Analysis on Crime Patterns in Boston

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1 Abstract

The objective of the project was to analyze the variety of crime patterns in the city of Boston between the years 2015 and 2023, by focusing on the variations and trends in Boston's demographically diverse districts. Data analysis was performed in R Studio via packages such as "ggplot", "tidyverse" and "dplyr", in order to visualize data, categorize groups, and help form analysis and conclusions regarding crime in Boston. The findings, based on the computationally created tables and visualizations, indicate that there may potentially be a correlation between crime in Boston and factors such as per capita income, crime density, single-parent households, education, offense description, time of day/week, weather conditions, and the COVID-19 pandemic.

2 Introduction

Large metropolitan areas around the world often have to deal with complex trends of crimes. The United States specifically has a particularly more complex issue of crime, with varying levels of racial, economic and cultural demographics. Often, the United States is referred to as the "melting pot of the world", where cultures and people from around the world come and mix with each other, creating a unified "American Culture". Large demographic variations however lead to many issues, namely inequality, which can exacerbate crime. Hence, studying the trends in crime can help mitigate the effects of a very important aspect of the American way of life.

Boston is one of the largest cities in the Northeastern part of the United States, being one of the original founding cities of the nation. The city is highly diverse, economically thriving and culturally an icon in the country. However, being such a large metropolitan area, the aforementioned issues also apply to the city, as there are many different districts with vastly different demographics. The goal of this project is to provide a comprehensive analysis on the variations of crime in the city, with respect to these demographic differences.

To explore the relationship between Boston and crime, four primary questions regarding the dataset were formed:

1. How do the per capita income, population density, single-parent household per capita, and education per capita impact the number of crimes in Boston?
2. How does the offense description, or type of crime, differ between districts in Boston?
3. How does the time of day/week impact crime in Boston?
4. How has the combination of the COVID-19 pandemic and weather conditions impact crime in Boston?

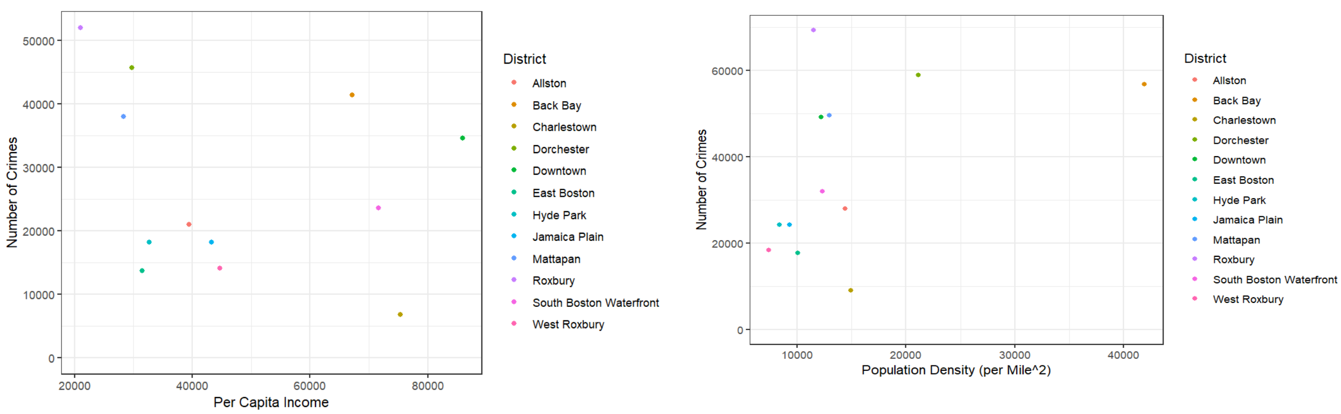
3 Data and Methods

The first step of the project was gathering and performing data cleaning procedures to ensure that the results produced accurately represented the trends in crime. First, we collected data related to crimes in Boston between 2015 to 2023 from the analyze boston website. The fields located within the csv file include: crime type (OFFENSE_CODE), where it happened (street, district codes), when it happened, and finally the location (lat,long). The data was polished via the exclusion of N/A observations and any data points that were not located within the city of Boston. In order to calculate and incorporate other variables of interest such as crime density and income per capita, which are decisive pieces of information in relation to crime, a second data set that includes demographics data in Boston was utilized. The second file contains 22 district names, and their corresponding aggregate income. The fields in the csv file were then used in order to calculate the income per capita as well as the crime density.

Next, to analyze the relationship between the demographic data and crime, we joined our demographics data with our crime data. Since the dataset did not include the district name, but rather the district code, we produced a leaflet script that plots the different district codes within Boston to better visualize the “hot spots" of crime. There were 22 district names within the demographics data, however, our crime data only had 12 codes. For this reason, we manually mutated the district_name to their corresponding district codes through a very tedious process. This is also the reason as to why some of the district names contain multiple areas. For example, Downtown includes North End, West End, Beacon Hill, and the entirety of the district itself.

Finally, we were able to visualize relationships between variables via the ggplot() function within R studio as well as including statistical tests such as fitting a linear model, in order to predict future crime trends.

