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Status Update on Exploring and Predicting Violent Crime in Chicago

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1. Abstract

The R programming language is used due to one of the authors’ familiarity with the language. The scope of the project is also slightly reduced and recommendations from the project proposal are applied. Most notably, geographic data collected are all aggregated based on the standardized community areas in Chicago. In addition, the dimension of time is not considered. In total, 12 explanatory variables are collected, each having a unit of ‘per community area’: average school rating, average SSL rating, total park area, number of hospitals, teenage mother birth rate, infant mortality rate, and proportion of Hispanics, blacks, whites, Asians, and other races, and percent of children in poverty.

Preliminary exploratory data analysis shows that many of these explanatory variables seem to be correlated with the class variable, the percentage of violent crime per community area. Teenage mother birth rate, infant mortality rate, percentage of black people, and percentage of children in poverty had a positive correlation with the class variable. In contrast, percentage of Hispanics, whites, and Asians had a negative correlation.

So far, regression and clustering analysis has been done. With both ordinary least squares and elastic nets linear regression, an of 0.82 was found, which seems to be reasonably accurate. Using the k-means algorithms and looking at the elbow curve, it seems clear that the data should be grouped into 3 clusters, and that these clusters generally seem to make sense: for example, low teen birth rate is clustered with low infant mortality rate; the vice versa is also clustered together.

1. Introduction

Crime in Chicago has been recorded since the last century by the Chicago Police Department, and throughout this entire period, Chicago has had a consistently higher rate of violent crimes compared to the U.S. average. As a result, the city has been under intense scrutiny for its high violent crime rates. In 2016, the murder rate in the U.S. rose about 13%, and almost half of that increase is solely due to violence in Chicago [1]. In fact, in recent years, Chicago had recorded more murders and victims of shooting than both Los Angeles and New York City combined [2]. Such high rates of violent crime naturally lead to a need for better police resource allocation to areas where violent crimes are most likely to occur.

The authors of this report hypothesize that there may be multiple city-related predictors such as demographic, educational, health, and urban planning data that may be correlated with the rate of violent crime in Chicago. These include: the quality of nearby schools, how close the crimes are to any parks or recreation areas, the demographics of the neighborhood that the crime took place in, teenage pregnancy rate, and many other variables that will be discussed. Each of these predictors will be grouped by ‘community area’. Chicago has 77 official community areas, and these areas have been historically used in sociological research of Chicago, and is thus deemed an appropriate geographic unit of choice for this project [3].

The authors of this report hope that a data science approach can prove to be beneficial in predicting where and when violent crimes are more likely to occur. These predictions can then aid police officers by helping them efficiently allocate required resources to crime hotspots. Furthermore, if clustering analysis can reveal that certain societal problems such as quality of education and health are related to increased crime, then these findings can help city officials reduce crime by persuading them to solve these other associated problems.

Firstly, a regression algorithm will be made in an attempt to accurately predict the rate of violent crime for each community area of Chicago via the city-related explanatory variables. Secondly, both a clustering algorithm and an association rule mining algorithm will be used to see if the explanatory variables are related in any way with each other. By reviewing extant academic literature, a specific set of variables were determined that the authors’ of this report hypothesize may be important predictors of crime.

The rest of the format of this report is as follows. The *Related Works* section describes related works in academic literature, and the sources of inspiration for the explanatory variables. The *Data Collection Progress* section describes the source of datasets and how the explanatory variables were collected for the clustering and predictive analysis. The *Numeric Regression Results*, *Clustering Analysis Results*, and *Association Rule Mining Results* explains the supervised and unsupervised learning results, using the collected data.

1. Related Works and Hypotheses

There are several related works that involve analyzing Chicago’s crime data. Firstly, a noteworthy prediction model called the “Strategic Subject List” (SSL) was made by the Illinois Institute of Technology for the Chicago Police Department. This list attempts to identify individuals, or ‘subjects’, who are most at risk of being either a victim or an offender in a shooting [4]. The authors hypothesize that a high SSL score for a community area may be correlated with a high violent crime rate for the same area.

The authors also hypothesize that the locations of schools and parks, and information associated with each of those locations as well, such as each school’s associated quality of education. The effect of education on crime has already been represented broadly in literature, such as in Lochner and Moretti’s paper [5]. In addition, there has been a paper by Schusler et al. that examined the association between the amount of tree canopy area and crime in each census tract boundary in Chicago, which led to the idea that the location of city parks and their size could also be relevant predictors as well. [6].

Finally, demographic and health data are also hypothesized to be relevant factors, as described in reputable sources such as Brantingham’s book, “Patterns in Crime”. In addition, there are also prominent health-related crime theories, such as the lead-crime hypothesis that claims blood lead levels in children have a direct correlation with crime [7]. These led the authors of this report to hypothesize that race, poverty rate, and available health information from Chicago’s public health datasets such as teenage pregnancy rate and infant mortality rate may be relevant predictors.

1. Data Collection Progress

Table 1 displays all of the final chosen datasets. From these datasets, explanatory variables are obtained.

Table 1. Information on Final Chosen Datasets.

|  |  |  |
| --- | --- | --- |
| Dataset | Number of Rows | What Does a Row Represent? |
| Crimes from 2001 [8] | 6,706,459 | Reported Crime |
| Strategic Subject List [4] | 398,684 | Person Likely to be Involved in a Shooting |
| Chicago Public Schools - School Profile Information SY1718 [9] | 661 | School |
| Population and Poverty Data by Chicago Community Area [10] | 77 | Community Area |
| Parks - Chicago Park District Park Boundaries (current) [11] | N/A (Shapely File of 597 Parks) | N/A (Shapely File of 597 Parks) |
| Boundaries - Community Areas (current) [12] | N/A (Shapely File of 77 Community Areas) | N/A (Shapely File of 77 Community Areas) |
| Hospitals – Chicago [13] | N/A (Shapely File of 42 Hospitals) | N/A (Shapely File of 42 Hospitals) |
| Public Health Statistics - Births to mothers aged 15-19 years old in Chicago, by year, 1999-2009 [14] | 77 | Community Area |
| Public Health Statistics- Infant mortality in Chicago, 2005– 2009 [15] | 77 | Community Area |

Table 2 lists all of 12 predictors included in this project for both supervised and unsupervised learning. Note that all 12 predictors are numerical variables.

Table 2. Explanatory Variables.

|  |  |
| --- | --- |
| Explanatory Variable | Description |
| avgSchoolRating | The average rating of all schools per community area. Rating from 1 to 5, where 5 is the best. Based on the inverse of Chicago Public School Board’s official “School Quality Rating Policy” [16] |
| avgSSLRating | The average “Strategic Subject List” score for all strategic subjects who committed a crime in a specific community area. Range between 0 to 500, where 500 represents that subjects in this community area are most likely to be involved in a future shooting. |
| totalParkArea | The total park area of a community area in km2. |
| numHospitals | The number of hospitals for a community area. |
| teenMomRate | The teenage pregnancy rate for a community area. |
| infantMortalityRate | The infant mortality rate for a community area. |
| hispanic | The percentage of people who are Hispanic in a community area. |
| black | The percentage of people who are black in a community area. |
| white | The percentage of people who are white in a community area. |
| asian | The percentage of people who are Asian in a community area. |
| other | The percentage of people who are designated as “other race” in a community area. |
| percentChildrenInPov | The percentage of children who are in poverty for a community area. Note that actual poverty rate per community area was not found by the authors of this report. However, the authors believe percentage of children in poverty to be an appropriate substitute. |

The Appendix section at the end of this report will describe in detail how all the predictors and the class variable are obtained and preprocessed from the aforementioned datasets.

1. Exploratory Data Analysis

Scatter plots, histograms, and box plots are used to analyse each variable. It is worth noting that some variables are not normally distributed, but rather exponentially distributed, including the class variable: the violent crime rate. Explanatory variables that have non-normal distributions include: total park area, number of hospitals, percentage of Hispanics, percentage of whites, and percentage of Asians. Interestingly, the distribution of the percentage of black people has an upside-down bell curve shape, which implies that community areas generally either have few to no black people, or have a large percentage of black people. Very few seem to have a moderate percentage of black people.

Finally, out of the 12 explanatory variables, 7 of them visually have a clear correlation with the class variable, as seen from scatter plots. The rest do not seem to have as strong of a correlation. Specifically, teenage mother birth rate, infant mortality rate, percentage of black people, and percentage of children in poverty had a strong positive correlation with the class variable. In contrast, the percentage of Hispanics, whites, and Asians had a strong negative correlation. Some of these correlations also seemed to be non-linear. These include: total park area, teenage mother birth rate, infant mortality rate, percentage of Hispanics, percentage of whites, percentage of Asians, and percentage of children in poverty.

Note that all scatter plots, histograms, and box plots, and comments on each are included in the Appendix.

1. Numeric Regression Results

Table 3, Table 4, and Table 5 illustrate sample data inputted into the various regression models used. Table 3 specifically also includes each row’s community area number and name. However, these two columns specifically are not inputted into the regression models.

Table 3. Class Variable for Numeric Regression.

|  |  |  |
| --- | --- | --- |
| community | communityAreaNum | percentViolentCrimePer1000Population |
| ROGERS PARK | 1 | 612.3729 |
| WEST RIDGE | 2 | 318.6595 |
| UPTOWN | 3 | 512.4375 |
| LINCOLN SQUARE | 4 | 297.2172 |
| NORTH CENTER | 5 | 239.0875 |

Table 4. Predictors for Numeric Regression (Part 1 of 2).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| avgschoolRating | avgSSLRating | totalParkArea | numHospitals | teenMomRate | infantMortRate |
| 3.571429 | 277.6664 | 287364.9 | 0 | 51.61818 | 6.4 |
| 3.5 | 286.1914 | 725446.2 | 0 | 31.52727 | 5.1 |
| 3.428571 | 266.0711 | 1437616 | 4 | 51.02727 | 6.5 |
| 4.2 | 281.7773 | 419080.8 | 3 | 37.98182 | 3.8 |
| 3.428571 | 282.6642 | 161026.1 | 0 | 37.07273 | 2.7 |

Table 5. Predictors for Numeric Regression (Part 2 of 2).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| hispanic | black | white | asian | other | percentChildrenInPov |
| 0.24 | 0.24 | 0.45 | 0.05 | 0.03 | 0.319509 |
| 0.2 | 0.13 | 0.41 | 0.21 | 0.04 | 0.372624 |
| 0.16 | 0.19 | 0.51 | 0.11 | 0.03 | 0.278424 |
| 0.18 | 0.06 | 0.62 | 0.1 | 0.04 | 0.168878 |
| 0.11 | 0.09 | 0.73 | 0.04 | 0.03 | 0.058669 |

Three types of regressions were used: ordinary least squares (OLS) linear regression, elastic net regularized regression, and generalized additive linear model. Elastic nets is seen as a better version of OLS, which is why it is being tested. It is a mixture of lasso and ridge regression, both of which penalize the coefficients in regular OLS regression in order to prevent overfitting. Ridge regression is where the square of each coefficient for each explanatory variable is penalized, and lasso regression is where the absolute value of all the coefficients for each explanatory variable is penalized. Lasso regression can force coefficients of uncorrelated features to be zero (which can be seen as feature selection), though this may lead to information loss. Thus, elastic nets are seen as the “best of both worlds”.

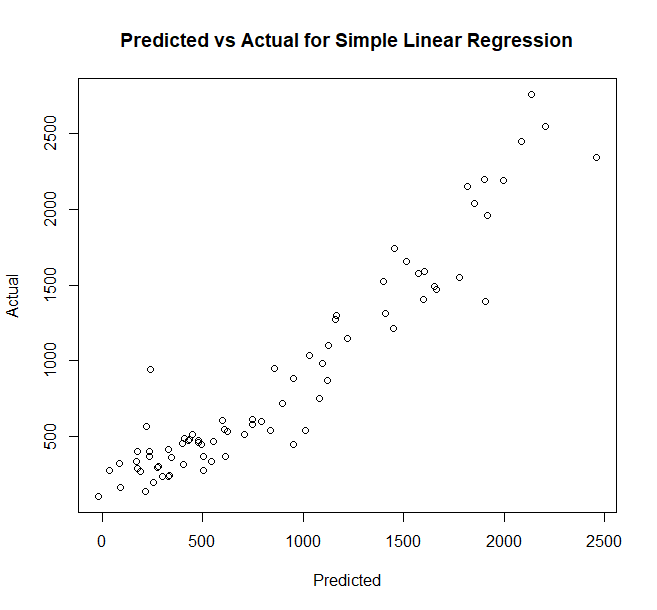
However, as seen from the previous section of this report, many of the relationships between the explanatory variables and the class variable seem to be nonlinear in nature. Thus, the authors believed GAM might also give fruitful results, since the GAM algorithm attempts to fit polynomial splines on the explanatory variables and conduct an additive linear regression on these transformed predictors.

