Upset Potential in the National Football League (NFL)

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**ABSTRACT**

Fantasy leagues, spread picks, as well as confidence points picks have become popular among fans of a variety of sports today. While the ultimate goal of these activities is to choose all winners, the place to gain a competitive edge over opponents is in picking upsets correctly. Nowhere is this more apparent than in confidence points picks. Placing too much confidence on a game that has a surprise upset could harm the overall score more than picking a few low confidence games incorrectly.

The goal of this project is to determine factors that influence the potential for upsets in the National Football League (NFL) through data mining techniques. Upon successful determination of these factors, I will attempt to predict upsets for current/real-time games.

**Categories and Subject Descriptors**

H.2.8 **[Database Management]** Database Applications – *Data mining*

**Keywords**

National Football League (NFL); Confidence picks; Exploratory data analysis; ~~Multivariate; Categorical;~~ Histogram; Scatterplot; Scatterplot Matrix; ~~Normalization;~~ Binning; K-means; ~~Regression Analysis;~~ Classification; Decision Tree Classification; Training and Testing; ~~Accuracy; Error Rate; Sensitivity; Specificity; Precision; Recall; F Measure;~~ Clustering; Cluster Analysis; Partitioning Approach; k-means; Silhouette Plot;

# INTRODUCTION

## Dataset

The data required for this analysis was widespread and was not available through one source.

Injury data was particularly difficult to standardize. While every team is allowed the same number of starting players, each team has the authority to assign them as they see fit. This means not only the positions that each team starts may vary, but also the number of players in a position may also vary. For example, on offense, every team will have a quarterback (QB) and a center (C), but one team may include a single running back (RB), another may have two running backs, and a third may have three fullbacks (FB). As for defense, some teams may include a nose tackle (NT), others a left/right outside linebacker (LOLB/ROLB), while others may have multiple defensive ends (DE). This made determining critical positions across all teams almost impossible; therefore, I opted to treat all positions with equal importance. Instead, I focused on whether the player for any starting position was probable/doubtful yet still played versus did not play at all. I gave more points towards the team’s total offense and defensive injury total if a player did not play at all versus played in a limited capacity.

~~We chose a dataset from the UCI Machine Learning Repository whose attributes are categorical in nature. This Community and Crime dataset comprises socioeconomic data from the 1990 US Census, law enforcement data from the 1990 US LEMAS survey, and crime data from the 1995 FBI UCR. The dataset contains information that describes or involves the community, such as the percent of the population considered urban and the median family income, as well as involve law enforcement, such as per capita number of police officers and percent of officers assigned to drug units. The issue of violent crime has been a contentious domestic political issue with sweeping implications. In this analysis, we will explore other indicators of communities along with its prevalence of violent crime to determine what relationships exist and suggest further areas of study.~~

### Data Attributes Selection and Values

~~The attributes selected for this dataset were from larger databases of census and crime information. They were included here if there was any plausible connection to crime and/or the attribute the dataset authors intended to be predicted, Per Capita Violent Crimes (ViolentCrimesPerPop). There are 1994 instances with some missing values (indicated by a ‘?’ value) and 128 attributes: 122 predictive, 5 non-predictive, and 1 goal.~~

Non-predictive values include:

*Team* - Name

*Score* – Number of point the team received for a game

*Ending* – Final versus overtime (OT)

*Outcome* – Win (W), Loss (L), or Tie (T)

*Date* – Day the game was or will be played

*DaysRest* – Number of days since last game played (null for first games of the season)

*Timezone* – Time zone in which the game was or will be played

*Weather+* – Other weather related information, such as high winds, rain, etc.

*Odds* – Amount by which a team is expected to win/lose

Predictive values include:

*AorH* – Away (A) or Home (H)

*Time* – Time at which the game began (home team local time)

*Weather* – Temperature at game time (or “Dome” if played indoors)

*UpsetAmt* – Magnitude of upset (0 if not an upset)

*Offense* - A representative number for a team’s offense injuries (1 or 2 points for each player injured)

*Defense* – A representative number for a team’s defense injuries (1 or 2 points for each player injured)

Goal values:

*Upset* – Yes (Y) or No (N) if the team predicted to win instead lost

### Limitations

~~Predictive and goal attributes (the numeric data in the dataset) was normalized into the decimal range 0.00-1.00 using an equal-interval binning method. Through this process, attributes retain their distribution and skew. Normalization also preserves the approximate ratios values within an attribute; however, it does not preserve relationships between attribute values. Hence, it is not possible/meaningful to compare the values for attributes such as whitePerCap against blackPerCap.~~

~~The values for the Per Capita Violent Crimes attribute was calculated using population data as well as the sum of crime variables considered violent crimes in the United States: murder, rape, robbery, and assault. A few states, many of which are in the Midwest, do not count rapes in the same manner as the others. This resulted in missing values for rapes and a skewed calculation of Per Capita Violent Crimes. These cities were therefore not included in the final dataset.~~

~~Information used for the LEMAS related attributes was limited to police departments with a minimum of 100 officers. A few smaller police departments were used as a random sample.~~

~~Communities that could not be found in both census and crime dataset were not included in this dataset. Since many communities in the census were missing LEMAS data, this eliminated those communities, limiting the data selection.~~

## Objective of Analysis

Knowing how factors such as time zone changes, number of days rest between games, overtime games played, weather, or key player injuries can affect the outcome of the game would help teams prepare themselves against an upset. This information can also be used to a team’s advantage by providing them ways to focus their training to upset other teams. The objective of this analysis is to explore the influence the selected factors have on a game’s outcome and suggest possible other factors for future analysis. Then using the information obtain from the analysis and utilizing techniques such as clustering, binning, and classification, I will attempt to predict upsets for current season.