4 Results



Figures 1 & 2 Per Capita Income & Density per Mile^2 Vs. Number of Crimes in Boston (2015-2019)

The purpose of Figure 1 was to create a scatter plot that displays the relationship between the per capita income for each district and the number of crimes per district. After examining the results, the most number of crimes occurs in Roxbury, which interestingly also has the lowest per capita income, when compared to the other districts in Boston. On the contrary, Downtown reported the highest per capita income, however, it did not report the lowest number of crimes. It should be noted that the general trend of the plot displays an inverse relationship between the per capita income and the number of crimes, however, there are definitely district outliers such as Back Bay and Downtown that have comparatively large per capita incomes, yet still report a large number of crimes. Furthermore, districts that reported a per capita income between 30,000 and 50,000 all noted between 25,000 and 50,000 crimes. The primary conclusion that can be drawn from Figure 1 is that the lowest per capita income, Roxbury, had the highest number of crimes, while the highest per capita income, Downtown, did not have the lowest per capita income.

On the other hand, the purpose of Figure 2 was to visualize the relationship between the population density and the number of crimes. Similar to Figure 1, Roxbury had the most number of crimes, however, it does not have the smallest population density. Contrary, Downtown reported one of the smallest population densities, yet had one of the largest number of crimes, only falling short to Back Bay, Dorchester, and Roxbury.

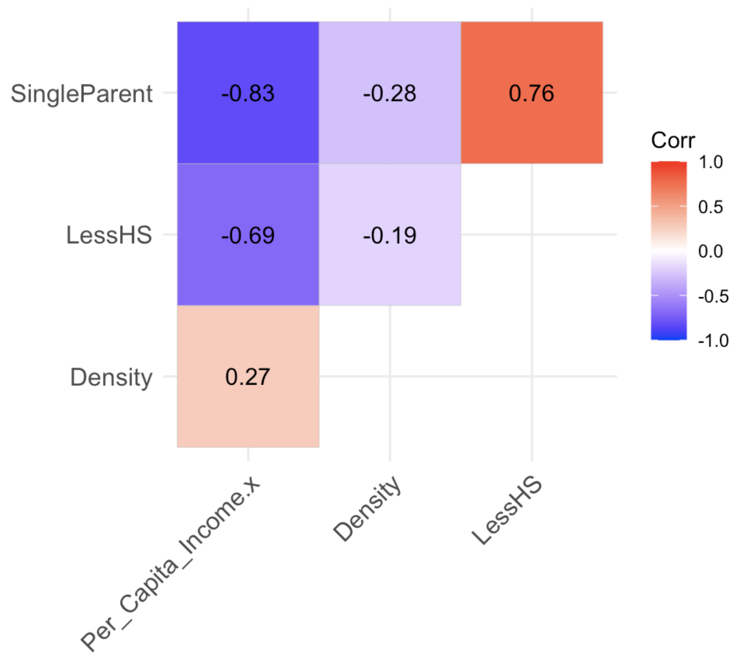


Figure 3. Correlation Matrix Between Proportion of Residents without a Highschool Degree, single-parent Households, Density, and Per Capita Income in Boston

In order to visualize the relationships between total crime, population density, number of high school graduates, single-parent households, and per capita income, a correlation matrix was produced.

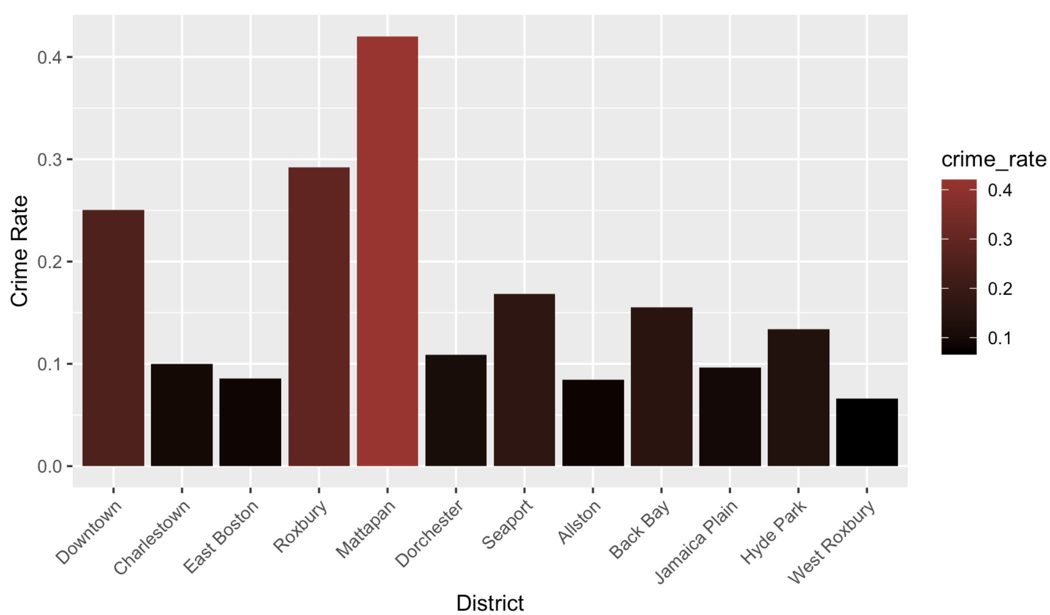


Figure 4. District Vs. Crime Rate in Boston Between 2015 & 2023

After joining the demographics dataset with the original dataset, we explored the relationship between the district and crime rate. By grouping the dataset by “district”, using computational tools to find the crime count per district, and computing the mean population corresponding to each district, a series of crime rates were produced. By analyzing the different crime rates, it is evident that Mattapan had the highest crime rate compared to the rest of the districts in Boston. Only 3 districts: Downtown, Roxbury, and Mattapan surpassed a crime rate threshold of 0.2, while 9 districts fell well below the threshold. The main conclusion that can be drawn from Figure 4 is that the two lowest income districts, Mattapan and Roxbury, had the highest crime rates in Boston. Downtown, which is the highest income district in Boston, reported the third highest crime rate of 0.25. Nevertheless, this is a steep difference from Mattapan, which has the highest crime rate in Boston surpassing 0.4.