10-fold cross validation was used to obtain the optimal alpha and lambda parameters for the elastic nets regression. Note that alpha is mixing parameter with a range from 0 to 1. A value of 0 represents 100% ridge regression, and a value of 1 represents 100% lasso regression. Also note that lambda is the amount of penalization with increasing coefficients for the explanatory variables in the final model.

Leave-one-out cross validation was used to obtain three performance metrics for each regression type, which include: root mean squared error, (RMSE), coefficient of determination (R2), and mean absolute error (MAE).

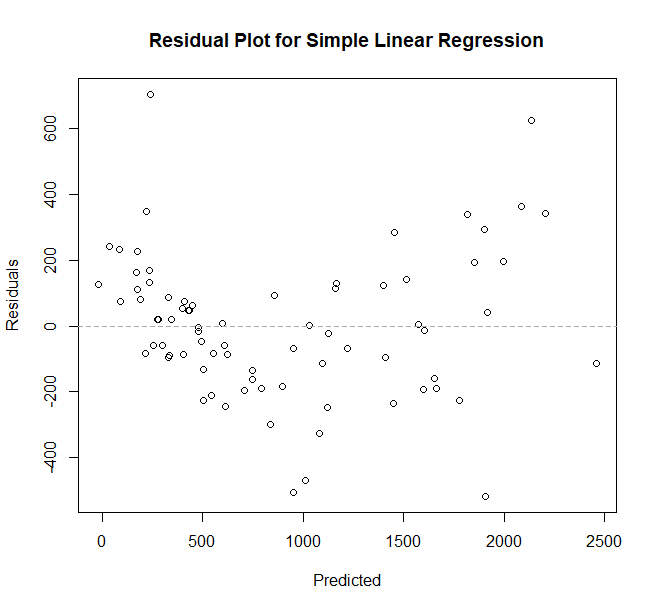
OLS Linear Regression

*Figure 1* shows the predicted class variables versus the actual class variables for OLS linear regression. Ideally, the points should be uniformly distributed around the line . As shown, the predictions have this trend, which means the predictions seem to be roughly accurate. However, the general trend has somewhat of a small nonlinear concave curve.



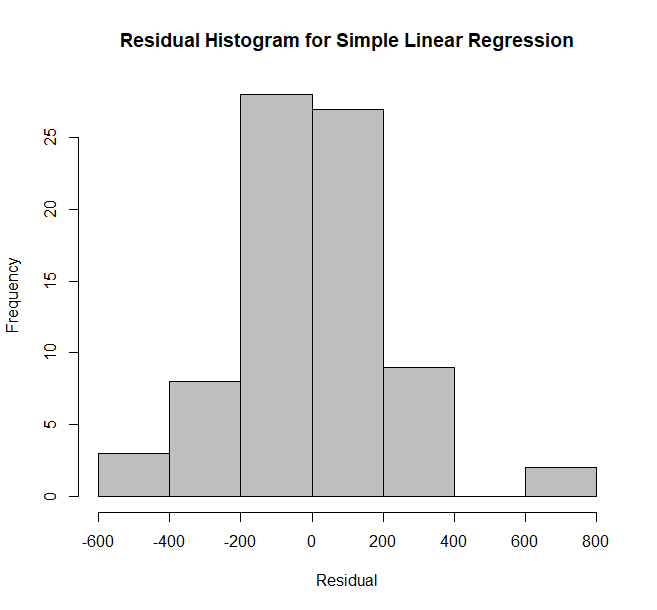
*Figure 1. Predicted Class Values vs Actual Values for OLS Linear Regression*

This concavity is more pronounced in the residual plot shown in *Figure 2*. Evidently, the scatter plots show that the data’s uniformity around the line is not independent of the value of x (the predicted values), which suggests linear regression may not be the best algorithm.



*Figure 2. Residual Plot for OLS Linear Regression.*

*Figure 3* shows the residual histogram for OLS linear regression. While it shows a roughly uniform distribution centred around 0, it does not show the concavity pattern from the previous figure, which is one weakness of histogram plots.



*Figure 3. Residual Histogram for OLS Linear Regression.*

Table 6 shows the performance metrics of this algorithm.

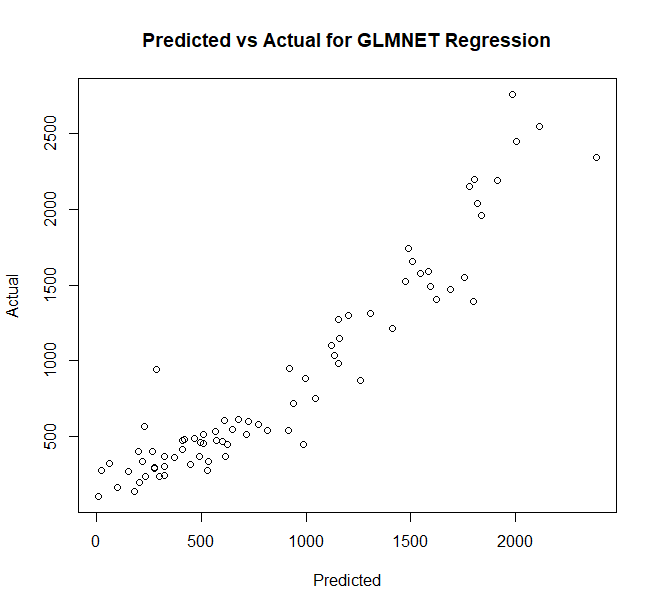
*Table 6. Performance Metrics for OLS Linear Regression*

|  |  |  |
| --- | --- | --- |
| RMSE | R2 | MAE |
| 285.243497339416 | 0.822397725231063 | 206.537526304179 |

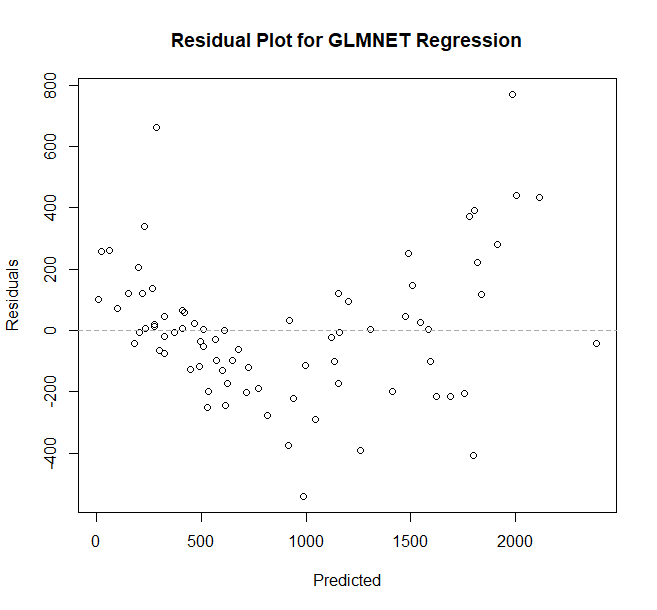
Elastic Net Regression

Using 10-fold cross validation, the best alpha and lambda values were determined to be 0 (100% ridge regression) and 1, respectively.

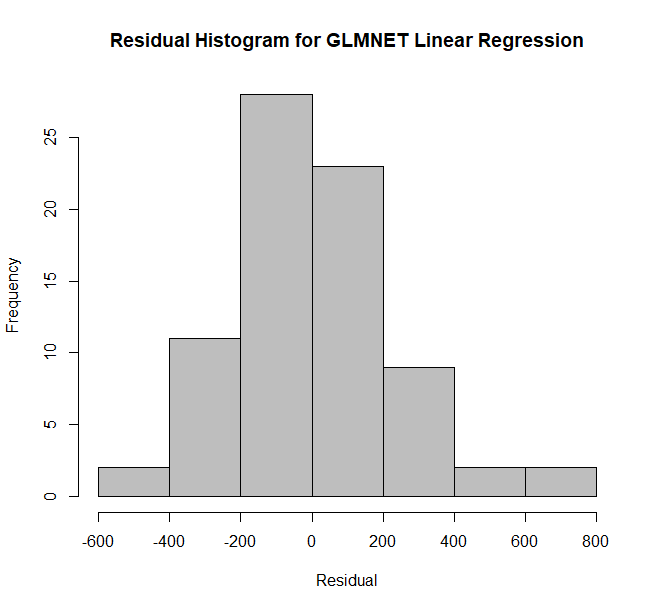
Figure 4, Figure5, and Figure6 show similar types of plots as ones shown for OLS regression in the last subsection. It seems that there is not a large visual difference between elastic net and OLS, though the histogram distribution slightly changed.



*Figure 4. Predicted Class Values vs Actual Values for Elastic Net Regression.*



*Figure 5. Residual Plot for Elastic Net Regression.*



*Figure 6. Residual Histogram for Elastic Net Regression.*

Ultimately, Table 7 shows that the performance metrics only improved very slightly from OLS. The changed digits are bolded for ease of reading.

*Table 7. Performance Metrics for Elastic Net Linear Regression*

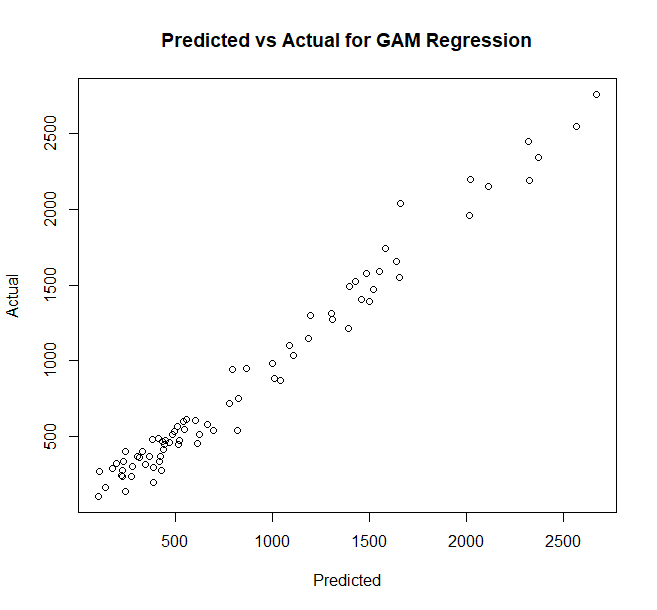
|  |  |  |
| --- | --- | --- |
| RMSE | R2 | MAE |
| 284.**112757633739** | 0.82**3577225374136** | 206.53**3355885329** |

GAM Regression

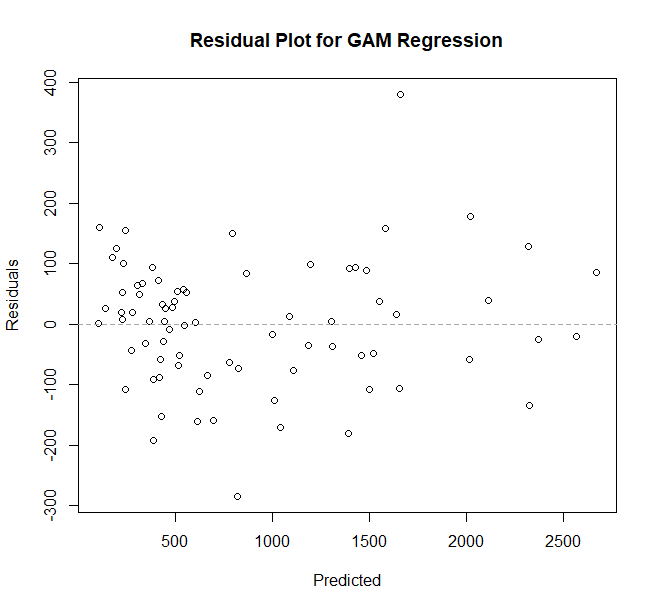
Using the scatter plots of each explanatory variable versus the class variable in the “Exploratory Data Analysis” section of this report, the relevant explanatory variables that may have nonlinear relationships with the class variable were identified. These include: total park area, birth rate for teenage mothers, infant mortality rate, percentage of Hispanics, percentage of white people, percentage of Asian people, and percentage of children in poverty. Thus, the resulting formula used is the following:

Where the function is a function that fits a spline between the input and the outcome.