## Risks

~~With a dataset this large, there is a high risk that we will not be able to filter out the “noise” to find a definite answer to our question. There are such a large number of factors contributing to any trends in the data that it may be hard to isolate which is actually the actual cause and what may be red herrings. To be clear, we are aiming to determine correlation and are not confident we will be able to determine causation without a time-lapse analysis. For example, without also utilizing FBI Uniform Crime Report datasets from previous years, we would not be able to analyze how the year-to-year changes in attributes may have resulted in a change to the violent crimes result.~~

# RELATED WORK

~~There has been many studies and papers on the importance of sharing information among law enforcement agencies as well as why the sharing of data is lagging. However, past efforts to solve this issue have failed and the problem still plagues law enforcement. The challenge in the past has simply been how to collect, share, aggregate, and standardize data. This challenge remains today as law enforcement agencies continue to use different standards in reporting crime. The Federal Bureau of Investigation’s Uniform Crime Report data has been the more extensive effort to solve this problem to date. It is not without flaws and oversights, and the interpretation/analysis of this data is highly contentious making all the more difficult for law enforcement agencies to benefit from it. There is also a significant effort to interpret the data into the more standard UCR, which smaller stations may not have the manpower to support. Since there are still large obstacles to overcome in the sharing of data, the analysis of the data becomes cumbersome when looking in several location for the type of data represented in this dataset. Other studies have looked at single types of data or data for a limited number of communities, but not as extensive research could be accomplished for data such as that in this dataset.~~

# METHODOLOGY

~~We will begin by taking an exploratory data analysis approach. We will first visualize the data we have gathered and then begin comparing multiple variables. By comparing multiple variables through histograms, scatter plots, and various other visualization trends, we will note any obvious patterns by examining their two-way interactions. We will try to describe this relationship with a type of relationship that best fits. Once we have completed most of our exploratory data analysis, we will begin to perform testing and cross-validation to determine if classification can be successfully completed on the data. Finally, we will attempt to analyze frequent itemsets to obtain more information about trends in the dataset.~~

## Preprocessing

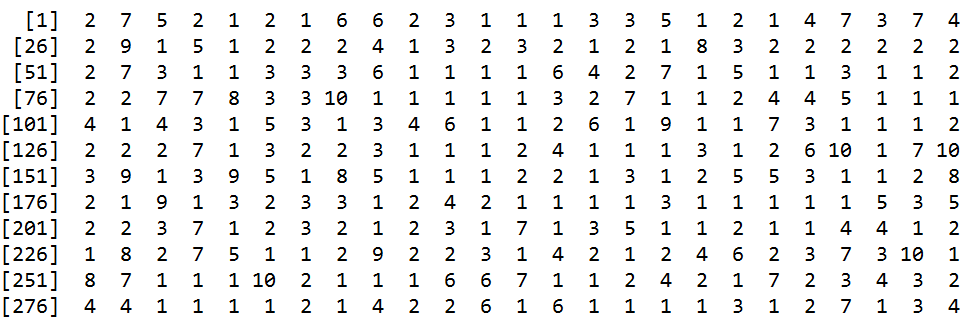
### Binning

~~Data binning, sometimes referred to as bucketing, is a technique used in data pre-processing to accommodate algorithms that use categorical rather than continuous variables. Since in our case we wish to not only perform classification, but also frequent itemset analysis, binning will be necessary for the attributes involved. When binning, the values for the attributes are each categorized into a group or “bin” which represents that field. There are four common methods to bin field values: equal width binning, equal frequency binning, binning by clustering, and binning based on predictive value. Since many of the values we are working with are percentages and have been normalized to values between 0.00 and 1.00, we felt the most appropriate technique was equal width.~~

#### Upset Amount Binning

~~In equal width binning, the attribute values are divided into~~ *~~k~~* ~~categories of equal width. While this is not one of the preferred methods of binning since outliers may influence the width of the bins, we thought it would work well with our data since our attribute values are representative of percentages.~~

Table 1. Sample of *k*=10 Bin of ViolentCrimesPerPop Data



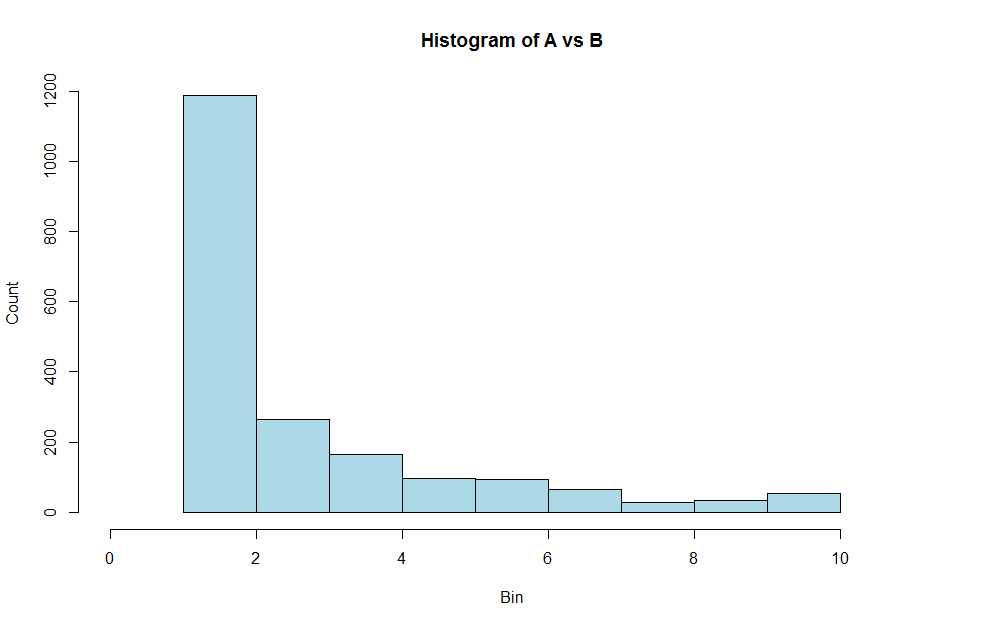
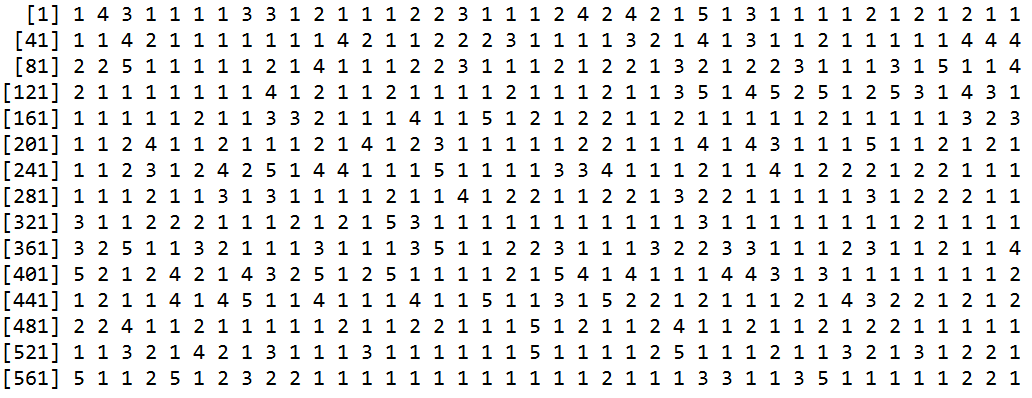