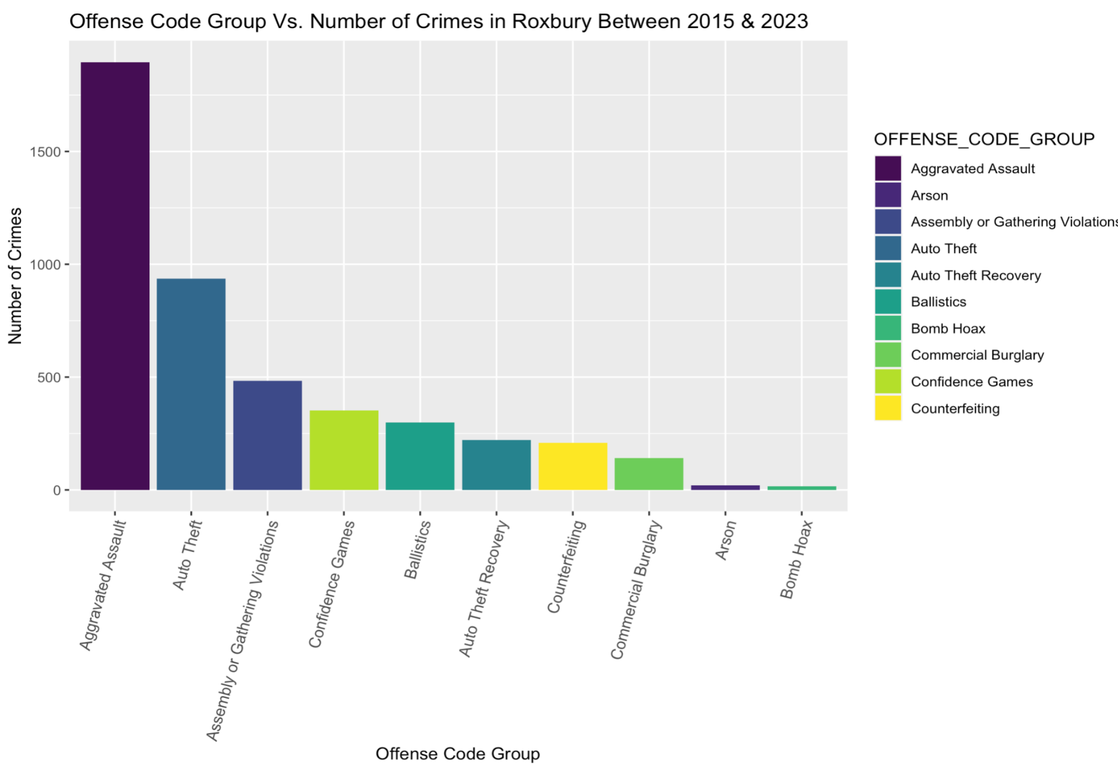


Figure 5. Offense Code Group Vs Number of Crimes in Roxbury Between 2015 & 2023

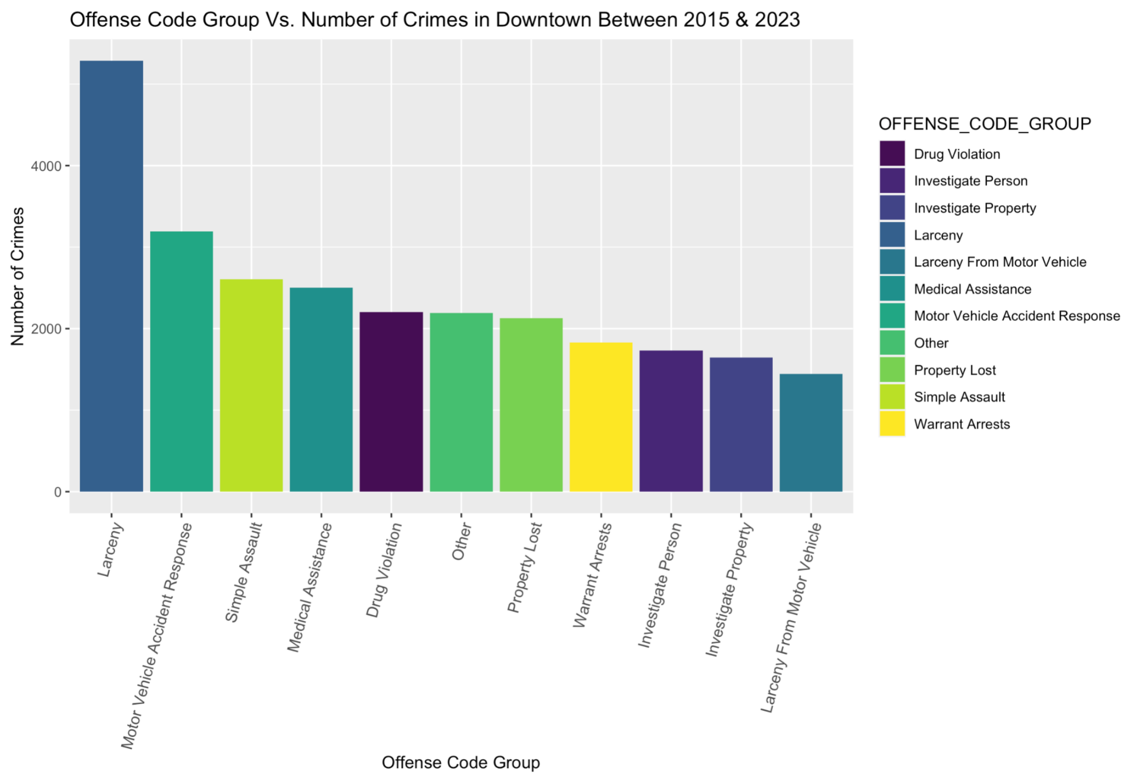


Figure 6. Offense Code Group Vs. Number of Crimes in Downtown Between 2015 & 2023