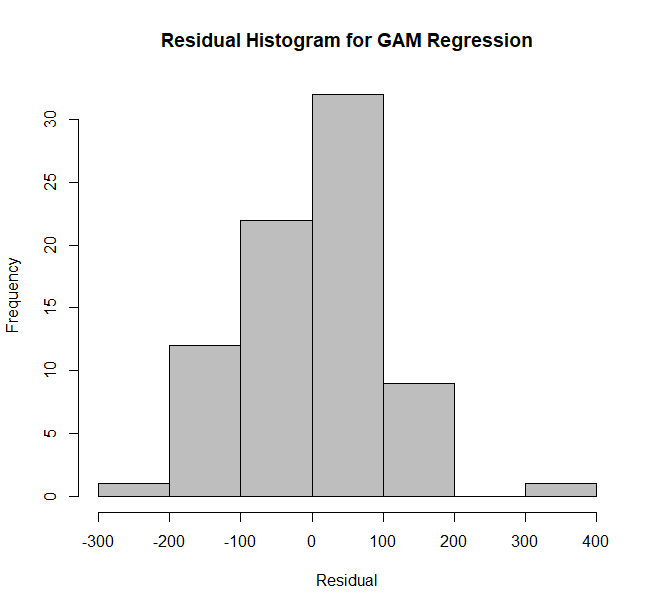
Figure 7 seems to indicate that the GAM model built on all 77 community area data points reduces the nonlinear concavity. In addition, Figure 8 and Figure 9 shows that the range of the residual decreased to . These all seem to indicate that the GAM model fits the data better.



*Figure 7. Predicted Class Values vs Actual Values for GAM Regression.*



*Figure 8. Residual Plot for GAM Regression.*



*Figure 9. Residual Histogram for GAM Regression.*

However, the performance metrics obtained from leave-one-out cross validation shown in Table 8 indicates that the GAM model performance on unseen data is actually worse than the previous two regression algorithms. With leave-one-out cross validation, 76 GAM models are each built from randomly selected 76 community area data points and tested on the single remaining community area.

*Table 8. Performance Metrics for GAM Regression.*

|  |  |  |
| --- | --- | --- |
| RMSE | R2 | MAE |
| **308.050825959162** | 0.**796551460938803** | **188.925268679306** |

Table 9 displays the performance metric of the GAM model built with all 77 community area data points. It is clear that by comparing Table 9 and Table 8, leaving even one data point out of the model significantly changes the performance metrics. Thus, the GAM algorithm heavily overfits.

*Table 9. Performance Metrics for GAM Regression (Built With All Data Points)*

|  |  |  |
| --- | --- | --- |
| RMSE | R2 | MAE |
| **103.30301646473** | 0.**976500401871001** | **79.55816922112** |

It seems that out of all three regression algorithms, elastic net regression performs the best, though it is only marginally better than OLS regression. Future recommendations include using other nonlinear regression algorithms other than GAM, as its fitted splines may use polynomials with higher than necessary orders, which can cause unnecessary overfitting to occur.

1. Clustering Analysis Results

The K-means clustering analysis is performed on the 12 explanatory variables using R Language’s  method, “kmeans”. Since clustering works the best under isotropic conditions, all of the explanatory variables are normalized and scaled to the range of 0 to 1. Table 10 and Table 11 display sample data of these 12 normalized variables.

Table 10. Normalized Explanatory Variables for Clustering (Part 1 of 2).

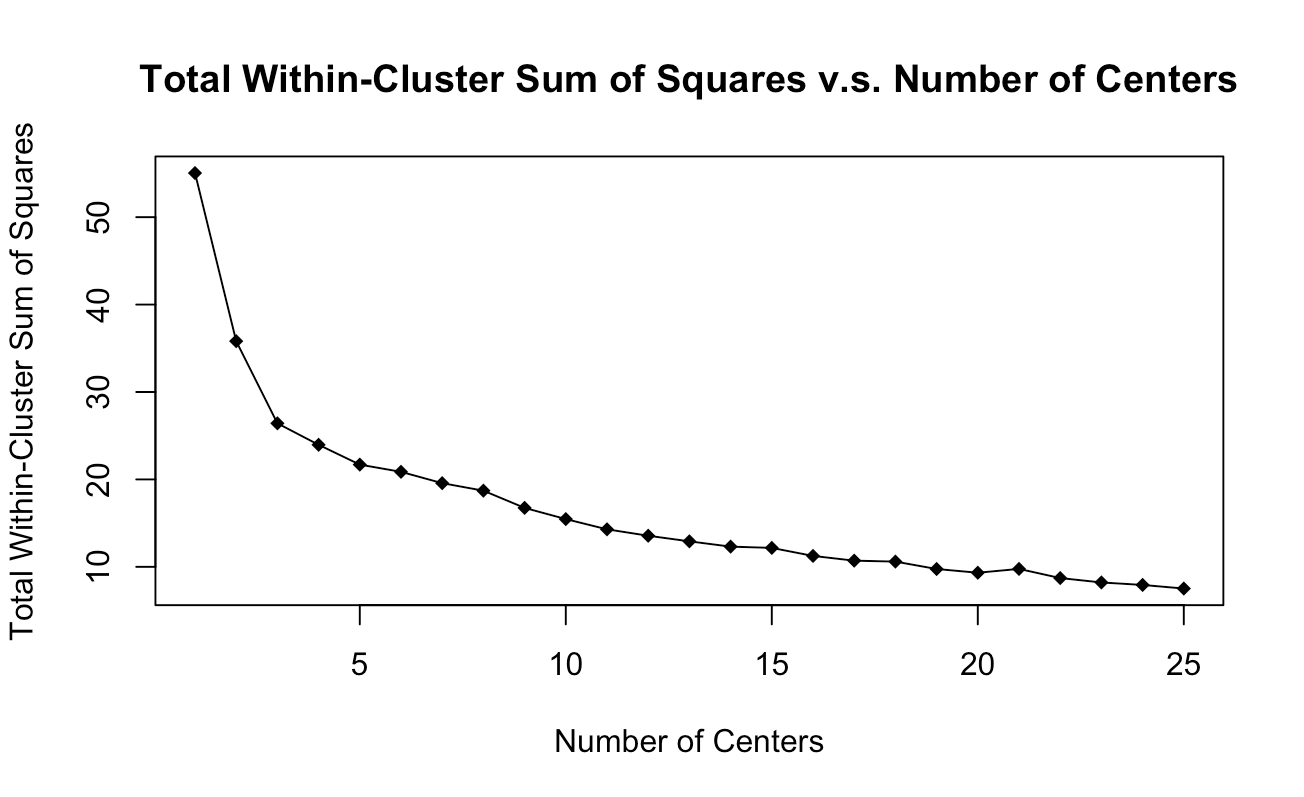
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| avgSchoolRating | avgSSLRating | totalParkArea | numHospitals | teenMomRate | infantMortalityRate |
| 0.5 | 0.3048546 | 0.1232683 | 0 | 0.42178033 | 0.232227488 |
| 0.475 | 0.5289858 | 0.3160378 | 0 | 0.25011651 | 0.170616114 |
| 0.45 | 0 | 0.6294148 | 1 | 0.41673139 | 0.236966825 |
| 0.72 | 0.4129330 | 0.1812274 | 0.75 | 0.30526642 | 0.109004739 |
| 0.45 | 0.4362516 | 0.0676753 | 0 | 0.29749883 | 0.056872038 |

Table 11. Normalized Explanatory Variables for Clustering (Part 2 of 2).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| hispanic | black | white | asian | other | percentChildrenInPov |
| 0.270588 | 0.247423 | 0.535714 | 0.102041 | 0.6 | 0.407143 |
| 0.223529 | 0.134021 | 0.488095 | 0.428571 | 0.8 | 0.481074 |
| 0.176471 | 0.195876 | 0.607143 | 0.22449 | 0.6 | 0.349956 |
| 0.2 | 0.061856 | 0.738095 | 0.204082 | 0.8 | 0.197479 |
| 0.117647 | 0.092784 | 0.869048 | 0.081633 | 0.6 | 0.044078 |

Analysis of Number of Centers

For the first part of this analysis, the optimal number of cluster centers from 1 to 25 is analyzed, with the total within-cluster sum of squares data being collected for each. The result is shown in Figure 10.

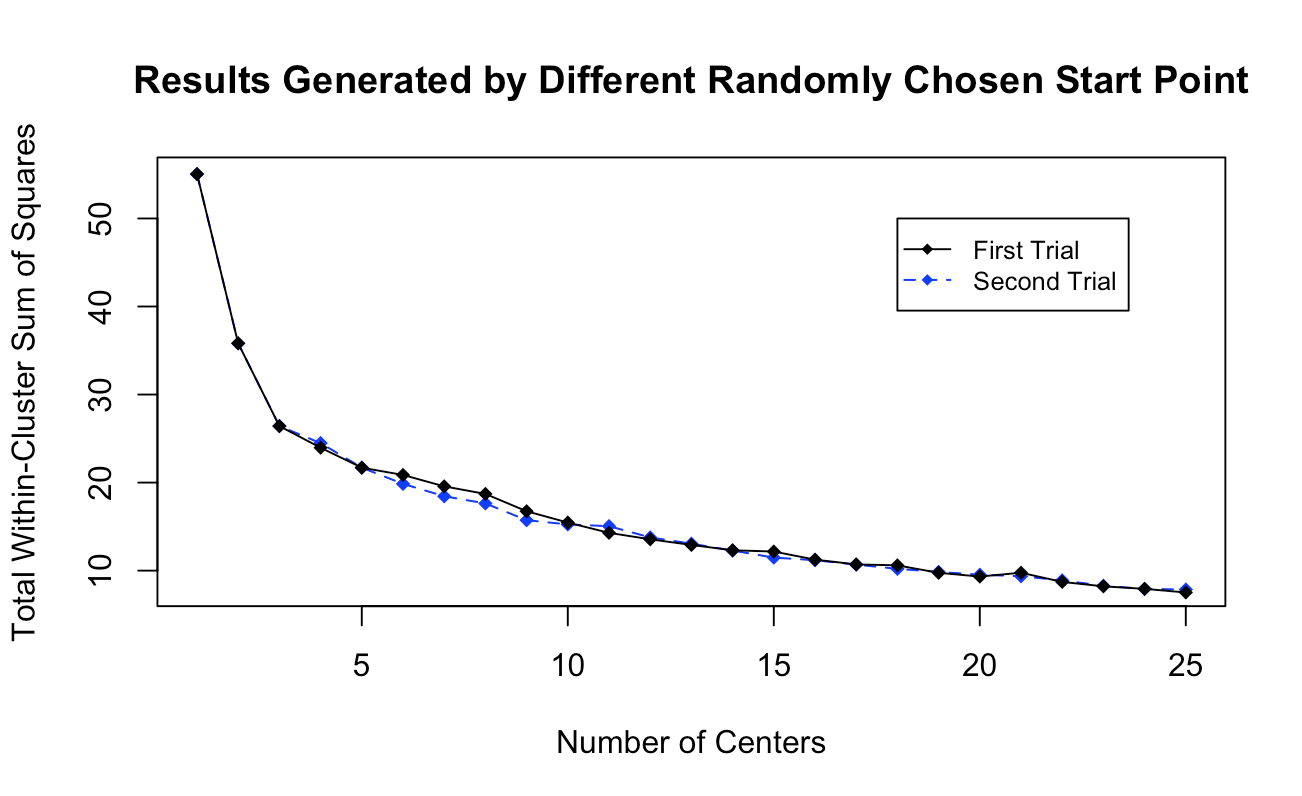


*Figure 10. Total within-cluster sum of squares versus the number of centers*

As shown in Figure 10, there is a significant drop in the sum of squares until the number of centers reaches 3. The decrease in the sum of squares substantially lowers as the number of centers increases from 3 to 25.