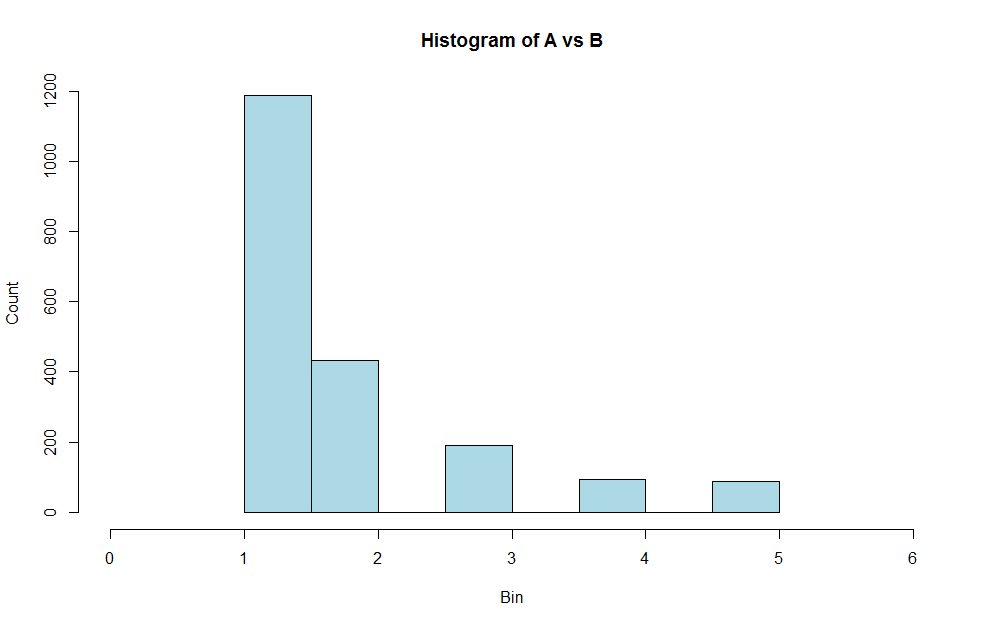
Figure 1. Histogram of Equal Width Binned Weight *k* = 10

#### Weather Binning

~~We binned the attribute values into groups of 10% (~~*~~k~~* ~~of 10) as well as 20% (~~*~~k~~* ~~of 5). Using the attribute ViolentCrimesPerPop as an example, with~~ *~~k~~* ~~of 5 (each bin representing 20%) Table 1 shows a sampling of the post-binned data and Figure 3 shows a histogram of the values binned. In addition, with~~ *~~k~~* ~~of 10 (each bin representing 10%) Table 2 shows a sampling of the post binned data and Figure 4 shows a histogram the values binned.~~

Table 2. Sample of *k*=5 Bin of ViolentCrimesPerPop Data





**Figure 2. Histogram of Equal Width Binned Weight *k* = 5**

## Experiment Design, Tools, & Approaches

### Clustering

#### Density-based Approach

~~The density-based approach to clustering is based on specified connectivity and density functions. Some of the advantages to density-based approach over other approaches is it can handle noise, cluster discovered can be of arbitrary shape, and only one scan of the data is needed.~~

~~Density-based clustering work with two parameters:~~

~~Eps: Maximum radius of the neighborhood~~

~~MinPts: Minimum number of points in an Eps-neighborhood (N~~~~Eps~~~~) of the point~~

~~Density-based approach also uses the concepts of density-reachable and density-connected. A point~~ *~~p~~* ~~is defined as density-reachable from a point~~ *~~q~~* ~~if there is a chain points such that~~ *~~p~~~~i+1~~* ~~is directly density-reachable from~~ *~~p~~~~i~~*~~. A point~~ *~~p~~* ~~is defined as density-connected to a point~~ *~~q~~* ~~if there is a point~~ *~~o~~* ~~such that both,~~ *~~p~~* ~~and~~ *~~q~~* ~~are density-reachable from~~ *~~o~~*~~.~~

##### DBSCAN

~~Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clusters data into maximal sets of density-connected points. In spatial databases with noise, clusters discovered through DBSCAN will be of arbitrary shape. The DBSCAN algorithm is as follows:~~

~~Arbitrarily select a point~~ *~~p~~*

~~Retrieve all points density-reachable from~~ *~~p~~* ~~w.r.t.~~ *~~Eps~~* ~~and~~ *~~MinPts~~*

~~If~~ *~~p~~* ~~is a core point, a cluster is formed~~

~~If~~ *~~p~~* ~~is a border point, no points are density-reachable from~~ *~~p~~* ~~and DBSCAN visits the next point of the dataset~~

~~Continue until all of the points have been processed~~

#### Partitioning Approach

The partitioning approach to clustering evaluates each item in a dataset by some criterion and divides, or partitions, into *k* clusters. The criteria for each chosen partition is chosen so as to optimize/minimize the sum of squared distances or

##### K-means

In k-means partitioning, each cluster is represented by one item at the center of the cluster. Evaluation of each dataset item to determine which cluster they belong to done using the following four steps:

1. Partition the dataset into *k* nonempty subsets
2. Compute the seed points as the mean point or centroid of the clusters current partitioning
3. Assign each object to the cluster with the nearest seed point
4. Repeat from step 2 until the assignments do not change

While K-means is sometimes known as a greedy algorithm, it is efficient running at *O*(*tkn*) where *n* is the number of instances, *k* is the number of clusters, and *t* is the number of iterations. However, k-means is not without its weaknesses. For k-means, the number of clusters in which to divide the data needs to be specified before the algorithm is run, which may require re-running to determine an optimal number of partitions. In addition, k-means can be sensitive to outliers as every item must be place in only the specified number of partitions.