Figures 5 and 6 were produced to analyze how crime type and frequency differs between the income district with the highest per capita in Boston, Downtown, and the district with the lowest per capita, Roxbury. Within the Roxbury community, the most prominent offense code group was aggravated assault, followed by auto theft, and assembly/gathering violations. On the other hand, both Arson and Bomb Hoaxes were the least frequently occurring crime codes. Based on Figure 5, the types of crimes associated with the Roxbury community are often related to violence and physical force such as auto theft and aggravated assault. The quantity of crimes in Roxbury varies from well below 100 crimes, corresponding to bomb hoaxes and arson, to greater than 500 crimes corresponding to aggravated assault and auto theft.

On the contrary, following analysis of Figure 6, it can be seen that the most frequently occurring offense code groups present within the Downtown community were different from the district with the lowest per capita income, Roxbury. The most frequently occurring crimes in Downtown were related to larceny, followed by motor vehicle accidents and simple assault. When comparing the top 5 most frequently occurring crimes between Roxbury and Downtown, common themes of thievery, larceny, and automobile related incidents can be seen. Despite having a variety of crimes, the number of crimes per code in Downtown varies between 1445 and 5285 crimes, which is far greater than Roxbury's variation of 17 to 1896 crimes per offense code!

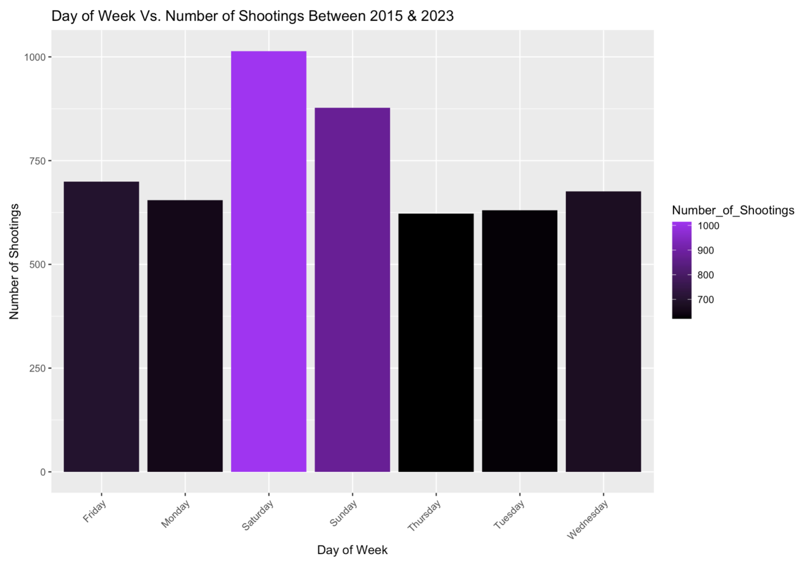


Figure 7. Bar Chart of Boston Day of Week Vs. Number of Shootings Between 2015 and 2023

Figure 7 was produced in order to visualize the potential relationship between the day of the week and the number of shootings. For example, based on Figure 7, there were more shootings on the weekend than on the weekdays. Saturday and Sunday both surpassed 750 shootings between 2015 and 2023, however, the rest of the days of the week did not. Interestingly, the day of the week with the least amount of shootings was Thursday, while the the most number of shootings occurred on Saturday.

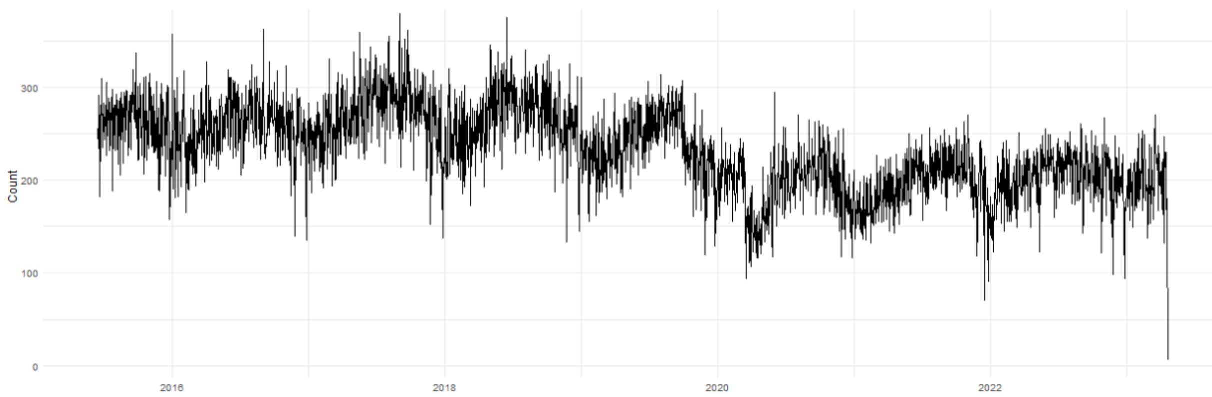


Figure 8. Line Graph of Total Crime Count Vs. Date(2015-2023)

Onwards, Figure 8 displays a line graph of the crime rates between 2015 and 2023. By analyzing the data, the recurrent trend of rising and falling by the end of each year can be seen. Although this pattern spans a majority of time between 2015 and 2023, the year of 2020 is an exception. In general this cyclical trend is shown regularly across the years in question.