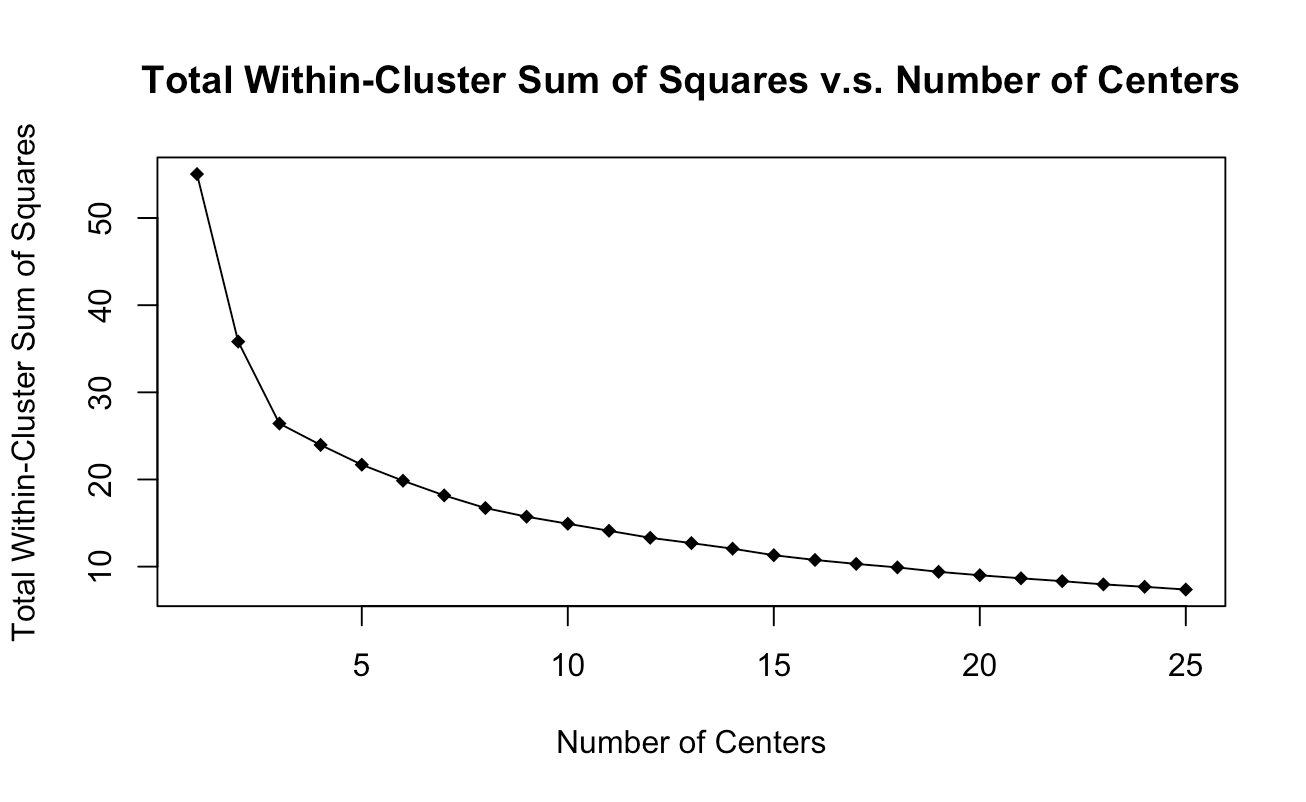
Analysis of Different Starting Points for Centers

Another analysis is performed on the resulting sum of squares when different starting points are randomly chosen for the clustering center. Two trials are executed, and the result is shown in Figure 11.



*Figure 11. Sum of squares by different randomly chosen start point of center*

As shown in the result, different choices of starting points of the clustering centers will result in different sum of squares, which is reasonable due to the randomized nature of the k-means algorithm. Another analysis is then conducted, with 50 different sets of starting points chosen. Figure 12 indicates the average sum of squares obtained from the 50 sets of centers for each number of centers.

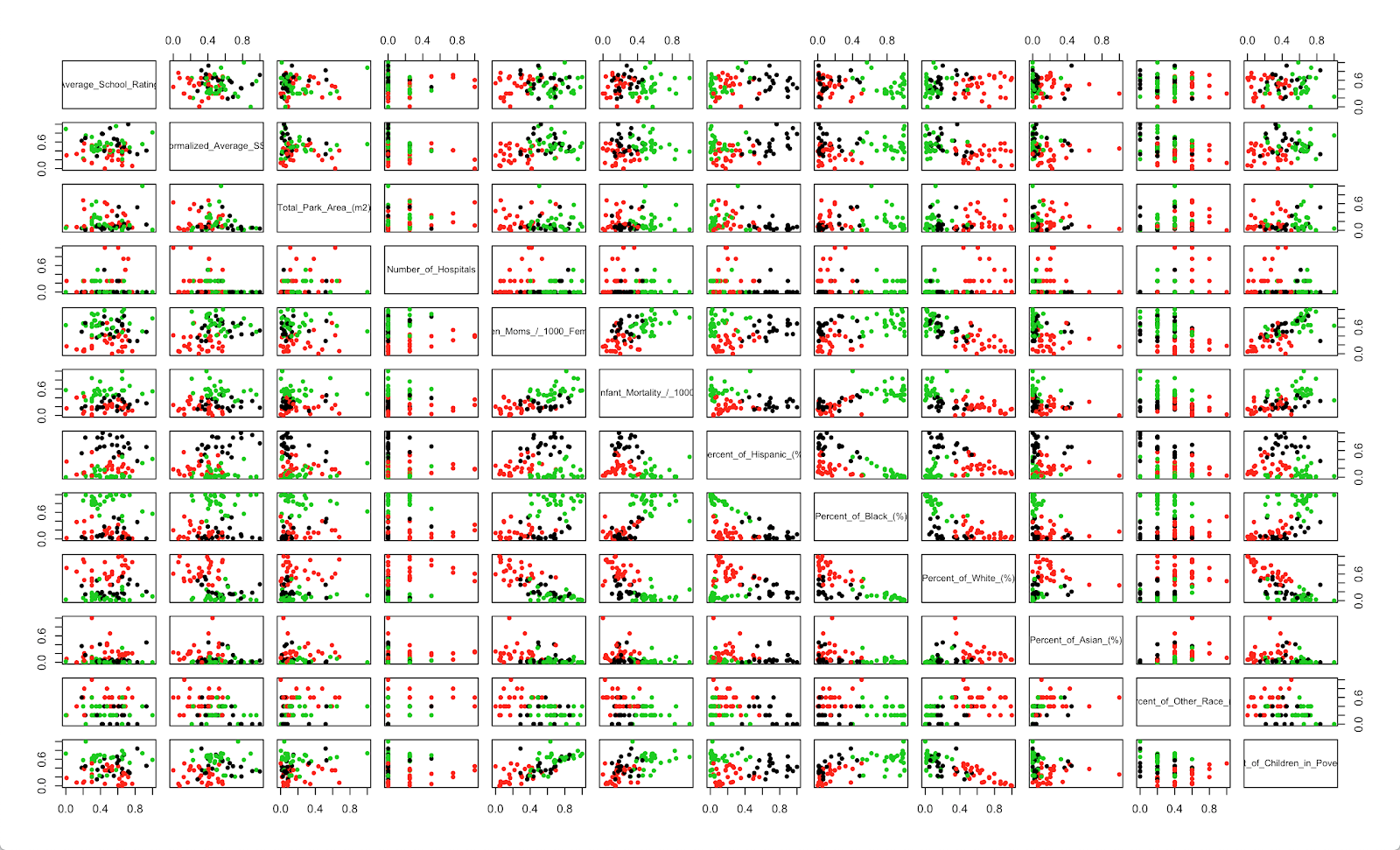


*Figure 12.* Average sum of squares with 50 sets of starting points

By looking at the above figure, it becomes evident that the significant drop in sum of squares still stops when 3 clustering centers is selected. Therefore, for the clustering analysis, the number of clustering centers is set to 3. The average total within-cluster sum of squares for 3 clustering centers is 26.416911.

Clustering between Each Two Explanatory Variables

After the number of clustering centers is determined, a plot is made to indicate the clustering between each two explanatory variables with 3 clustering centers, as shown in Figure 13.



*Figure 13. Clustering Relationship between Each Two Explanatory Variables*

Figure 13 shows that most of the plots are cleanly divided into the three clusters from the k-means algorithm, specifically at columns 5, 6, 7, 8, 9, and 12, representing teen mom birth rate, infant mortality rate, percent of Hispanic, percent of black, percent of white, and percent of children in poverty, respectively. For example, it can be observed from the plot in column 5 and row 6 (the plot which shows the clustering between teenage mom rate and infant mortality rate), that low teenage mom rate seems to be associated with low infant mortality rate, and high teenage mom rate is associated with high infant mortality rate. More details will be discussed and included in the final report of the project.

1. Association Rule Mining Analysis

Apriori algorithm, an algorithm for association rule mining, is applied to both the class variable and the explanatory variables to obtain the most frequent itemsets in the sample of data. Since most of the explanatory variables are numerical and continuous, data binning is required to divide the numerical values into buckets.

Binning

Number of Bins

To determine the optimal number of bins, Freedman–Diaconis rule [link] is utilized, which is a rule to select the size of bins to be used in a histogram. The equation for the rule is

where IQR(x) is the interquartile range of the data and n is number of observations in sample x. The numbers of bins obtained for every variable using this rule are later used to bin the data. To get the accurate results, two methods, fixed width and adaptive width binning, are used as the binning strategies and the results are compared in the later section.

Fixed Width Binning

Fixed width binning divides data into bins with intervals of equal length. The advantages of this strategy include that it is simple to implement, and it produces a straight-forward and reasonable abstraction of data. On the other hand, this method is unsupervised, and as a consequence, it is hard to know just from the result of binning that if data are divided in a desired way.

Adaptive Width Binning

Adaptive width binning divides data into intervals with equal content via quantiles. Depending on the data distribution, this strategy may give a better classification of data. However, there are several pitfalls of this method. Equalizing the interval height may lead to an over-weighting of outliers, and data points with the same value may fall in different groups.

Although Freedman-Diaconis rule is designated for equal width binning, for consistency, the same numbers of bins are used for each variable in both methods.

Results

Since the dataset only contains 77 samples (77 communities), in order to obtain rules that are more general, a higher support is required compared with bigger datasets. The starting point is set to be 0.5 support and 0.8 confidence. The support value is lowered by step of 0.1 or 0.05 through the analysis process, to help with the selection of proper support value used in the final analysis. The confidence is unchanged through the process since it is decided that 80% is the lowest acceptable confidence in this analysis and the rules with higher confidence would be automatically included.

Fixed Width Binning

For the data binned with fix width binning method, every itemset with higher than 0.5 support only has one items. Table 12 shows the result generated by Apriori algorithm with 0.4 support and 0.8 confidence.

*Table 12. Association Rules with Fixed Width Binning*

*with 0.4 Support and 0.8 Confidence.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Antecedents** | **Consequents** | **Support** | **Confidence** |
| 1 | {crimes(105,550]} | {black(-0.097,48.5]} | 0.487 | 0.974 |
| 2 | {white(-0.084,16.8]} | {asian(-0.049,4.9]} | 0.436 | 0.895 |

The first association rules in Table 12 indicates that the communities that have low violent crime rates also have low percentages of black people. The second rule says that the communities with low percentages of white people also have low percentages of Asian people.

As the support value is decreased to 0.3, the following list in Table 13is appended to the previous list in Table 12.

*Table 13. Association Rules with Fixed Width Binning*

*with 0.3 Support and 0.8 Confidence.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Antecedents** | **Consequents** | **Support** | **Confidence** |
| 1 | {hospital 0,  crimes (105,550]} | {black (-0.097,48.5]} | 0.321 | 0.962 |
| 2 | {black (48.5,97.1]} | {hispanic (0.915,18]} | 0.321 | 0.893 |
| 3 | {black (48.5,97.1]} | {white (-0.084,16.8]} | 0.321 | 0.893 |
| 4 | {hospital 0,  black (-0.097,48.5]} | {crimes (105,550]} | 0.321 | 0.806 |
| 5 | {other 1} | {asian (-0.049,4.9]} | 0.308 | 0.923 |
| 6 | {black (48.5,97.1]} | {asian (-0.049,4.9]} | 0.308 | 0.857 |

The appended list tells the relationship between percentages of races in communities, that communities with high percentages of black people usually have low percentages of Hispanic, white and Asian people. The rules with 0 hospitals in the itemsets do not indicate much since about two thirds of the communities do not have a hospital.

Adaptive Width Binning

For the data binned with adaptive width binning method, every itemset with higher than 0.3 support only has one items. Table 14shows the result using adaptive width binning with 0.2 support and 0.8 confidence.