### Classification

#### Training and Testing

~~The Holdout Method is a type of cross validation for classification. In the method, the entire data set is randomly partitioned into two independent sets of specified size: the training set and the test set. The training set is used for model construction and the test set is used to evaluate the accuracy of the constructed model. In the case of our analysis, the data was partitioned with 70% in the training set and 30% in the test set. Both sets contain examples of each classification type.~~

#### Decision Tree

Decision Tree classification uses a flowchart-like tree structure for classification. In the tree, an internal tree node represents each test on an attribute, a tree branch represents each outcome of the attribute test, and each tree leaf node has a classification label. A path from the root to a leaf node is a representation of a classification rule.

The tree is constructed in a divide-and-conquer manner with no backtracking. The training examples are all at the root at the start of tree construction and are partitioned reclusively based on the provided selected attributes as the construction proceeds. Partitioning ends when all the samples for a given node belong to the same class, there are no remaining attributes for further partitioning, and there are no samples left to partition.

## Factor Analysis

### ??

# EVALUATION METHODOLOGY

## Evaluation Metrics

### Classification

#### Accuracy and Error Rate

Accuracy is calculated as the percentage of test samples correctly calculated (TP is true positive, TN is true negative):

Error rate is calculated as the opposite, or 1 - accuracy (FP is false positive, FN is false negative):

#### Sensitivity and Specificity

Sensitivity is calculated as the true positive (TP) recognition rate:

Specificity is calculated as the true negative (TN) recognition rate:

Accuracy can be written as a function of both sensitivity and specificity:

#### Precision and Recall

There is an inverse relationship between precision and recall.

Precision is measured as a percentage of the samples classified with a positive label that are actually positive, or exactness:

Recall is measured as a percentage of positive samples actually classified with a positive label, or completeness.

A perfect score would be 1.0 or 100%.

#### F-Measures

F-measure is a type of accuracy measurement, which takes into account both precision and recall, with the resulting score assigned is between 0 and 1.

F-measure can also be a weighted measurement as follows:

# RESULTS

## Upset Amount Analysis

### Clustering

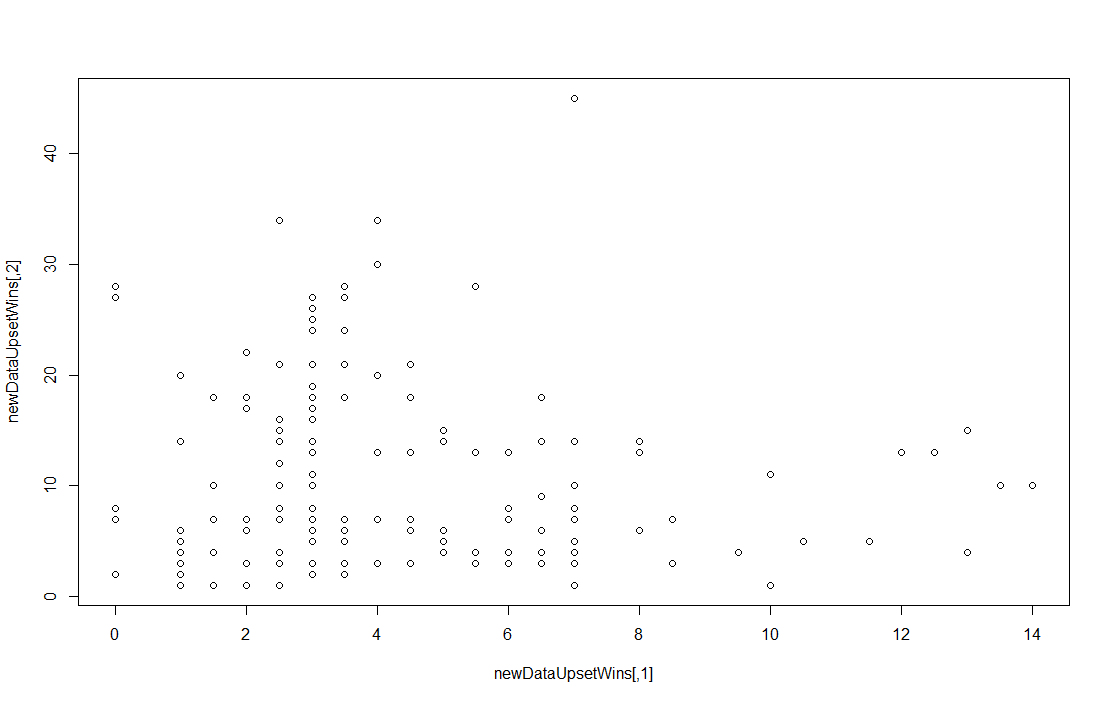


Figure 3. Odds and UpsetAmt for Clustering

#### Density Approach

##### DBSCAN

~~I first ran the DBSCAN with an Eps value of 5. The results (see Figure 10. DBSCAN Clustering for Eps=5Figure 10) showed some clustering but still many outliers. I then re-ran the DBSCAN with an Eps value of 10. The results (see Figure 11) were much improved; however, there were still a few outliers. I decided to see if it was possible to eliminate the remaining outliers. To do this I again increased the Eps value to 15 and re-ran the test. This result (see Figure 12) was not well clustered at all, so I knew I needed a Eps value closer to the last good clustering or Eps of 10. I tried a few other Eps values (see results for Eps 11 in Figure 13 and Eps 11.5 in Figure 14) until I found the results I considered the best for Eps value of 11.1 (see Figure 15) with as few outliers as possible.~~