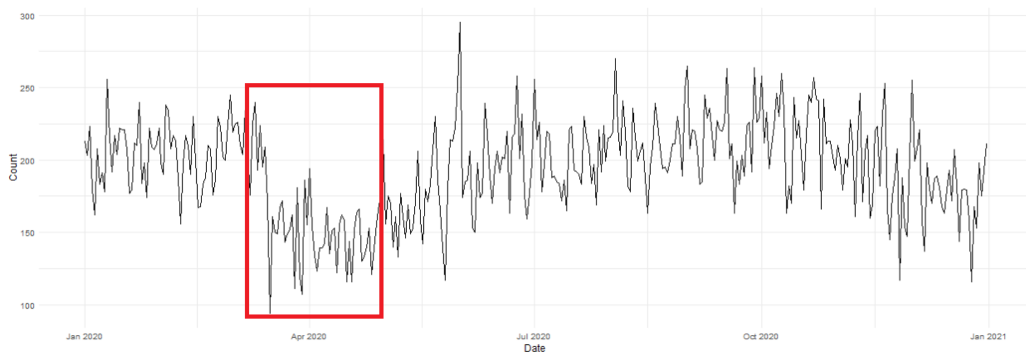
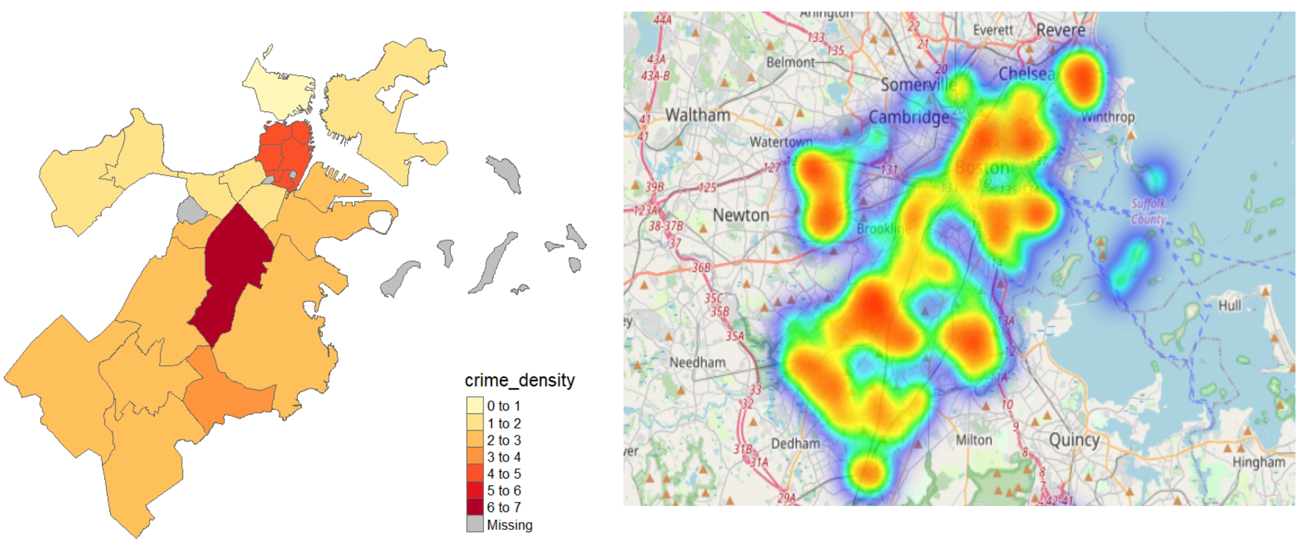


Figure 9. Line Graph of Crime County in 2020 Vs. Count

By specifically isolating the line graph for the year 2020 in Figure 9, the key deviation that occurs from the established pattern of crime rates rising and falling can be seen. It should be noted that roughly around April 2020 was when the United States went into a lockdown due to the COVID-19 pandemic.



Figures 10 & 11. Heatmap of Crime Densities by District (left) & Heatmap of Crime Total Between 2015-2023 (right)

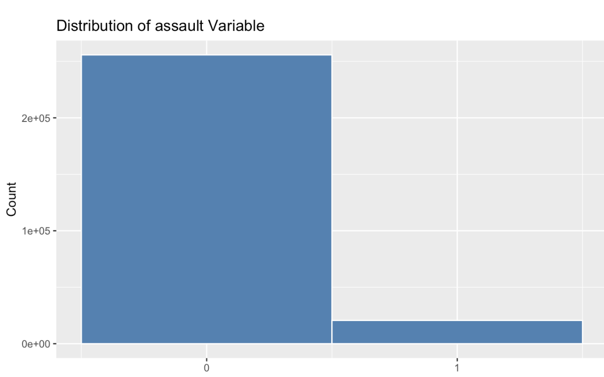
In order to visualize the districts of Boston that correspond to crime density and total crime, figures 10 and 11 were produced. By joining the number of crime data with the geometry shp files and visualizing the result produced, the relationship between the crime total and population density in each district was revealed. The population density was calculated by dividing the population by the total population squared. Via the population density, the crime density was calculated by dividing the total number of crimes by the population density. After analyzing figures 10 and 11, it is evident that the Roxbury, Downtown (including West End, North End, Beacon Hill), and Mattapan districts reported the highest crime densities within Boston. On the contrary, Charlestown has the least crime density value, when compared to the other 22 districts in Boston.

