Analysis of the Effects of Regulation on Railroad Safety

Implementation of Data Mining Algorithms to explore Causality and Trends in Railroad Accidents

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ABSTRACT

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1 Introduction

Accidents at highway-railroad intersections cause tremendous losses of lives and resources. For example, on June 27th, 2022, an Amtrak passenger train struck a dump truck in rural Missouri. The truck was crossing a passive intersection with no crossing bars, lights, or bells. Several trains and locomotives derailed causing the death of 4 individuals and over 150 injuries. It is estimated that there are over 130,000 passive railroad crossings in the US. The implementation of active restraints on an intersection like the one described in the accident would cost around $400,000 [1]. Due to the loss of life and high expenses of derailment, this case has again brought up debate about whether the investment in railroad restraints or alteration to regulations between highways and railroads is needed.

Regulation has been one avenue of effort to minimize the number of accidents between highways and railroads. Governments have invested in putting barricades between the intersections during crossings, adding signs, and multiple types of indicators. These are improvements to the intersections themselves. However, certain regulations have also been geared to improving the safety of trains themselves.

The Rail Safety Improvement act of 2008 mandated the implementation of Positive Train Control (PTC) systems on Class 1 railroads and all main lines over which intercity or commuter rail passenger transportation is provided. PTC systems attempt to automatically reduce accidents by only permitting a train to move if it has positive authority to do so. This contrasts with typical train operation in which a train has authority to move unless given a stop signal. This system is intended to prevent head-to-head collisions and prevent trains from going into control or restricted zones to potentially avoid collisions.

Beyond regulations, infrastructure is also an important aspect of railroad operations. Trains are designed to carry various cargoes through various different locations. The development, zoning, and transportation schedules of each location has a large impact on the risk of accidents. Transport routes are determined by the resource requirements of each location, and if a location has high need for transport, it may cause conflicts between rail and highway transportation systems that result in higher risk of crashes. Such conflicts could be diminished after they are discovered by careful civil planning, such as rezoning and rerouting.

There has been much work in creating physical barriers and auditory and visual warning signals to alert vehicle drivers of an oncoming train. However, these systems are costly to implement and are sometimes viewed as irritating to neighbors of railroads. Therefore, it is important to understand the degree of effectivity of these measures. Additionally, there are unique topological attributes of the interaction between the highway and railroad that could potentially create a higher likelihood of accidents. These characteristics also could be changed through modifications which could increase safety at the expense of construction projects.

This project aims to consider the impacts of new regulations, locations of intersections, and the characteristics/topography of intersections to determine which features promote safety and which features do not.

2 Related Work

The Federal Railroad Administration attempted to develop a model for predicting accidents and their severity using data mining techniques using statistical analysis [2]. Though this work does not inherently use data mining techniques, it has relevance due to its exploration of the same data set and the ways it chose to select data and include variables. It also developed a frequency variable called exposure that normalized intersections based upon the amount of exposure to accidents they have. This statistical analysis can also be used as a baseline for the results we discover in this paper to compare to.

Data mining techniques have been successfully applied to investigate the FRA dataset as well as similar datasets generated in other countries. Liu et al utilized chi-squared analysis to look at the causes of rail accidents in the FRA dataset from 2001 to 2010 and the effects of those causes on accident rates [3]. A similar dataset has been generated by the Iranian Railway (RAI) which utilized association rules to identify if-then relations between rail accidents and their potential causes [4]. A survey paper by Bala et al gives a good overview of the literature as it relates to data mining of rail accident data sets [5]. A similar paper by Lu et al compares various generalized linear and data mining models for crash prediction and compares their effectiveness using a test dataset [6]. After a thorough review of rail accident data mining research, it has been determined that none have considered use of a random forest classification or frequent pattern growth (FP-Growth) in their analyses.