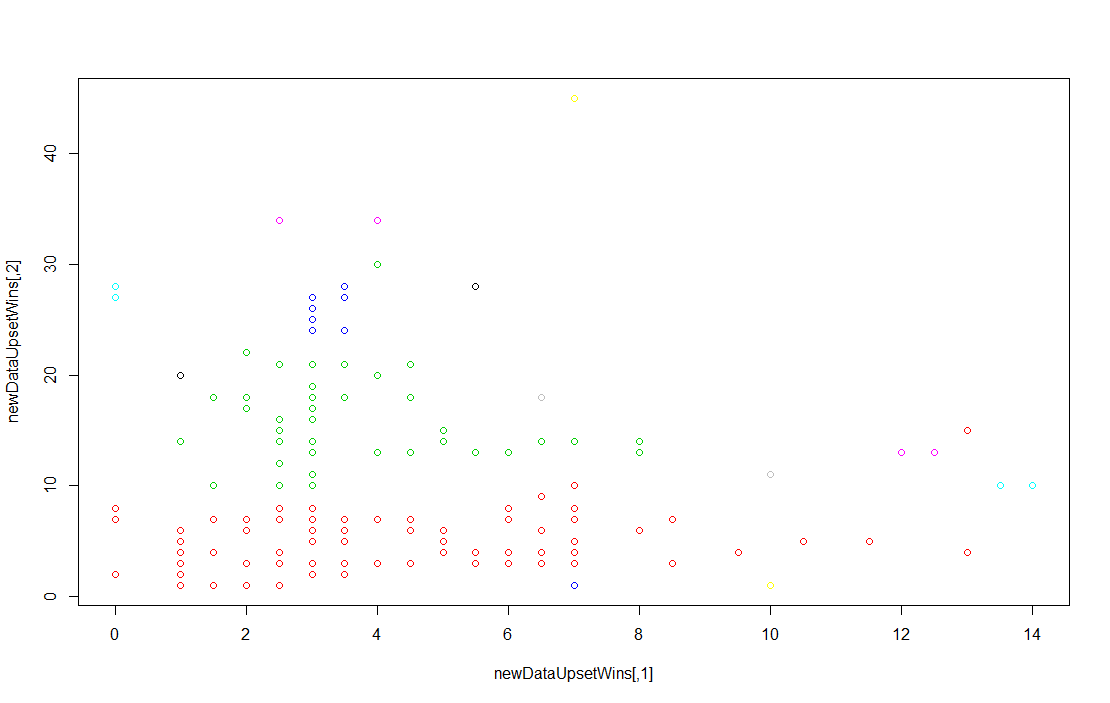


Figure 4. DBSCAN Clustering for Eps=1.75

#### Partitioning Approach

~~For both partitioning methods, a~~ *~~k~~* ~~value for the number of partitions needs to be specified ahead of time. To determine the best value I used the Elbow method, which looks at the sum of squared error (SSE) within groups as a function of the number of clusters (see Figure 3). Looking for the bend of elbow in the plot gives a good indication of a value for~~ *~~k~~*~~. In this case, 8 or 10 clusters seemed to be good bend/elbow locations so I used both those values for~~ *~~k~~* ~~in my analysis.~~

##### 

Figure 5. Number of Clusters to Determine Best *k* Value

##### K-means

~~Using~~ *~~k=8~~* ~~for the k-means partitioning approach gave the highest average silhouette width (see Figure 16) of the partitioning approaches as well as density-based approaches at 0.53. The silhouette plot shows no outliers and seems to fit the data best.~~

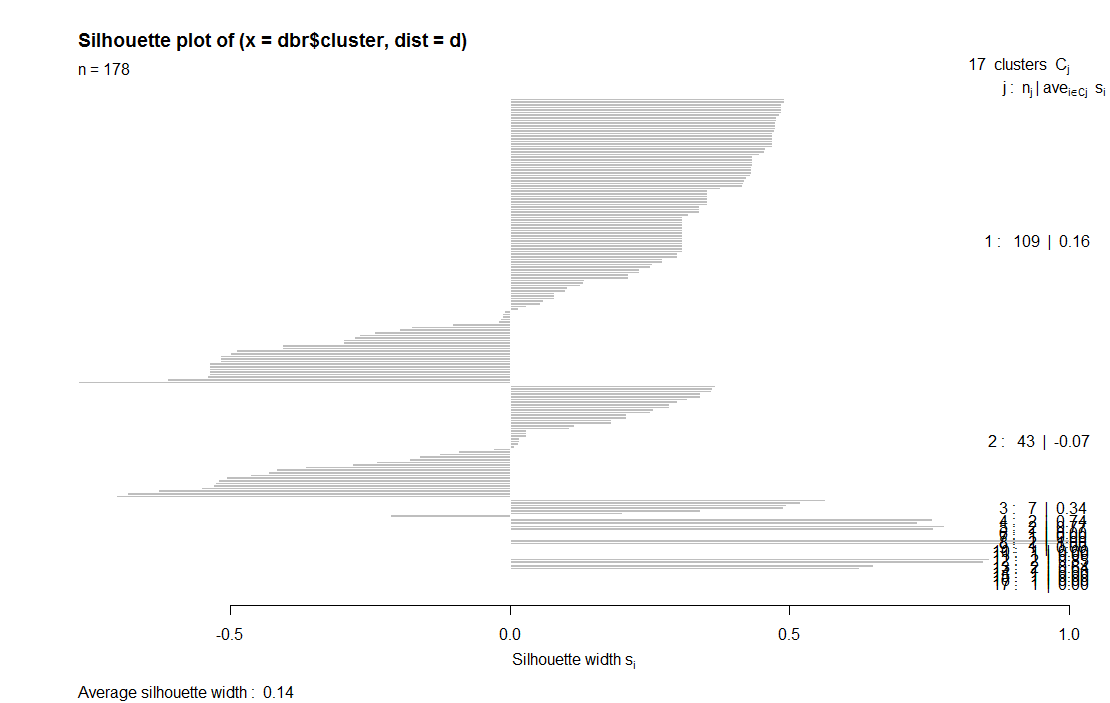


Figure 6. K-means Silhouette Plot for *k*=3

### Classification

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#### Decision Tree

~~The Decision Tree from constructed from the training set was more complicated than I had expected (see Figure 1). When I looked at the below Figure 2 of the relative error and complexity point (CP) it the complexity of the tree made more sense. As the size of the tree grew, the CP continued to decrease as well as the relative error. One interesting part of the resulting tree was even with the increase in tree size, the algorithm still did not determine a great way to classify balanced scales. The resulting Decision Tree from the training set had no leaf nodes with classification balanced despite numerous examples in the training data. The Decision Tree confusion matrix shown in Table 1 also confirms the trouble the Decision Tree classification had showing no balanced classifications for any of the test data.~~