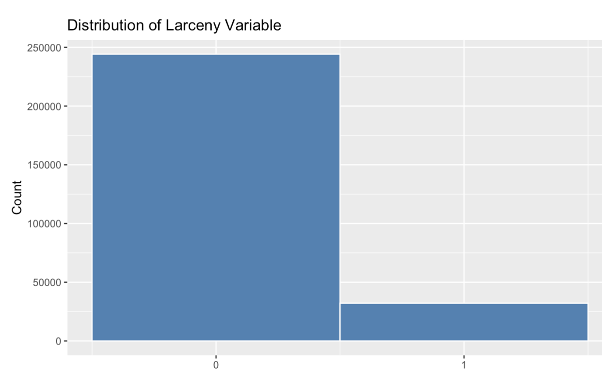
A machine learning approach can be used to implement a classification system to determine the offense code given the district, month, and year. To implement this preliminary model two main methods were used. One of which is logistic regression. First, the data had to be cleaned to perform analysis. With logistic regression a binary outcome is required, therefore a function “assign_afew” was created as shown in Figure 12.

```
assign_afew<- function(offense_code_group) {
  if(offense_code_group %in% c("Larceny", "Larceny From Motor Vehicle", "Simple Assault",
                               "Aggravated Assault", "Fraud", "Arson", "Residential Burglary",
                               "Robbery", "Auto Theft", "Confidence Games",
                               "Prisoner Related Incidents")) {
    return(1)
  } else {
    return(0)
  }
}
```

Figure 12. Function to create binary outcome

As defined above the "assign_afew" function assigns 1 to "Larceny", "Larceny From Motor Vehicle", "Simple Assault", "Aggravated Assault", "Fraud", "Arson", "Residential Burglary", "Robbery", "Auto Theft", "Confidence Games", "Prisoner Related Incidents". Otherwise it assigns 0. This function creates a column named “deg1” which are crimes deemed to be more significant than the rest. The reason for creating a new type of observation “deg1” was to combat the blatant imbalance of classes created if you take certain crimes alone. For example, this is demonstrated in figures 13 and 14 with larceny and assault.





Figures 13 and 14. Distribution of “assault” Variable (left) and Distribution of “Larceny” Variable (right)

If we compare this to deg1 in Figure 15 the imbalance of classes is far less significant.

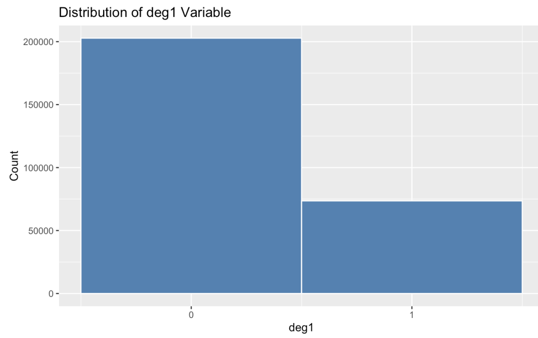


Figure 15. Distribution of “deg1” Variable

After cleaning the data a train/test split was applied to create the training set and testing set for the model. 80% of the cleaned dataset was to be used for training and the leftover 20% would be used for testing and validation. The model’s confusion matrix is shown in Figure 16.

```
## Confusion Matrix and Statistics
##
##            NA
## predictions     0     1
##           0 32486 10127
##           1  8090  4567
##
##                Accuracy : 0.6704
##                  95% CI : (0.6665, 0.6743)
##     No Information Rate : 0.7341
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.1166
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8006
##             Specificity : 0.3108
##          Pos Pred Value : 0.7623
##          Neg Pred Value : 0.3608
##              Prevalence : 0.7341
##          Detection Rate : 0.5878
##    Detection Prevalence : 0.7710
##       Balanced Accuracy : 0.5557
##
##        'Positive' Class : 0
##
```

```
## Confusion Matrix and Statistics
##
##            NA
## predictions   0   1
##           0 697 210
##           1  43  50
##
##                Accuracy : 0.747
##                  95% CI : (0.7189, 0.7737)
##     No Information Rate : 0.74
##     P-Value [Acc > NIR] : 0.3213
##
##                   Kappa : 0.1695
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9419
##             Specificity : 0.1923
##          Pos Pred Value : 0.7685
##          Neg Pred Value : 0.5376
##              Prevalence : 0.7400
##          Detection Rate : 0.6970
##    Detection Prevalence : 0.9070
##       Balanced Accuracy : 0.5671
##
##        'Positive' Class : 0
##
```

Figure 16 & 17. Confusion matrix for Logistic Regression and Confusion matrix for SVM (left)

As mentioned above, due to the high imbalance in the two classes, there is a noticeable difference in sensitivity and specificity. This is a bias in the estimation of the model parameter, which arises from the imbalance of the two classes in the data. A low specificity means that the model has a high false positive rate, which means it incorrectly identifies positive cases as negative. However, this model maintains an accuracy of around 67%. Again, this number could be increased with a higher specificity. One way of tuning the model could be to employ a different sampling method, such as upsampling or downsampling one of the classes. A more nuanced approach would be to use a rare event logistic regression model or a Firth Logistic regression model. These models can be found in the R library "logistf". The logistic regression model utilizes a cutoff probability for the classifier which is set to 0.3 in this case based on empirical observation. However, there are optimal cutoff algorithms to determine the ideal cutoff probability. Using methods such as ROC or the Youden metrics in the "cutpointr" library we may be able to determine an optimal cutoff point for this probability. For the purposes of a preliminary model, this was not necessary as some of these solutions have the potential of introducing bias.