In addition to rail, data mining has been utilized in similar large datasets composed of accident reports, mainly around the topic of occupational safety. Several variations of frequent pattern generation including temporal, elevated severity, and high impact were performed by Singh et al using a proprietary data set generated from a steel manufacturing plant in India [7]. Another group led by Khosrowabadi used association rules and K-means clustering to identify the factors affecting occupational safety in industrial paint halls in Tehran [8]. These additional studies help demonstrate that more advanced frequent pattern techniques and classification techniques are promising future areas of investigation for accident analysis.

3 Data Set

The chosen data set was selected based on the large number of papers on railroad safety implementing data mining techniques using different categories within the Federal Railroad Administration (FRA) Office of Safety Analysis’ database. There are multiple different tables based upon different reporting forms. The FRA requires the reporting of accidents and fatalities using specific forms as defined by the circumstance. The specific grouping of data that was chosen was all the accidents between railroads and highways due to the many variances in causalities that it provides. The data set contains all the reported information from 1970 to May 2022.

There are 159 attributes within the data set allowing for a wealth of potential factors of causality to be explored. There are 242,021 rows of data, or accidents, during the period and there are a total of 25,448,378 non-empty entries within the data set.

The attributes provide comprehensive data about railroad operations at the time and location of each data object representing an individual incident at a highway-railroad crossing.

Attributes include the time of incident, the number and types of advance warnings, and the activation of other warning systems – painting a clear picture of when the incident occurred and what was done to mitigate it. Additionally, there is a record of the number of injuries and fatalities that occurred in total, on the train, and within the vehicle hit.

The attributes document geographic locations of incidents, including the city, highway, and railroad line in which each incident occurs. Information is provided regarding land use and the weather conditions that were experienced during the specific incident.

Information about the characteristics of the intersection of incident is recorded, including rail design, road design, illumination, visual obstructions, and surface materials.

The wealth of information in this dataset allows many different relations to be mined regarding temporal and spatial influences on incident risk.

All the group members have successfully downloaded the data set at the URL below:

<https://catalog.data.gov/dataset/highway-rail-grade-crossing-accident-data>

4 Main Techniques Applied

The data set contained many rows of unfilled information, several attributes that included textual information, and many coded options for characteristics regarding the intersection. Due to this, cleaning and pre-processing of the data was needed before trying to apply data mining algorithms.

Various mining techniques were chosen to allow for knowledge to be gained through differing perspectives and to be analyzed in such a way as to impact future regulatory decisions. For example, decision tree techniques were applied to be able to understand if certain attributes of intersections would increase the probability of many injuries during railroad accidents. Clustering techniques were applied to understand the effect of geography and weather on the severity of railroad accidents. Finally, a Frequent Pattern Growth algorithm was implemented to attempt to understand associations and interesting patterns between attributes that result in higher numbers of injuries. These techniques combined aimed to paint an overall picture of the contributing factors of high-injury accidents to drive future regulation decisions.

**4.1** **Data Cleaning**

Since there was interest in knowing if there had been significant reduction in train accident severity after the implementation of PTC, there was a need to separate the month, year, and date from the single date and time entry. A function was created to separate the day, month, and year from the combined date entry that includes all time components in one string. This allowed for individual months, years, and days of the month to be queried, to determine if there has been any significant change in accident severity by month or over time.

There were also text entries that contained geographic information needed that were indicative of the same place but entered the dataset in different ways. To reduce this redundancy, a function was created to abbreviate common text entries, such as address terms like street and avenue, to minimize the number of unique entries. To further reduce redundancies, a function was made to remove all spaces, periods, dashes, and that capitalized all text. This helped to further reduce the number of unique entries and to reduce repeated entries with slight variations. Finally, there was a need to consolidate all the different null space indicators into a single, consistent one. To do this, a function was made that replaced blank entries with “NA” while applying the same text rules above so that there were not multiple ways in which null information was stored.

**4.2** **Data Preprocessing**

The dataset needed to be preprocessed in slightly varying ways for each of the three interesting questions this report attempts to address. This was to account for the unique lists of attributes used for each question.