*Table 14. Association Rules with Adaptive Width Binning*

*with 0.2 Support and 0.8 Confidence.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Antecedents** | **Consequents** | **Support** | **Confidence** |
| 1 | {asian (-0.049,0]} | {black (24,97.1]} | 0.231 | 0.900 |
| 2 | {hispanic (0.915,4]} | {black (24,97.1]} | 0.205 | 0.941 |
| 3 | {white (-0.084,5]} | {black (24,97.1]} | 0.205 | 0.941 |

Unlike the result obtained from fixed width binning section, the association rules with highest support with the adaptive width binned data do not involve the class variable, instead, they reveal a relationship between percentages of races in communities: there is usually a high percentage of black people if there is low percentage of Asian, Hispanic, or white people.

The support is decreased to 0.15 and the following list in Table 15is appended to the current association rule list.

*Table 15. Association Rules with Adaptive Width Binning*

*with 0.15 Support and 0.8 Confidence.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Antecedents** | **Consequents** | **Support** | **Confidence** |
| 1 | {hispanic (53.8,86.1]} | {black (-0.097,24]} | 0.192 | 0.938 |
| 2 | {white (50.8,84.1]} | {black (-0.097,24]} | 0.192 | 0.938 |
| 3 | {hospital 0,  hispanic (53.8,86.1]} | {black (-0.097,24]} | 0.179 | 1.000 |
| 4 | {black (-0.097,24],  hispanic (53.8,86.1]} | {hospital 0} | 0.179 | 0.933 |
| 5 | {hispanic (53.8,86.1]} | {hospital 0} | 0.179 | 0.875 |
| 6 | {hispanic (53.8,86.1]} | {hospital 0,  black (-0.097,24]} | 0.179 | 0.875 |
| 7 | {white (-0.084,5]} | {asian (-0.049,0]} | 0.179 | 0.824 |
| 8 | {crimes (1560,2760]} | {black (24,97.1]} | 0.167 | 1.000 |
| 9 | {white (13,30.6]} | {hospital 0} | 0.167 | 1.000 |
| 10 | {white (-0.084,5],  asian (-0.049,0]} | {black (24,97.1]} | 0.167 | 0.929 |
| 11 | {hospital 0,  asian (-0.049,0]} | {black (24,97.1]} | 0.167 | 0.867 |
| 12 | {white (-0.084,5],  black (24,97.1]} | {asian (-0.049,0]} | 0.167 | 0.813 |
| 13 | {crimes (105,313]} | {black (-0.097,24]} | 0.154 | 0.923 |
| 14 | {crimes (451,548]} | {black (-0.097,24]} | 0.154 | 0.923 |
| 15 | {other 3} | {black (-0.097,24]} | 0.154 | 0.857 |

As explained in the previous section, association rules with item “hospital 0” can be ignored in this analysis since most of the communities do not have a hospital. Row 8, 13, and 14 in Table 15indicate a relationship between class variables and percentage of black people. To conclude, communities that have high violent crime rates also have high percentages of black people; communities that have relatively low violent crime rates also have low percentages of black people. The rest of the rules are all about percentage of races, most of which disclose the conflict between percentages of black people and all the other races: when there is a low percentage of Hispanic, Asian, and white people, there is usually a high percentage of black people.

Conclusion

The fixed width binning provides a better classification in this case, as association rules with higher support are obtained with Apriori algorithm, which means that the rules generated are more generic for the current sample of community data.

Results from both strategies indicate that there is a strong relationship between the class variable and the percentage of black people. Both include rules that where there is low violent crime rate, there is usually a low percentage of black people, while adaptive width binning also gives that where there is a high violent crime rate, there is usually a high percentage of black people. In addition, results from both strategies reveals a complementary relationship between the percentage of black people and percentage of all the other races in a community.

1. Conclusion
2. Bibliography

|  |  |
| --- | --- |
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1. Appendix

Data Collection and Preprocessing Method

Class Variable

The class variable is the rate of violent crime in an area. In order to scale the results so that communities with higher populations are not overrepresented, the class variable is calculated as the percent of violent crime per 1000 people in the specified community area. This is obtained via the following formula:

*violentCrimeForCommunityArea \* 1000 / populationOfCommunityArea*

Note that the multiplier of 1000 is not important in prediction, as all of the constants of a regression model will simply be scaled up. It is also not important in clustering or association rule mining, as the former normalizes all of its explanatory variables, and the latter bins them. This multiplier is simply included as it is a standard way to assess rate by population in social sciences [17].

In order to obtain the total number of violent crime in a community area, the “Crimes from 2001” dataset is used. In this dataset, each crime is given a type and the community area the crime occurred in, and each crime’s type was used to filter for violent types only. Examples of violent crime types include: assault, battery, and homicide. Finally, the population of each community area is obtained from census data.

Average School Rating

The average school rating is the average rating of schools in a certain community area, and it is obtained by formula:

*Sum(schoolRatingForCommunityArea) / numSchoolsInCommunityArea*

The ratings for each school are from dataset, “Chicago Public Schools - School Profile Information SY1718” [9]. In this dataset, the general information about schools is given, such as names, location, ratings, and student count. The strings representing school levels in the “Overall\_Rating” column is translated to numerical scores from 1 to 5 according to the level, where 1 is the worst and 5 is the best.

Average SSL Rating

Recall that the SSL is defined as a numerical score with a range of 0 to 500, representing the likelihood of an offender to be involved in a shooting in the near future. 0 is extremely low risk and 500 is extremely high risk. Thus, the average SSL rating predictor is simply calculated as the average SSL rating of all strategic subject people in a certain community area. The SSL ratings is from the dataset, “Strategic Subject List” [4], which takes samples from the list of arrest data from August 1, 2012 to July 31, 2016.

Total Park Area

To obtain the total park area for each community area, all park shape files [11] and all community area shape files [12] were obtained. Then, using the Raster library in R, the intersection area of each park with each community area is calculated. These intersection areas are then summated for each community area.

Number of Hospitals

Obtaining the number of hospitals for each community area from the hospital data [13] was simple, since each hospital data point included the community area it is located in.

Birth Rate by Teenage Mothers

The dataset of birth rate by teenage mothers has all the rates from 1999 to 2009 [14]. The average of all these birth rates for each community areas is used to try to filter out birthrates which may be outliers.

Infant Mortality Rate

Similar to teenage mother birth rate, infant mortality rate for each community area is calculated as the average infant mortality rate from all years in which data was available: from 2005 to 2009 [15]. Two values for one community area from two years had null values, so the average of the non-null values was calculated.

Proportion of Hispanic People

Nothing was needed to be transformed for this predictor [10].

Proportion of Black People

Nothing was needed to be transformed for this predictor [10].

Proportion of White People

Nothing was needed to be transformed for this predictor [10].

Proportion of Asians

Nothing was needed to be transformed for this predictor [10].

Proportion of Other Races

Nothing was needed to be transformed for this predictor [10].

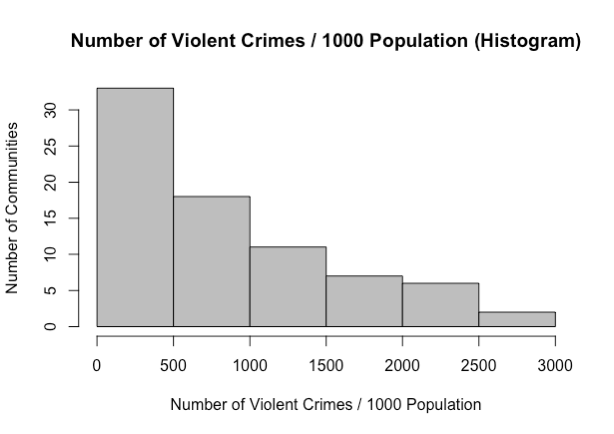
Percent of Children in Poverty

Note that actual poverty rate was unable to be obtained, but percentage of children in poverty was easily obtainable and thus is used instead.

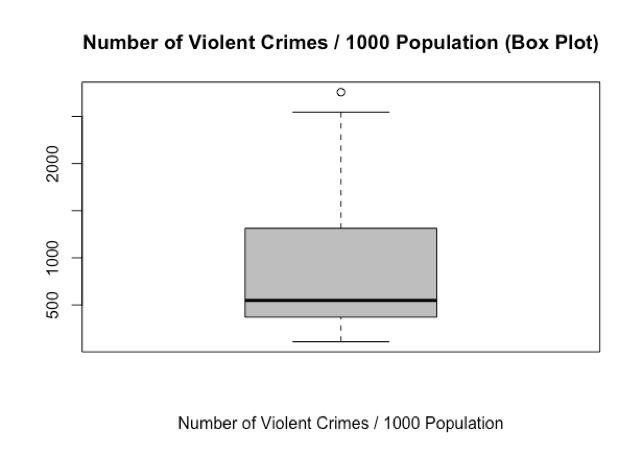
The original dataset of children poverty rates in 2018 has children separated between ages 0 to 5 and ages 6 to 12, and each of these two groups had a poverty rate percentage [10]. A weighted average based on the total population of these two groups was used to obtain the average poverty rate of all children across these two age ranges. This was done in Excel rather than in R, so no code for this data preprocessing exists in the Appendix section.

Exploratory Data Analysis Plots and Detailed Comments

Class Variable



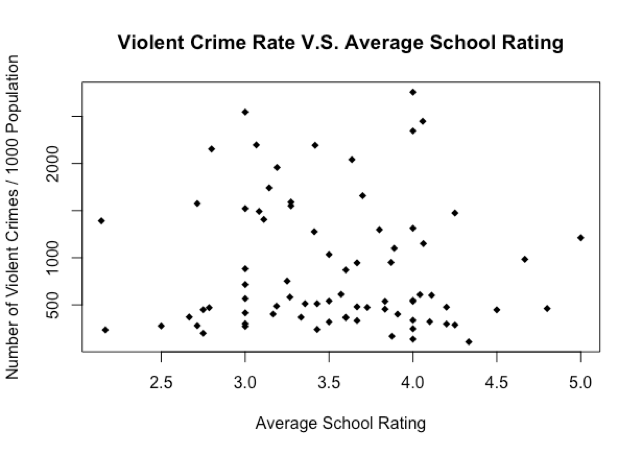
*Figure 14. Histogram of Class Variable*



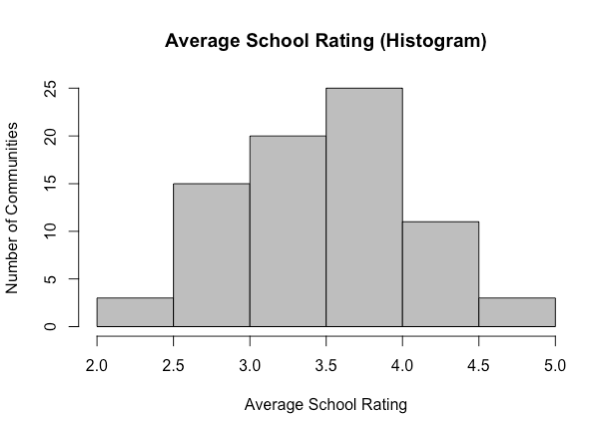
*Figure 15. Box Plot of Class Variable*

From the histogram, the number of communities exponentially decreases from low to high number of violent crimes. About half of the communities have under 500 cumulative violent crimes per 1000 people since 2001. Two communities, Washington Park and Fuller Park, have more than 2500 cumulative violent crimes per 1000 people. The only one outlier shown in the box plot is also Fuller Park, with 2757 calculated cumulative violent crimes per 1000 people and only 2876 population in 2010. This explains why it does not take too many criminal acts to boost its violent crime rate and why the community area is frequently in the news as one of the most dangerous places to live in Chicago.