Some models handle imbalance better, one such model is a Support Vector Machine (SVM). Using the same split as before the model returns the results in Figure 17.

Due to the complex algorithm SVM uses, the model takes a considerable amount of time to run. In most instances, it can help to use a smaller dataset. The model, using the smaller dataset, returns an accuracy of around 75% which is better than the Logistic regression model. However, the specificity is lower with a value of ~0.2 the sensitivity is higher at ~0.95.

This model uses a 5 fold cross-validation. A k-fold cross-val is a procedure used to validate the performance of the trained model on new data. SVM is a good candidate for k-fold cross validation, as there is a parameter to implement a trainControl in the algorithm which allows you to make sure that any observation can be in the training or testing set. There are optimal ways to select 'k' in k-fold, but it makes sense to select 5 arbitrarily as the convention is to go up by odd numbers for k-fold (I.E: 3,5,7,9...). Splitting the data 5 ways is enough to gain effectiveness from validation, but not too many splits, where we would be prone to a high run time. The difference in sensitivity and specificity of the two models suggests that using the models in ensemble could be beneficial.

High °F	Low °F		High °C	Low °C
37	23	January	3	-5
39	25	February	4	-4
46	31	March	8	0
56	41	April	14	5
67	50	May	19	10
76	60	June	25	15
82	66	July	28	19
80	65	August	27	18
73	58	September	23	15
62	48	October	17	9
52	38	November	11	3
42	29	December	6	-2

Figure 18 . Weather Trends in Boston between 1991 and 2020

Figure 18, displays the average temperatures in Boston from 1991 to 2020 and also showcases notable climate trends over the three-decade period. The purpose of the Figure is to analyze any patterns in the weather that could potentially have an impact on the crime rates of different districts of Boston. The

Figure emphasizes seasonal variations, with winter months being colder and summer months exhibiting warmer temperatures.

5 Discussion

The primary purpose of this project was to analyze a plethora of factors that are thought to have been impacting crime patterns in Boston within the 2015 to 2023 timeframe. Specifically, our group was interested in how a variety of factors have impacted Boston crime such as per capita income, crime density, single-parent households, education, offense description, time of day/week, weather conditions, and the COVID-19 pandemic.

To begin, according to Figures 1 and 2, the number of crimes are explored according to the aforementioned two factors. Roxbury seems to have the most amount of crime, while having the least income per capita. Back Bay has a population density far greater than all others, while having the third most amount of crime. As seen in Figure 3, there is not necessarily any correlation between population density and income per capita, explaining the difference in patterns in Figures 1 and 2. The data provided in Figure 3 was also very crucial for analyzing the effects of the four mentioned factors on total crime. The figure shows that the number of people without high school degrees or equivalent per capita, single-parent households and income per capita are related.

Three separate models were made, each of which analyzed a single correlated factor, while also maintaining a constant density. In addition, since all of the variables were on different scales and demographics, the variables were standardized to see the effects of increase. Density was kept constant, with all other variables having an additional polynomial variable to assess the non-linear relationships between variables and total crime, as well as seeing the marginal effect of the variables.

The results show that per capita income regressed onto total crime, holding density consistent is statistically significant. For every decrease in a standard deviation for per capita income, total crime increases by 0.91 standard deviations. Un-standardizing total crime would yield this to be a 13,791 increase in the number of crimes. The variable and the model were both statistically significant at a significance level of 0.05. Additionally at a significance level of 0.05, the effect of single-parent households on total crime is significant. The model showed that there was a quadratic relationship between the variables as when single-parent households increased by one standard deviation, total crime would increase by 0.89 standard deviations. Un-standardizing total crime would show an increase in total crime by 3,932. All other variables on their own were not statistically significant when predicting the number of total crimes.

However, when regressing the percentage of single-parent households and the number of people without high school degrees onto per capita income, it was shown that both were statistically significant at a significance level of 0.05. For every standard deviation increase in single-parent households, income per capita decreased by 0.83 standard deviations. Un-standardizing per capita income would yield a decrease of 13,573 dollars per capita. Additionally an increase in one standard deviation of people without high school degrees would lead to per capita income to decrease by 0.69 standard deviations. Un-standardizing per capita income would yield around 14,872 dollars per capita. Both of these results show that there is evidence to believe the statistically significant variable when pertaining to total crime, being per capita income, is affected by single-parent households and the number of people with less than a high school degree in that respective district.

Researchers and the Heritage Foundation[6] and Federal Reserve[7] found similar results with regards to single-parent households and education, respectively. It was shown that a 10% increase in single-parent households would increase juvenile delinquency by 17%, which would exacerbate levels of income. Additionally, the difference in median wealth between those who have a high school degree and those who do not is around $60,000 dollars. These were consistent with what we found with respect to effects on per capita income which was statistically significant for predicting total crime.

Knowing this, keeping in mind possible omitted variable bias and multicollinearity, a final regression analysis was conducted factoring in the single-parent households and number of people without high school education, without the polynomial factor. The result at a 0.05 significance level showed that there is evidence to believe that per capita income and density were both statistically significant when determining the total crime.