Location data included the state, county, and city of each incident as well as location-relevant information such as weather and visibility, which correlates to local climate. For state, county, and city, the dataset already contained label-encoded values for each which are usable for mining. Some data objects were missing records for city, with the implication that the incident did not happen within city limits. For data preprocessing, these blanks were consolidated into one “No City” value so that we can find patterns among incidents occurring outside of city limits. Values like weather and visibility are label-encoded in the dataset, but are one-hot encoded for data mining purposes due to the compact set of unique values.

In the investigation of the effects of PTC on train accidents, in addition to the cleaning already performed, functions were written to remove previously encoded values which were already represented by categorical data. Further, all text was casted to lower case and transcoded into a one-hot sparse matrix. Specific redundant and unnecessary attributes were removed such as data related to who filed a report and when a report was filed, and multiple encodings of the date or location.

To address how the characteristics of the intersection architecture and design impact the probability of death and injury from an accident, a particular list of related attributes was generated. Attributes that were included the allowed speed of the train, illumination of the crossing, view obstructions, warnings, signals, and type of intersection. For each of these attributes, some entries needed to be cleaned including values that did not stand for any codes or were mistyped values. These were replaced by finding all the unique values and their frequency. If the frequency was low enough, the entry was looked for in the dataset and identified if it was an error. If it was an error, it was replaced by another value. Most of these were assigned to the corresponding unknown value. These attributes were transformed using one-hot encoding from numerical codes to binary options for each of the given choices.

Finally, the dataset needed to be split for training and testing to effectively analyze the performance characteristics of the data mining attempts. For this, the data was split into training set containing 80% of the data and a testing set containing 20% of the data.

**4.3** **Techniques Used for Crossing Location**

Location identifiers were primarily ordinal and numerical: temperature values were numerical, and weather values were ordinal – lower values indicated clearer weather, while higher values indicated rain and snow. Longitude and latitude were not part of the dataset, and had to be interpolated from the FIPS county codes provided using a database. Using the longitude and latitude of accident county attributes allowed data mining based on location-dependent values, such as temperature and weather.

4.4 Techniques Used for PTC Analysis

**Fix Tense**

In the investigation of PTC implementation, to reduce the number of attributes and improve final pattern discovery and classification, concept hierarchies will be identified to mine at different abstraction levels. Data values will be selectively smoothed and discretized iteratively as required to improve results. One-hot encoding and a vertical reformatting will be performed for encoded enumerated attributes if model run time proves to be too slow.

4.5 Techniques Used for Intersection Study

**Fix Tense**

Pre-processing the data for the study on the effects of the intersection characteristics will require the crossing surface age to be calculated from the difference of the installation date and the date of accident. There are many attributes with ID’s that will need to be changed to one-hot encoding for use in the FP-growth algorithm. The binary recording system for multiple attributes will also be changed from 2 means no to 0 means no. This will allow for uniformity within the data set.

For the sake of focusing this study on intersection characteristics, all attributes that are specific to the location, train characteristics, or datasheet administrative categories will be removed prior to implementing the algorithms.

After implementing the cleaning and pre-processing measures, the modified data will be implemented into both Random Forest and FP-growth algorithms and will be evaluated for its performance.

4.6 Evaluation Methods

**Fix Tense**

Evaluation of each of the questions will be performed using three classic data mining methods for classification – Decision Tree classification, FP-Growth classification, and K-means clustering classification. The goal of these methods is to yield results which can easily be interpreted to generate clear action plans to reduce future rail accidents.

Frequent pattern growth or FP-Growth is an effective and efficient method of finding frequent patterns in very large data sets. These frequent patterns will yield a sequence of attributes that are related to outcomes of interest for each question, and the output is easily interpreted to provide insight into the factors most associated with the outcomes, so recommendations could be devised to improve future outcomes. FP-Growth addresses the large memory limitation required by the Apriori algorithm because it maintains a tree rather than generating a list of all candidates, and it also can be parallelized by partitioning the database. (The pyspark Python library by Apache Spark contains a pre-built function for implementing FP-Growth. If the model run time proves to be slow even with parallelization, a vertical data format can be explored. Evaluation of the model will be performed using a selection of the following metrics dependent on the performance on the data: support, lift, confidence, X2, Kulczynski measure, and cosine measure. Thresholds for these measures are still to be determined.