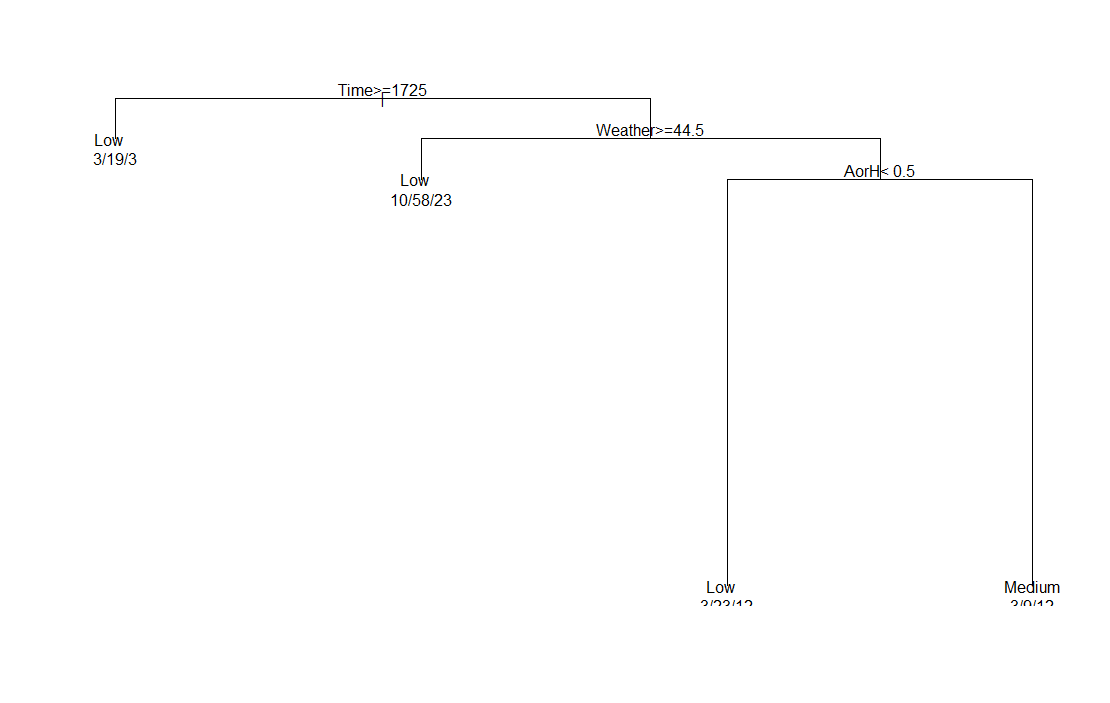


Figure 7. Decision Tree

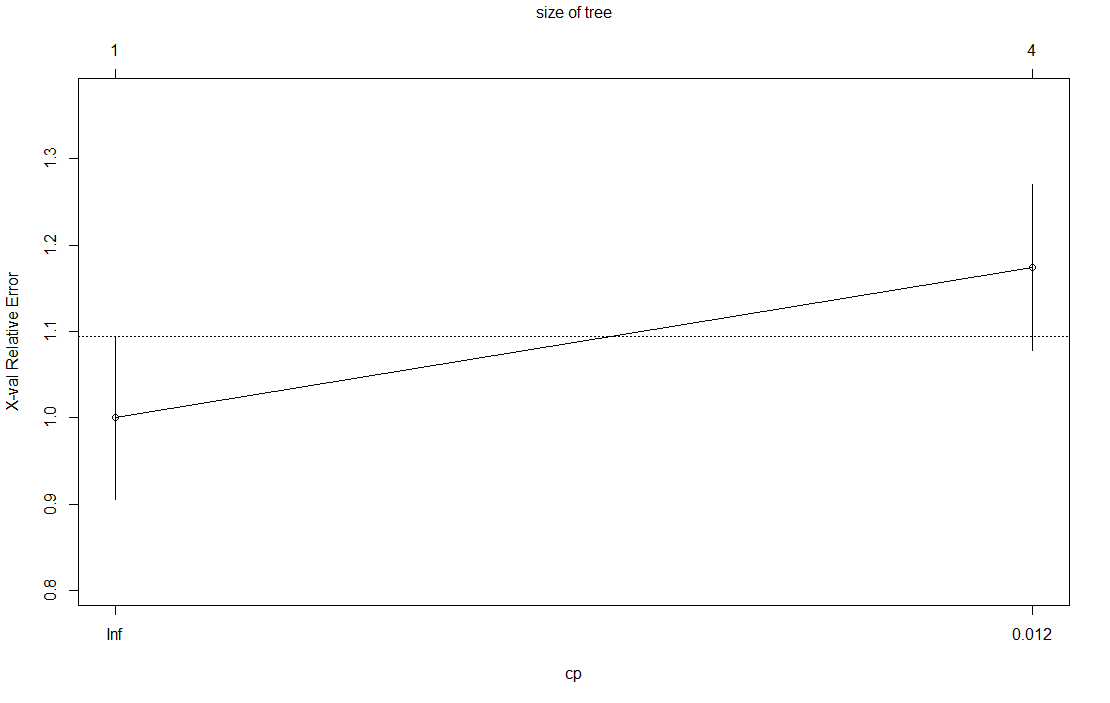
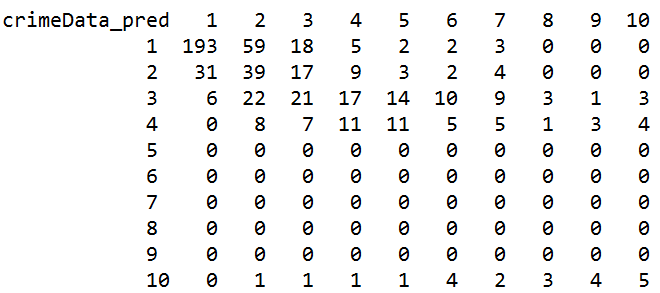