Additionally, based on the analysis performed it is evident that crime has disproportionately impacted lower income areas more than higher income areas. Based on Figures 5 and 6, it is evident that there is a juxtaposition in crime rates between the highest and lowest income districts in Boston. In the 1960s the Boston Redevelopment Authority tore down Boston's red light district, which in turn forced many adult industry businesses to an area adjacent to Washington Street, which runs through the Roxbury district. As an adult entertainment district, city officials and police officers often did not enforce crimes such as drug dealing, selling illegal guns, and unfortunately perpetuated the problem through corruption[2]. As a potential consequence of its previous roots in the combat zone, today Roxbury has a comparatively large poverty rate, with almost 33.9% of the population falling under the poverty line. In a recent study by Tufts University regarding poverty in the Roxbury, Dorchester, and Mattapan districts, Dr. James Jennings explains how poverty is a direct root cause of hunger, physical illness, social exclusion, and even unsafe environments[2]. The unfortunate hardships that people in poverty face could be a potential factor/reason for heightened crime in these areas since they would be more inclined to take extreme measures to maintain proper health and stability.

Moreover, by contrasting figures 5 and 6, the offense type and frequencies of offense groups that are located within the Downtown community were generally different from the Roxbury district. Similar to Roxbury, Downtown also reported violent crimes such as simple assault, however, the frequency of these crimes is far greater than in Roxbury. Furthermore, it should be noted that the types of crimes in Roxbury were usually more violent than Downtown, such as aggravated assault, burglary, ballistics, and even arson. By cross referencing the analysis with the Figure 1 scatter plot, it can be noted that all parts of Downtown do not face the same economic challenges that Roxbury deals with on a daily basis. Based on research findings by Dr. Jennings, the lower income per capita seen in Roxbury could potentially be a factor as to why Roxbury frequently sees the same type of violent crimes, such as aggravated assault, and why Downtown does not.

Onwards, based on Figure 7, it is evident that Saturday and Sunday are the two most common days for deaths from gunshots in Boston between 2015 and 2023. According to an article by the New England Journal of Medicine, patients that enter the hospital with a serious injury, such as a gunshot, and require acute treatment on the weekends are more than likely going to die compared to a patient that is admitted on the weekdays[3]. This could potentially be due to the fact that the levels of medical staff on the weekends tends to be lower than on the weekdays, due to the majority of employees in the United States having days off on Saturday and Sunday. In industrialized countries, the population death count increases heavily on the weekends[3].

Next, based on Figure 8, it can be seen that the weather in Boston can potentially impact crime rates all year long in Boston, with a cyclical pattern that peaks in the summer and drops as time moves closer to December. People spend more time outdoors as the temperature rises and the days grow longer, which fosters an environment that is more conducive to criminal activities. As the weather gets warmer, social interactions and gatherings open up opportunities for a variety of criminal activities, ranging anywhere from stealing to violent crimes. Based on a recent 2019 study, the presence of warm weather can have an impact on aggressive motives and behaviors of individuals[4]. On the other hand, once the winter weather arrives and the city's daytime hours shorten, people start to spend more time inside, which could lead to a drop in criminal activity. This decrease in crime could potentially be the result of a dip in social events and outdoor activities, as well as the potential deterrent effect of adverse weather conditions. Furthermore, a comparison between figures 8 and 18 reveals a striking similarity in the pattern of crime rates and average weather temperatures in Boston. As temperatures rise and fall throughout the year, we observe a corresponding fluctuation in crime rates, suggesting a potential correlation between these two variables. The recurring trend illustrates how the dynamics of crime rates in Boston are potentially influenced by the weather in each year with the exception of 2020.

We noticed that the COVID-19 pandemic had an impact on the crime rate of different districts in Boston. The recurring trend of the Boston crime rate rising and then falling by the end of each year can be visible in Figure 8. By examining 2020 specifically in Figure 9, it can be seen that this pattern deviates in March. The COVID-19 epidemic started to spread quickly in March 2020, which prompted governments all over the world to impose stringent lockdown measures to stop its spread. As a consequence, crime rates significantly decreased during this time. The prospects for criminal activity were reduced because people were confined to their houses and public areas were essentially empty. The number of thefts, burglaries, and other property crimes also decreased as a result of the closing of social venues, non-essential enterprises, and public transportation services. Additionally, law enforcement organizations shifted their attention to ensuring that public health regulations were followed, which also helped to reduce criminal activity. As a result, at the start of 2020, the regular up-and-down trend seen in past years was not noticeable.

Based on the knowledge of the month, location, and temperature potentially impacting the instance rate of offenses, it is possible to then attempt to classify the type of offense in a particular area. Given that Saturday and Sunday are likely to be the most common days for gunshots, adding the day of the week into a classification model would be a useful parameter. Since the temperature changes per season, implementing a month parameter would be useful to track the change in temperature. Using months instead of individual temperatures would be better since the model would not be impacted by weather anomalies. Finally, adding a parameter for location would be beneficial as it is clear from figures 5 and 6 that the difference in type crimes can potentially be attributed to the district. Using the district, month, and day of the week a classification system that may potentially identify the offense code can be fitted based on the data.

6 Conclusion

In conclusion, after analyzing a multitude of factors that potentially impact the crime rate in Boston, we concluded that there is not one specific factor that directly dictates the rate of crime within Boston, but rather a plethora. Through computational analysis, we were able to analyze the relationship between a multitude of factors such as income per capita, crime density, education levels, day of week, temperature, COVID-19 pandemic, and crime in Boston. Although our analysis indicates that there may be a relationship between these factors and the crime rate in Boston, collecting supplemental information regarding mental health of individuals, data expanding outside of range of 2015-2023, or even drug abuse data within Boston could reveal alternate confounding variables that may have an impact on the overall Boston crime rate.

7 Appendix/Citations

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