In addition to FP-Growth, a Random Forest Decision Tree approach will be used to generate a classification around each question’s target label, after which rules will be extracted. The rules will provide and easily interpreted understanding of the potential cause and known effect which can be communicated to industry experts to improve future rail accident outcomes. The Random Forest will be generated using an 80/20 test/train split with sampling without replacement using the built-in sklearn python library. Like the FP-Growth implementation, this decision tree implementation can also be parallelized. Metrics of accuracy, sensitivity, precision, specificity, F1, and Fb will be used to evaluate performance using k-fold cross-validation as per industry standard.

For location-related attributes, K-means clustering was used to determine clusters in 2D space on an incident heatmap, with temperature and weather as selection attributes. Validity was evaluated using the mean silhouette score, which measures the combined cohesion and separation of all clustered data.

4.7 Tools Used

**Fix Tense**

It was decided to implement the data mining methods proposed in this paper using built-in Python toolboxes to simplify the work and to learn commonly used approaches to these problems.

The Python *pandas* toolbox will be used for data cleaning. The *unique()* function can be used to determine all of the unique values in string attributes such as incident descriptions and locations and determine if there are any misspelled instances or instances that should be combined. The functions *isna()* and *isnull()* can be used to determine missing values and in conjunction with the *unique()* can find all forms of null cells.

The Python *numpy* toolbox will be used to transform the data so that it is easier to manage and manipulate.

The Python toolbox, *sklearn*, will be used to alter attributes to one-hot encoding to prepare the data for the machine learning algorithms. It can also be used to split the data into training and testing groups to evaluate the performance of the methods. Additionally, it can be used for performing the random tree method by using the functionalities for the Random Forest techniques. Finally, it was used to perform K-means clustering on location data.

The Python toolbox, *pyspark*, will be used to mine frequent itemsets using the FP-growth algorithm. This toolbox could also be used to perform Pearson’s independence test and the correlation for each attribute.

The Python toolbox, matplotlib, was used for plotting points for the K-means clusters by latitude and longitude.

5 Key Results

Preliminary decision tree induction was performed for the characteristics of the intersection. Most of the early decision points were based upon the speed of the train at the time of the accident. This may suggest that a large potential legislative point could be to restrict the speed of trains through certain intersections.

K-means clustering of locational data based on temperature and weather indicated that climate plays a large part in the circumstances of crashes. Specifically, more work may need to be done for blizzard-proofing northern highway-rail intersections.

5.1 Intersection Characteristic Results

The decision tree type classification algorithm was applied to attributes describing the characteristics of the railroad-highway intersection. The classification algorithm used a target variable of total injured as the means of sorting. There were 4 classification categories to sort between including 0, 1, 2, or 3 or more injuries.

The algorithm was applied as both a decision tree and random forest algorithm. The attributes were modified to either include instances of unknown information or to exclude them.

Initially a decision tree algorithm was implemented to develop an image of the decision tree to be able visualize the decisions that classified the instances. Using this decision tree, it was possible to estimate the percent of instances that resulted in the number of injuries. These results were used to determine potential courses of action in developing or maintaining regulation regarding railroad-highway intersection design.

A random forest model was created to increase the accuracy of the decision tree model in predicting the number of injuries. Table I shows a confusion matrix with the number of entries for each prediction and each actual classification. Table II shows the performance characteristics including precision, recall, F1 score, and support for each classification category. The accuracy, macro, and weighted averages are depicted for each score category as well.