Figure 8. Relative Error and Complexity Point (CP)

Table 3. Decision Tree Confusion Matrix Results



## Upset Analysis

### Classification

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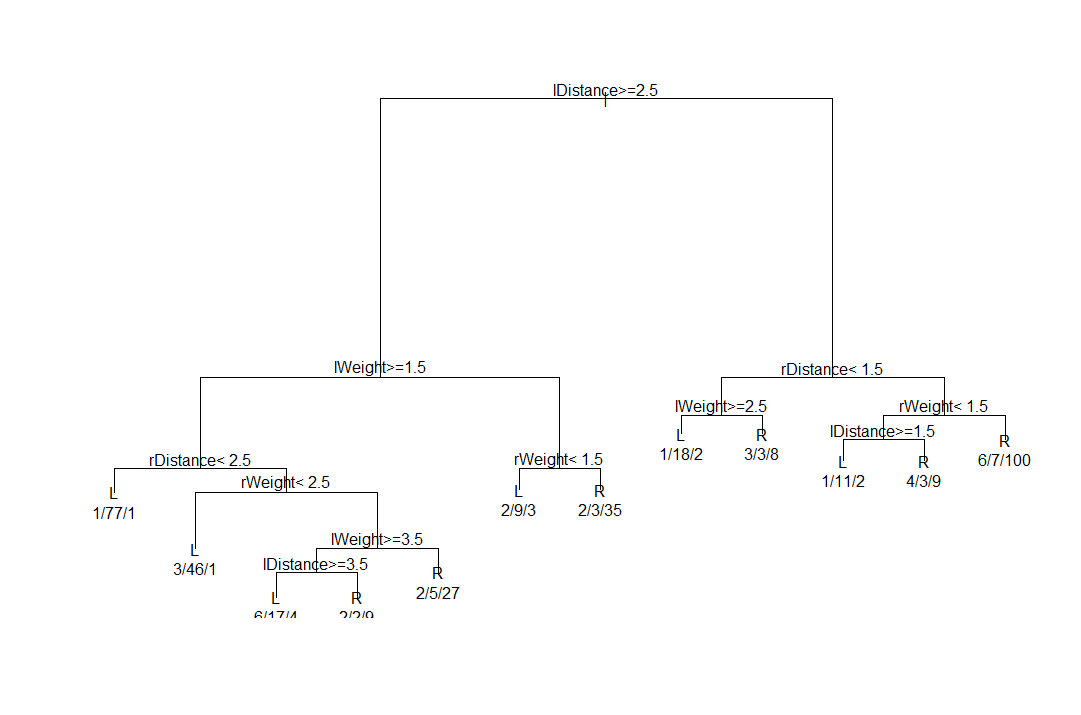


Figure 9. Decision Tree

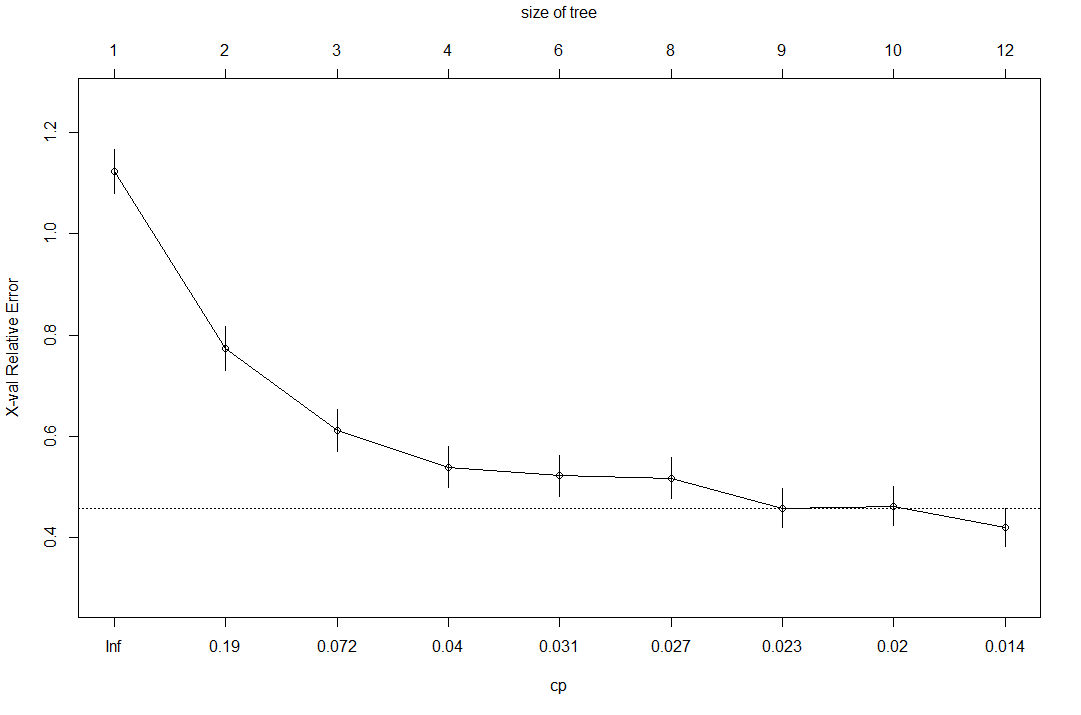
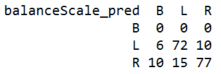


Figure 10. Relative Error and Complexity Point (CP)

Table 4. Decision Tree Confusion Matrix Results



## Analysis

#### Accuracy and Error Rate

~~The overall accuracy for the~~ *~~k~~* ~~of 10 binned data could be calculated using Table 3 as follows:~~

~~(193 + 39 + 21+ 11 + 0 + 0 + 0 + 0 + 0 + 5) / 570~~

~~= 0.467 ≈ 47%~~

~~The overall error rate for the~~ *~~k~~* ~~of 10 binned data could be calculated using Table 3 as follows:~~