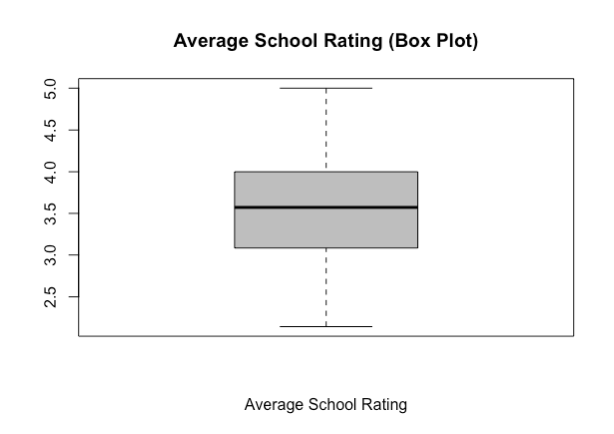
Average School Rating



*Figure 16. Scatter Plot for Average School Rating*



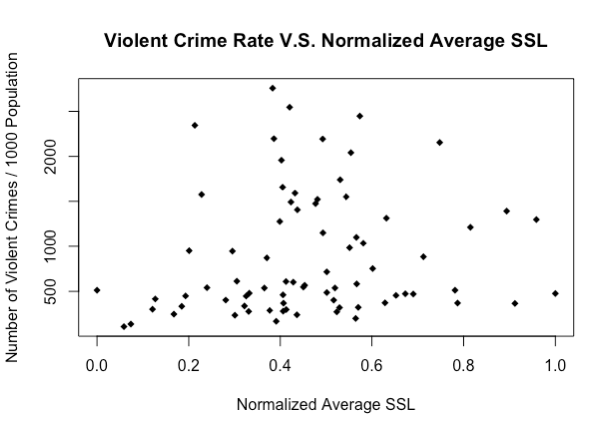
*Figure 17. Histogram for Average School Rating*



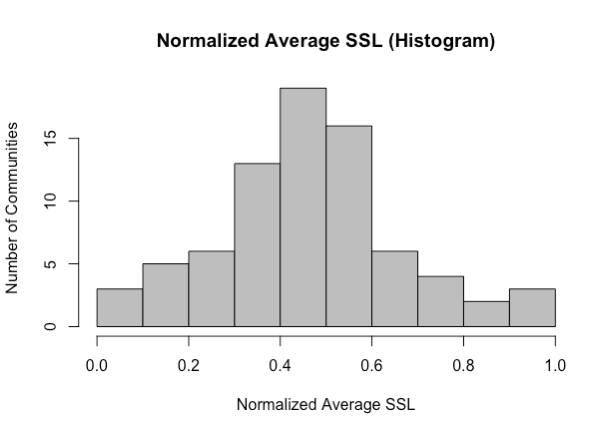
*Figure 18. Box Plot for Average School Rating*

The histogram and the box plot show that the average school rating is normally distributed. No clear correlation is indicated in the scatter plot, therefore, the average school rating should have no or a very small weight in the prediction model.

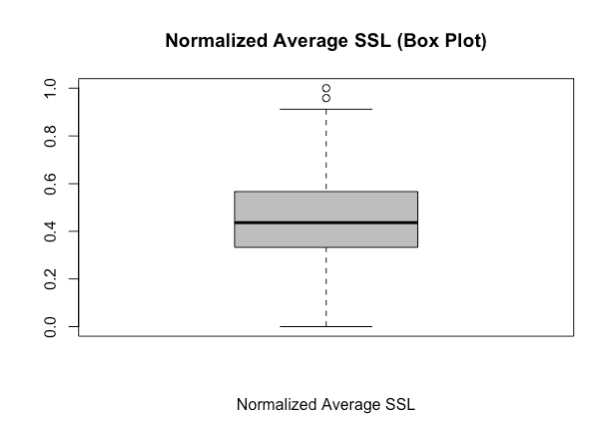
Average SSL Rating



*Figure 19. Scatter Plot for Normalized Average SSL Rating*



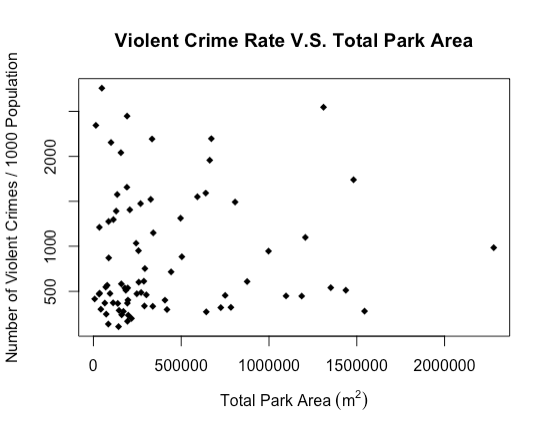
*Figure 20. Histogram for Normalized Average SSL Rating*



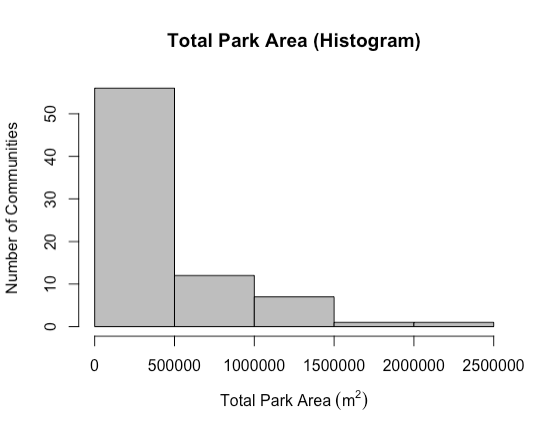
*Figure 21. Box Plot for Normalized Average SSL Rating*

Note that the average SSL rating is normalized and scaled down from the original 266 to 304 range to 0 to 1 range. It is normally distributed, and there is no evident correlation between the SSL rating and the number of violent crimes.

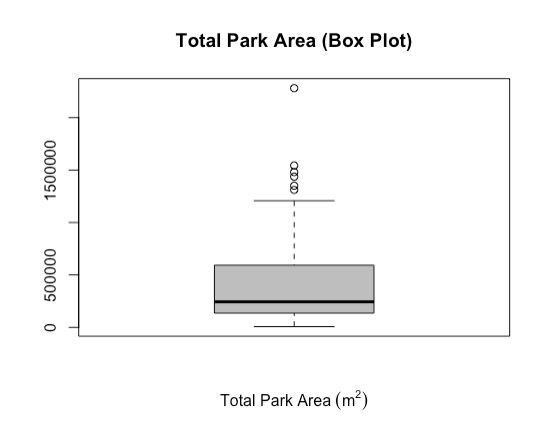
Total Park Area



*Figure 22. Scatter Plot for Total Park Area*



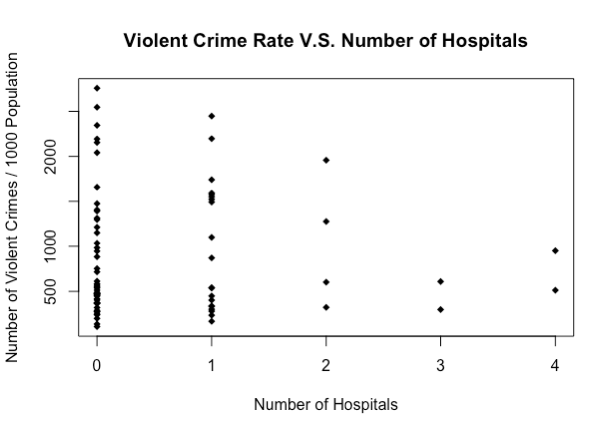
*Figure 23. Histogram for Total Park Area*



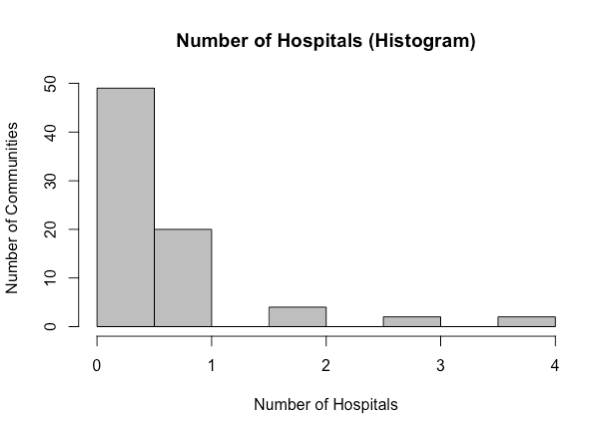
*Figure 24. Box Plot for Total Park Area*

Over 50 communities have less than 500000 m2 of park area. A negative exponential relationship can be observed from the scatter plot. However, since the number of samples with large park areas is low, it requires more analysis when building the prediction model to see if there is a real correlation.

Number of Hospitals



*Figure 25. Scatter Plot for Number of Hospitals*

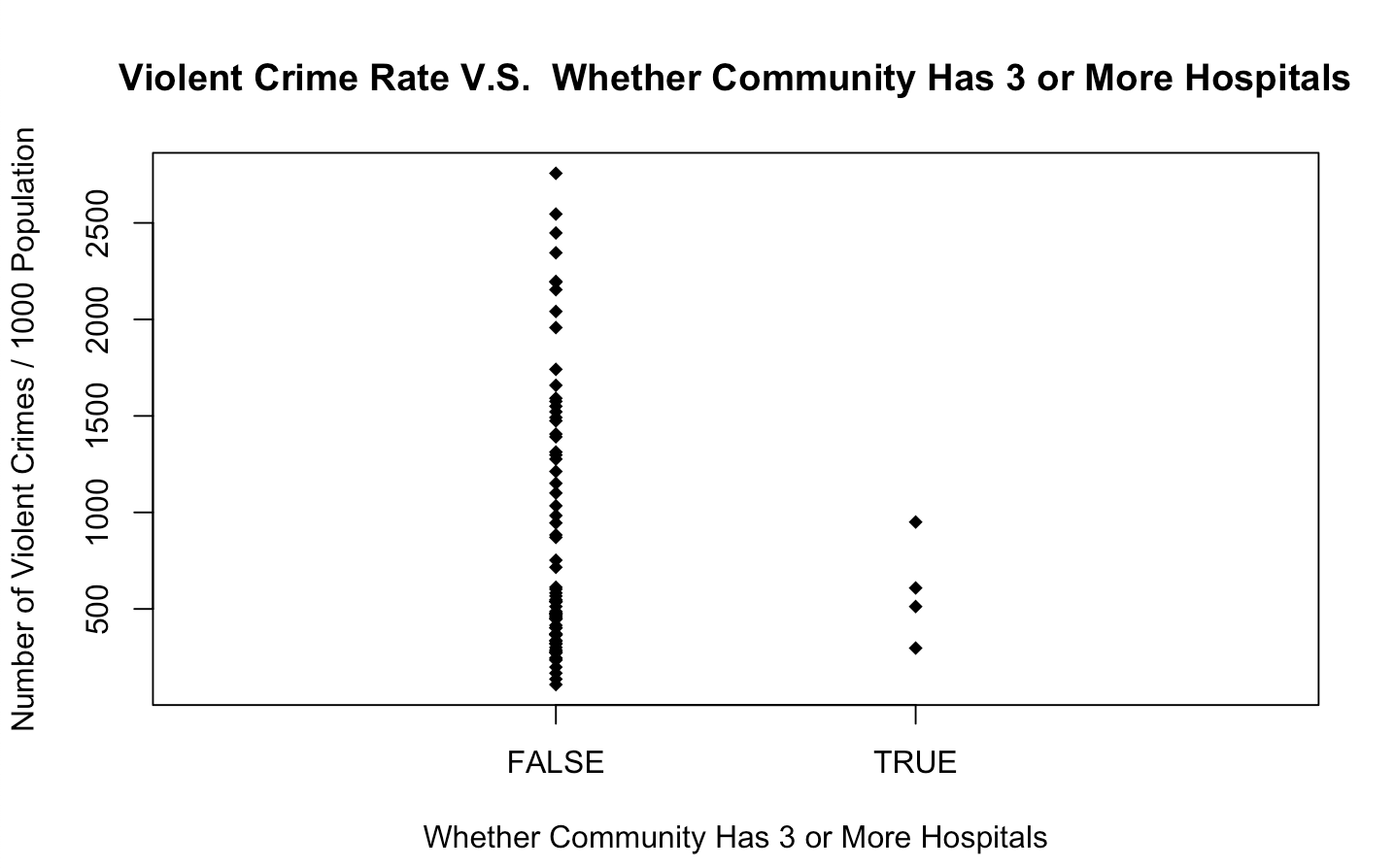


*Figure 26. Histogram for Number of Hospitals*



*Figure 27. Box Plot for Number of Hospitals*

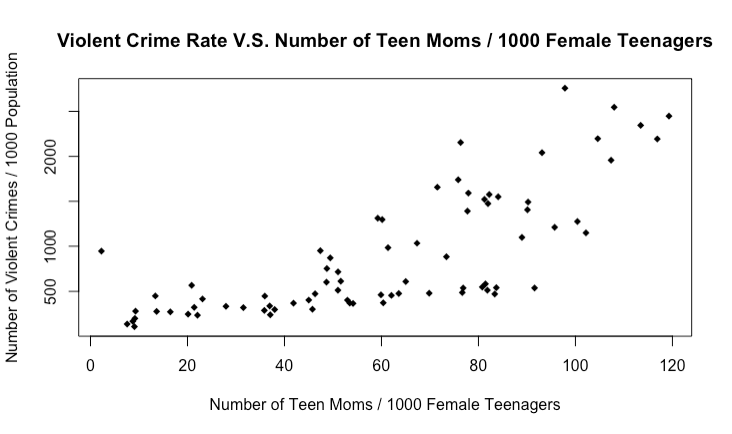
As shown in all the above plots, a majority of the communities do not have hospitals. There are 4 outliers: Uptown and West Town with 3 hospitals, and Lincoln Square and New West Side with 4 hospitals.