Table I. Confusion Matrix with Unknown Attributes

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | | Predicted Class | | | |
|  |  | **0** | | **1** | **2** | **3+** |
| Actual Class | **0** | 33867 | | 834 | 89 | 34 |
| **1** | 9889 | | 272 | 35 | 9 |
| **2** | 1924 | | 64 | 6 | 0 |
| **3+** | 851 | | 43 | 4 | 0 |

Table II. Performance Characteristics of Random Forest including Unknowns

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 Score | Support |
| 0 | .7278 | .9725 | .8326 | 34824 |
| 1 | .2242 | .0267 | .0476 | 10205 |
| 2 | .0448 | .0030 | .0056 | 1994 |
| 3+ | .0000 | .0000 | .0000 | 898 |
| Accuracy |  | | .7125 | 47921 |
| Macro Average | .2492 | .2505 | .2215 | 47921 |
| Weighted  Average | .5785 | .7125 | .6154 | 47921 |

To improve the accuracy of the model, attributes with unknown rows were excluded from the results. The confusion matrix in Table III showed slightly higher correct predictions than the original in Table I. The random forest method led to a slight increase in performance characteristics as shown in Table IV compared to Table II.

Table III. Confusion Matrix without Unknowns

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | | Predicted Class | | | |
|  |  | **0** | | **1** | **2** | **3+** |
| Actual Class | **0** | 33884 | | 826 | 84 | 30 |
| **1** | 9889 | | 277 | 32 | 7 |
| **2** | 1924 | | 63 | 7 | 0 |
| **3+** | 855 | | 38 | 5 | 0 |

Table IV. Performance Characteristics of Random Forest without Unknowns

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Precision | Recall | F1 Score | Support |
| 0 | .7279 | .9730 | .8328 | 34824 |
| 1 | .2301 | .0271 | .0486 | 10205 |
| 2 | .0547 | .0035 | .0066 | 1994 |
| 3+ | .0000 | .0000 | .0000 | 898 |
| Accuracy |  | | .7130 | 47921 |
| Macro Average | .2532 | .2509 | .2220 | 47921 |
| Weighted  Average | .5802 | .7130 | .6158 | 47921 |

The K-means clustering model with four clusters selected on temperature and weather presented four clusters: chilly (56.5 F) and raining, freezing (22.9 F) and snowing, hot (74.6 F) and clear, and cold (33.2 F) and clear. Freezing and snowing crash conditions were predominantly in the northern US, with the highest density in the Midwest. Chilly and raining crash conditions were predominantly in the southern US, with the highest density in Georgia. Clear weather clusters were not locationally centralized.

K-means clustering used temperature and weather as the selection variables, but longitude and latitude for plot visualization as seen in Figure I. The data showed that climate-related weather conditions strongly impacted crash conditions.

The mean silhouette score was 0.492, indicating that the clustering is fairly compact and valid with some overlap.

6 Applications

Upon deeper investigation into the decision tree developed by the algorithm, certain attributes seem to have a greater causality than others. For example, 3.43% of accidents in which the train was moving 60 MPH or faster resulted in 3 or more injuries. Overall, 1.87% of accidents resulted in 3 or more injuries. Diving deeper, we find that if the view of the intersection is obstructed and the train is between 60 and 70 MPH, it raises the probability of an accident with 3 or more injuries to 4.92%. If those same traits are paired with a lack of illumination, the probability raises to 5.21%.

