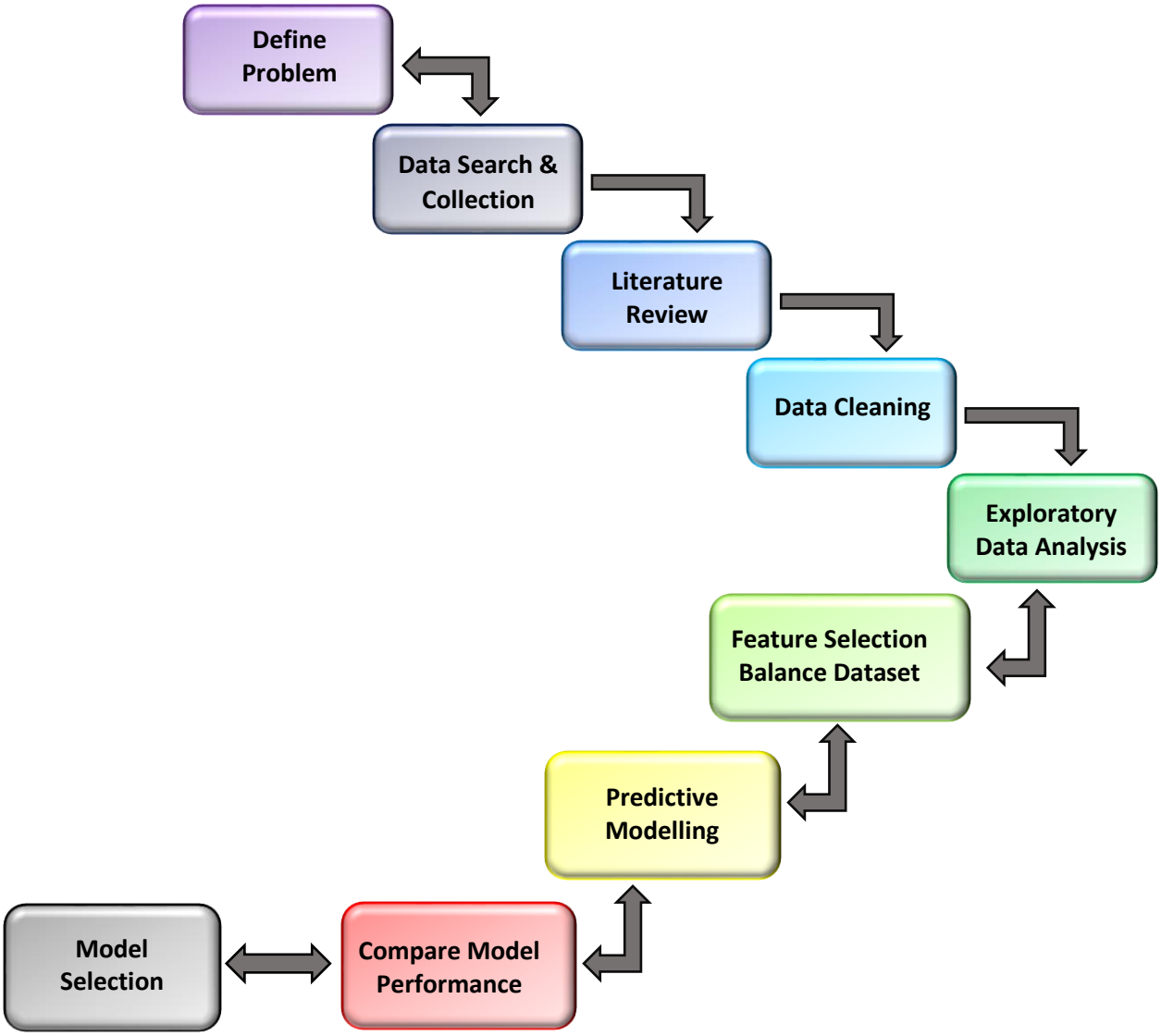


Figure 26: Tentative project methodology

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