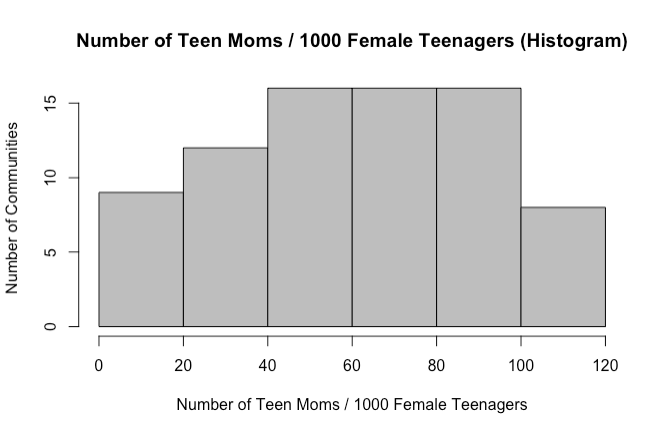
*Figure 28. Scatter Plot for Whether Community Has 3 or More Hospitals*

Another plot is made with a Boolean of whether the community has 3 or more hospitals as the x axis. All four communities which have 3 or 4 hospitals have lower than 1000 violent crimes per 1000 population.

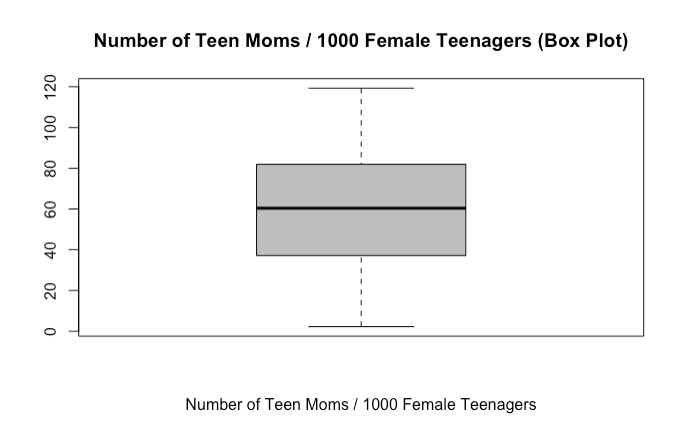
Birth Rate by Teenage Mothers



*Figure 29. Scatter Plot for Birth Rate by Teenage Mothers*



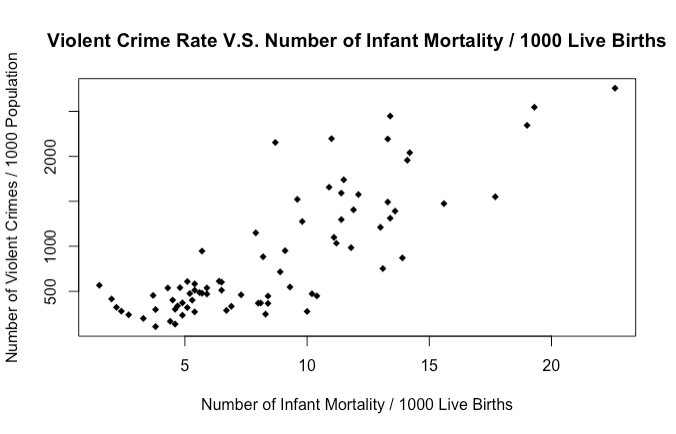
*Figure 30. Histogram Plot for Birth Rate by Teenage Mothers*



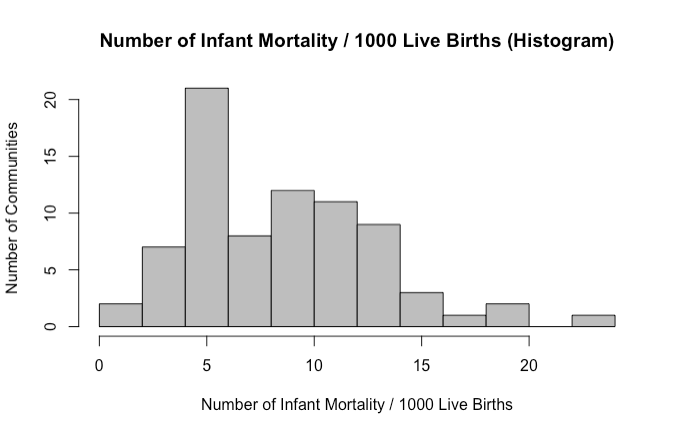
*Figure 31. Box Plot for Birth Rate by Teenage Mothers*

The number of teenage moms per 1000 female teenagers is also normally distributed in a 0 to 120 range. As indicated in the scatter plot, there is a clear positive relationship between the number of teenage moms and the number of violent crimes.

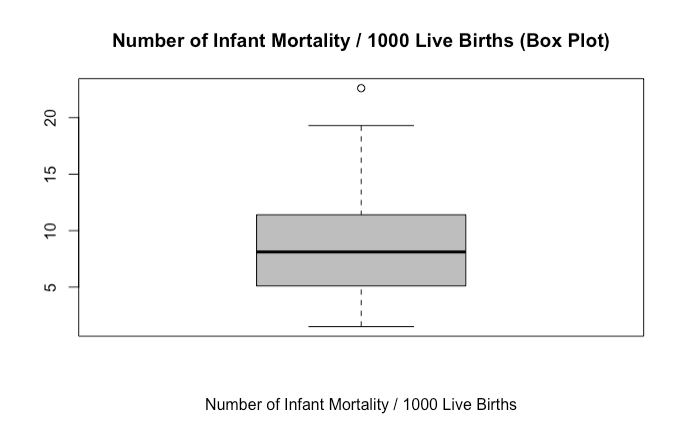
Infant Mortality Rate



*Figure 32. Scatter Plot for Infant Mortality Rate*



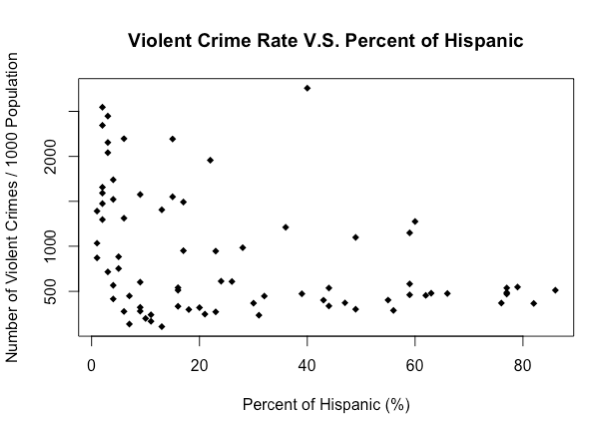
*Figure 33. Histogram for Infant Mortality Rate*



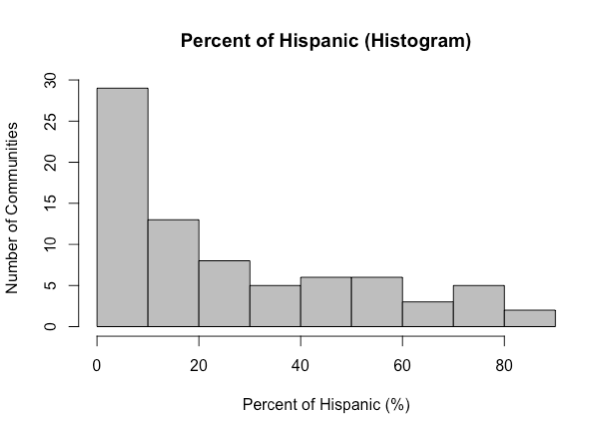
*Figure 34. Box Plot for Infant Mortality Rate*

From the scatter plot, it can be observed that there is a clear positive relationship between the number of infant mortalities per 1000 live births and the number of violent crimes per 1000 people. The only outlier indicated in the box plot is Fuller Park, which has 22.6 infant mortalities per 1000 live births. This result matches what is observed from plotting the class variable.

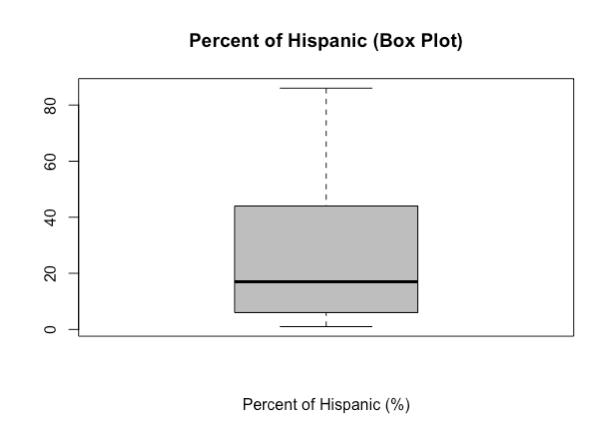
Proportion of Hispanic People



*Figure 35. Scatter Plot for Proportion of Hispanic People*



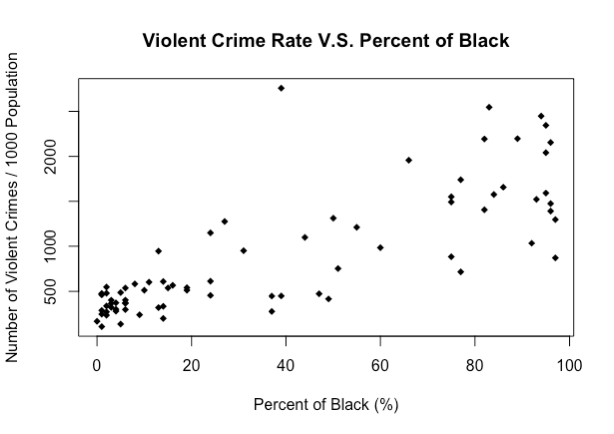
*Figure 36. Histogram for Proportion of Hispanic People*



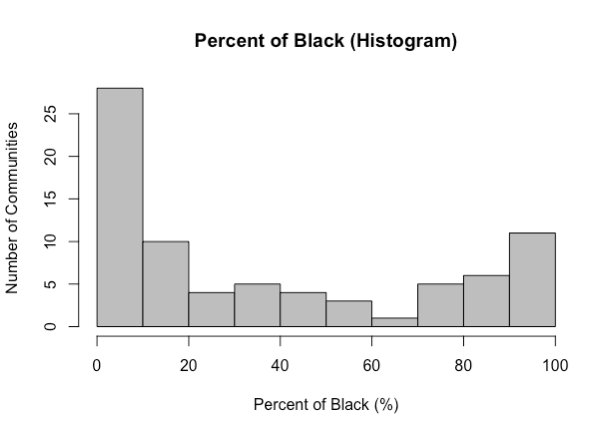
*Figure 37. Box Plot for Proportion of Hispanic People*

The violent crime rate exponentially decreases as the percentage of hispanic people increases from 0 to 90%, as shown in the scatter plot. The histogram also indicates that the distribution is not normal, but rather exponential as well.