~~(37 + 90 + 43 + 32 + 31 + 23 + 23 + 7 + 8 + 7) / 570~~

~~= 0.528 ≈ 53%~~

~~With an error rate greater than the accuracy, we determined it was futile to continuing to calculate the rest of the classification evaluation metrics for~~ *~~k~~* ~~of 10 binned data. As inaccurate and error prone as the~~ *~~k~~* ~~of 10 binned data was obviously at determining classification, it would not provide us useful results. However, we continued the evaluation with the~~ *~~k~~* ~~of 5 binned data.~~

~~The overall accuracy for the~~ *~~k~~* ~~of 5 binned data could be calculated using Table 4 as follows:~~

~~(324 + 49 + 0 + 0 + 9) / 570 = 0.67 ≈ 67%~~

~~The overall error rate for the~~ *~~k~~* ~~of 5 binned data could be calculated using Table 4 as follows:~~

~~(35 + 58 + 54 + 30 + 11) / 570 = 0.33 ≈ 33%~~

~~With an accuracy near 2/3 and an error rate closer to 1/3, the results for~~ *~~k~~* ~~of 5 binned data were much better than those of the~~ *~~k~~* ~~of 10 binned data.~~

#### Sensitivity and Specificity

~~The sensitivity for each value for~~ *~~k~~* ~~of 5 binned data classification can be calculated using Table 4 as follows:~~

~~1: 324 / 395 = 0.82 ≈ 82%~~

~~2: 49 / 103 = 0.32 ≈ 32%~~

~~3 & 4: 0 / 0 so they cannot be calculated~~

~~5: 9 / 22 = 0.41 ≈ 41%~~

~~The specificity for each value for~~ *~~k~~* ~~of 5 binned data classification can be calculated using Table 4 as follows:~~

~~1: 140 / 175 = 0.8 ≈ 80%~~

~~2: 359 / 417 = 0.861 ≈ 86.1%~~

~~3: 516 / 570 = 0.905 ≈ 90.5%~~

~~4: 540 / 570 = 0.95 ≈ 95%~~

~~5: 537 / 570 = 0.98 ≈ 98%~~

#### Precision and Recall

~~The precision for each value for the~~ *~~k~~* ~~of 5 classification can be calculated using Table 4 as follows:~~

~~1: 324 / (324 + 106) = 0.75 ≈ 75%~~

~~2: 49 / (49 + 162) = 0.23 ≈ 23%~~

~~3: 0 / (0 + 54) = 0%~~

~~4: 0 / (0 + 30) = 0%~~

~~5: 9 / (9 + 24) = 0.273 ≈ 27.3%~~

~~The recall for each value for the~~ *~~k~~* ~~of 5 classification can be calculated using Table 4 as follows:~~

~~1: 324 / (324 + 71) = 0.82 ≈ 82%~~

~~2: 49 / (49 + 104) = 0.32 ≈ 32%~~

~~3: 0 / (0 + 0) so it cannot be calculated~~

~~4: 0 / (0 + 0) so it cannot be calculated~~

~~5: 9 / (9 + 13) = 0.41 ≈ 41%~~

#### F-Measures

~~The F-measure for each value for the~~ *~~k~~* ~~of 5 classification can be calculated using Table 4 as follows:~~

~~1: (2 \* 0.75 \* 0.82) / (0.75 + 0.82) = 0.78 ≈ 78%~~

~~2: (2 \* 0.23 \* 0.32) / (0.23 + 0.32) = 0.27 ≈ 27%~~

~~3: cannot be calculated since recall could not be calculated~~

~~4: cannot be calculated since recall could not be calculated~~

~~5: (2 \* 0.828 \* 0.41) / (0.828 + 0.41) = 0.33 ≈ 33%~~

# DISCUSSION

~~We had originally hypothesized that factors such as percentage of police per capita, per capita income, and percentage of population with Bachelor’s degrees or higher would be significant in terms of violent crimes per capita. It turned out that these are indirectly related to the attributes that we found most significant.~~

~~Also in our original hypothesis was the percentage of police per capita. This too was a poor predictor of the incidents of violent crime per capita. We believe this result is biased in that the communities with police departments that had less than 100 police officers were not included in the data set minus a few randomly sampled examples.~~

~~Investment income was one of the attributes we determined to a factor in violent crimes per capita. It is indirectly related to per capita income in that investment income is usually thought of as the difference between income and expenses. It is also common for areas with high incomes per capita to be areas with a very high cost of living. Therefore, if we were to use purely per capita income the perceived wealth/income would be skewed in this scenario. Investment income is a better indicated of how well a community is doing relative to its cost of living.~~

~~In addition, there was not a significant separation between communities with a more educated resident base beyond a high school degree. It is possible that a high school degree was sufficient for a comfortable standard of living in the 1980s and 1990s. It would be interesting to explore this today and see if the threshold has increased to a bachelor’s degree.~~

# CONCLUSIONS

~~In our analysis, we saw a slight proportional relationship between high violent crime per capita and high percentage of divorcees as well as a high percentage of the population without a high school degree. We also saw a slight inverse proportional relationship between high violent crime per capita and communities with higher percentage of investment income as well as largely Caucasian communities.~~

~~When there was lower percentage of the population without a high school degree, a lower percentage of divorcees and higher percentage of Caucasians were found frequently. In addition, a higher percentage of Caucasians in the community was frequently found associated with a higher percentage of the population with investment income. High percentages of Caucasians in a community were also many times found with low to mid percentages of divorcees in the community.~~

~~The error rate for the classification was very high. There were also very few results in our frequent itemset analysis with the low percentage of violent crime per capita the only bin producing results. Even with the large size of the dataset, the fact that there was so much error and so little results does not give us confidence that the attributes we selected do have a strong case for influencing violent crime per capita.~~

~~We feel it would be useful to extend this study to analyze how change in any specific attribute is correlated with an increase or decrease in violent crime per capita. This would require additional datasets in preceding and/or succeeding years. This additional data would also help in determining outliers in the data, which could be used to improve the results of any analysis.~~

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