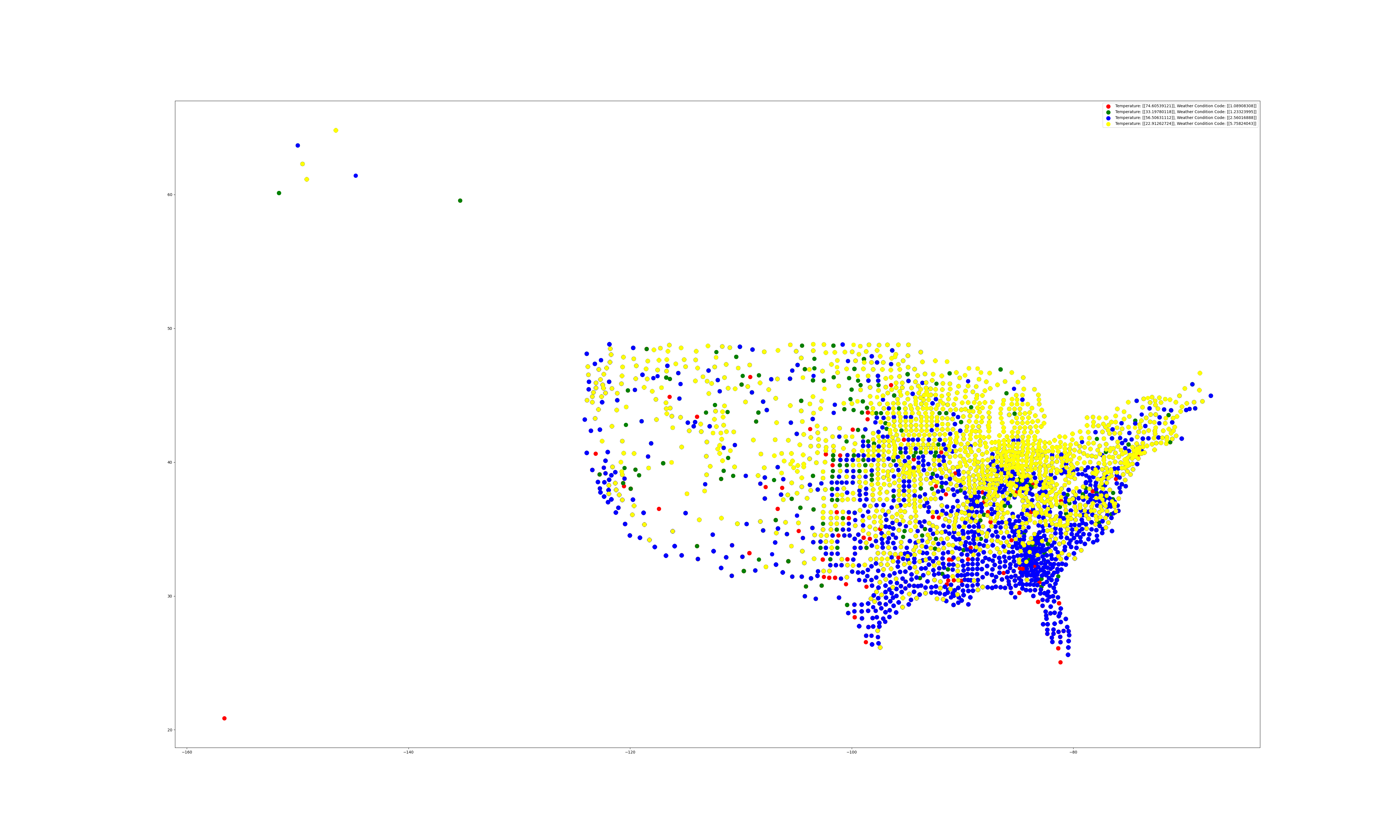
These results might suggest that train speeds should be limited to below 60 MPH through intersections with highways. Additionally, efforts to remove obstructions from intersections and to illuminate the intersections could reduce the likelihood of injury. Statistical analysis could be conducted to see if the reduction of injuries would be significant or if it would be worth the financial investment.

Reviewing the K-means clustering revealed that more work may need to be done on blizzard-proofing highway-rail intersections in the northern US and rainstorm-proofing highway-rail intersections in the southern US. Visibility-reducing weather appears to play a large role in crashes in the majority of cases. Conversely, temperature alone does not appear to play a large part in crashes, as long as the weather is clear.

7 Visualizations

Matplotlib was used to visualize the K-means clustering information.

Figure I. K-means Clustering of Temperature and Weather, Plotted Using Latitude and Longitude

Cluster Means:

Red: Temperature 74.6 F, Weather 1.1

Green: Temperature 33.2 F, Weather 1.2

Blue: Temperature 56.6 F, Weather 2.6

Yellow: Temperature 22.9 F, Weather 5.8

Weather Codes:

1 = Clear

2 = Cloudy

3 = Rain

4 = Fog

5 = Sleet

6 = Snow

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