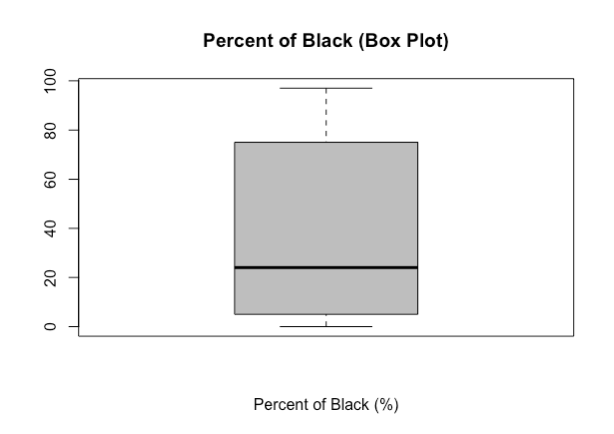
Proportion of Black People



*Figure 38. Scatter Plot for Proportion of Black People*



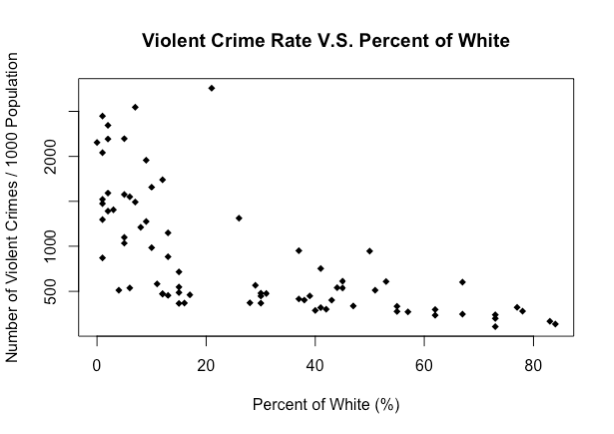
*Figure 39. Histogram for Proportion of Black People*



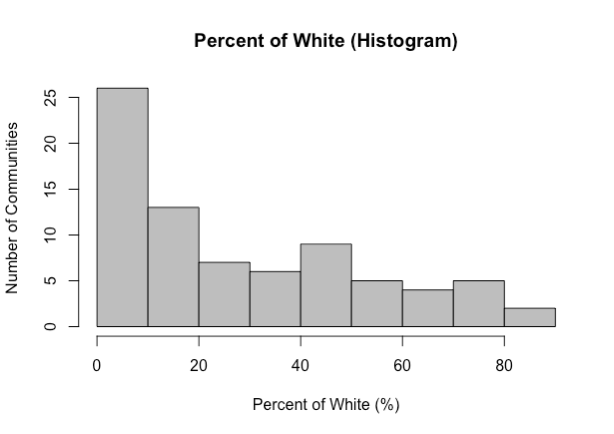
*Figure 40. Box Plot for Proportion of Black People*

The number of communities decreases and then increases as the percentage of black people increases from 0 to 100%. About 28 communities have 0 to 10% black people; about 10 communities have 10% - 20% and about 10 communities have 90% - 100%. A very low number of communities have 20% - 90% of black people. In addition, there is a clear positive relationship that can be observed with the class variable from the scatter plot.

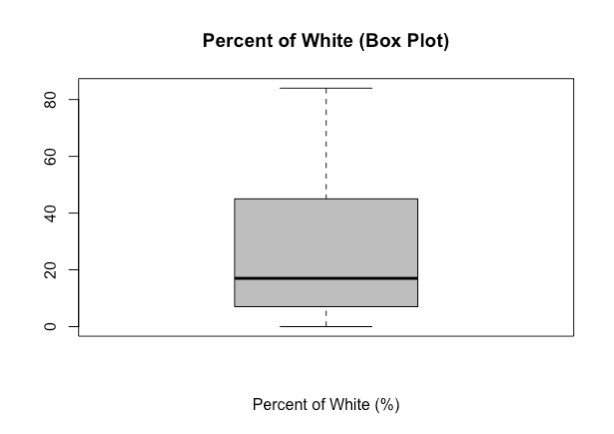
Proportion of White People



*Figure 41. Scatter Plot for Proportion of White People*



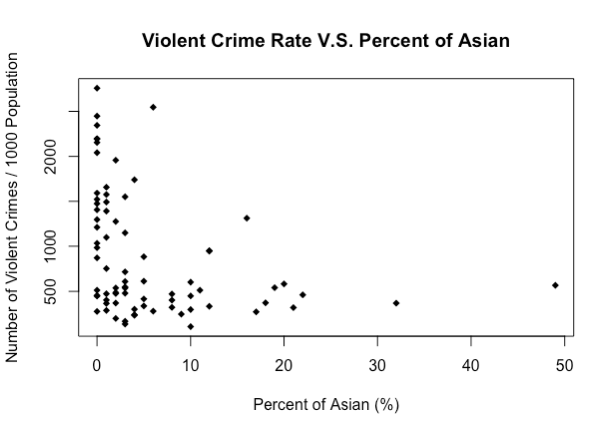
*Figure 42. Histogram for Proportion of White People*



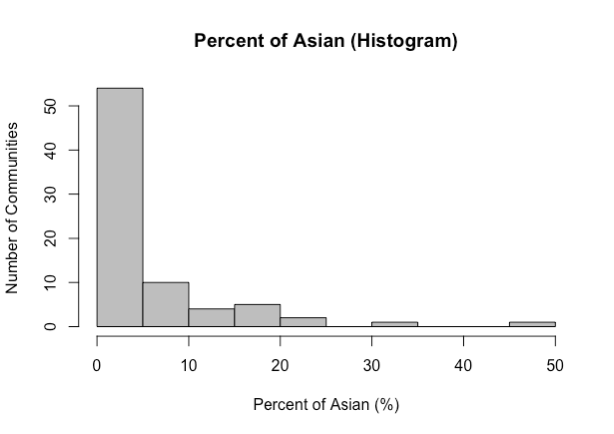
*Figure 43. Box Plot for Proportion of White People*

The distribution of the histogram is a exponential, in that the number of communities exponentially decreases as the percentage of white people increases. Furthermore, as shown in the scatter plot, there is a negative exponential relationship with the class variable.

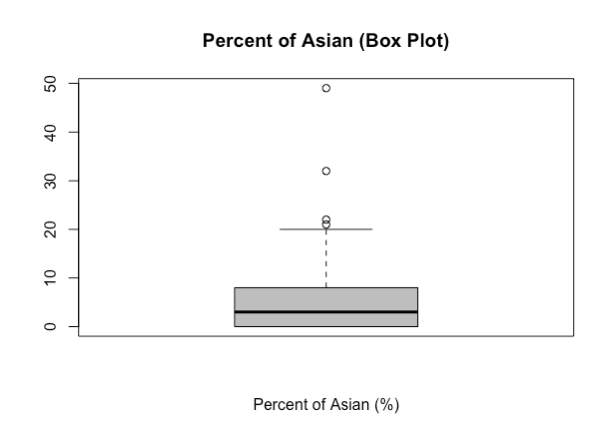
Proportion of Asians



*Figure 44. Scatter Plot for Proportion of Asian People*



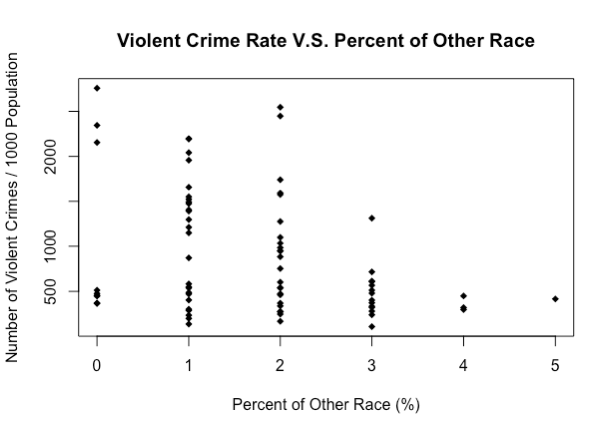
*Figure 45. Histogram for Proportion of Asian People*



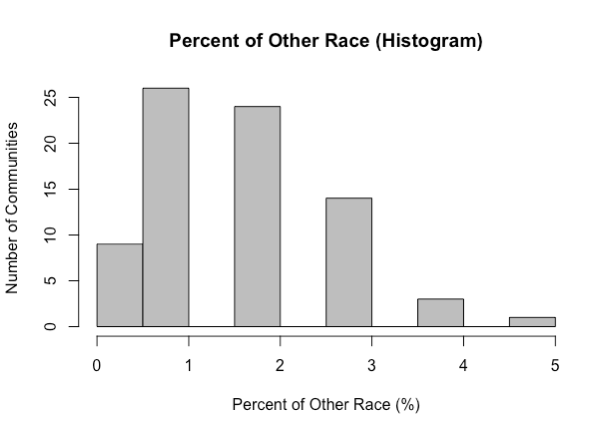
*Figure 46. Box Plot for Proportion of Asian People*

Similar to percentage of white people, the number of communities exponentially decreases as the percentage of Asian people increases from 0 to 50%. As shown in the scatter plot, there is a negative exponential relationship with the class variable. However, it is not clear due to the low number of samples with a high Asian percentage rate.

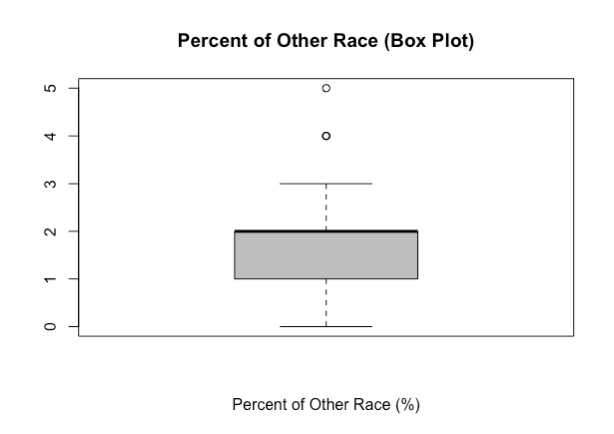
Proportion of Other Races



*Figure 47. Scatter Plot for Proportion of Other Races*



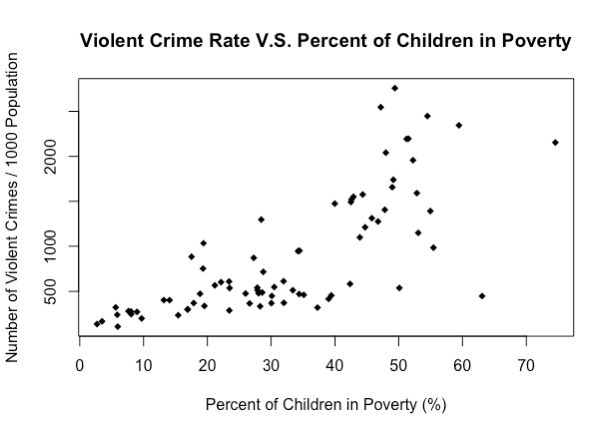
*Figure 48. Histogram for Proportion of Other Races*



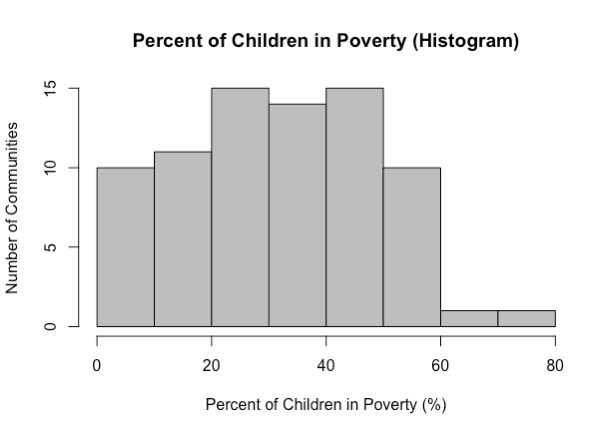
*Figure 49. Box Plot for Proportion of Other Races*

The percentage of other races does not seem indicate any strong correlation with the class variable. There are also very few communities with a percentage of people of “other races” of 4% or more.

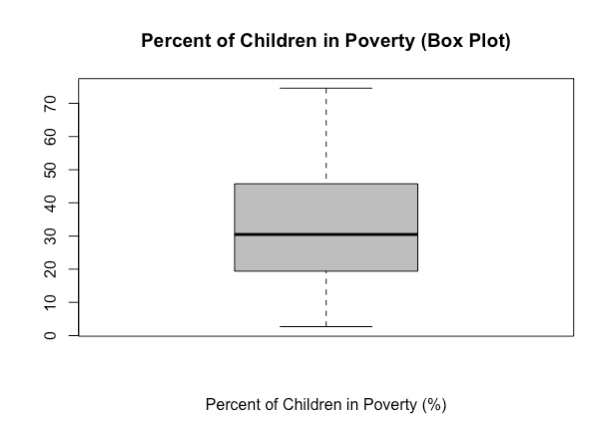
Percent of Children in Poverty



*Figure 50. Scatter Plot for Percent of Children in Poverty*



*Figure 51. Histogram for Percent of Children in Poverty*



*Figure 52. Box Plot for Percent of Children in Poverty*

From the scatter plot, it can be observed that there is a clear positive relationship between the percentage of children in poverty and the rate of violent crimes. The percentage of children in poverty ranges from 0 to 80%, concentrated between the range of 0 to 60%.