SYS 6018 Data Mining Final Project Report - Fatality Analysis

Elena Gillis (emg3sc), Kanika Dawar (kd2hr), Varshini Sriram (vs4vx)

1. The Problem

Introduction

Every year a large number of highway crashes occur that involve one or more fatalities per crash. There are numerous factors that contribute to the situation, which can be influenced in order to impact the outcome. In this project, we aim to identify the main factors of a fatal crash, predict the number of deaths, and contribute to the understanding of the effectiveness of motor vehicle safety standards and highway safety programs.

Descriptive Analysis

- Fatality Analysis Reporting System (FARS) is a nationwide census providing public yearly data regarding fatal injuries suffered in motor vehicle traffic crashes. This data is critical to understanding the characteristics of the environment, trafficway, vehicles, and persons involved in the crash.
- We aim to analyze data ranging from 2015-2017 obtained from National Highway Traffic Safety Administration (NHTSA) website to help understand the factors contributing to car crashes and subsequently influence the system to reduce the number of motor vehicle crashes and deaths on our nation's highways. The data provides us with details of variables such as no of pax, drunk drivers, vision, speed, etc which play an important role in helping us understand the chances of a fatal accident occurring and what can and should be changed to impact the outcome.
- External events such as national holidays, dance and music concerts, etc. which have not been explicitly taken into account could potentially have a significant impact and lead to bias in the analysis

Normative Analysis

- Once the factors leading to fatal accidents are identified, measures can be taken to improve the road regulations and safety conditions leading to fewer accidents and subsequently, to fewer fatalities

Stakeholders

- NHTSA, General Public, Insurance Companies

Impact

- Fewer casualties in vehicle crashes
- Reduction of economic loss

2. Objectives and Metrics

Objectives

- Predict total fatal crashes for the year 2018
- Classify a fatal car crash into levels of accident severity - low/mid/high based on number of casualties
- Understand the most important factors for a car crash involving fatalities

Metrics

- Mean Square error in prediction
- Misclassification error
- Relevance of factors identified with general government consensus

3. State-of-the-Art

- The following data sources were already investigated for traffic fatality analysis: NHTSA's FARS, FastFARS (FF), and Monthly Fatality Counts (MFC). FARS is a census of fatal traffic crashes. The FF program is an Early Fatality Notification System to capture fatality counts from States more rapidly and in real-time. The MFC data provides monthly fatality counts by State through sources that are independent of the FastFARS or FARS systems.
- Data mining methods such as Time Series Analysis and Regression Techniques were applied to the traffic data to predict fatality rates, to understand where crashes happen most often, what conditions correlate with collisions and which road users are most vulnerable. [8]
- The methods have been evaluated using MSE. Ridge Regression proved to be the most successful method in terms of predicting fatalities. ARIMA model worked best for forecasting fatality rates. [8]
- It's hard to predict the fatalities in a car crash because of the wide number of factors involved. Even if we identify the factors, it is hard to anticipate the predicted conditions. Incorporating the external factors and enforcing safety regulations that are coherent with the factors identified makes it a difficult problem. [9] [10]

4. Hypotheses and Approach

Hypotheses

- We anticipate that factors such as usage of safety equipment, drunk driving, seasonality and light conditions are the most common factors contributing to increased fatality rates.
- Data mining methods such as Decision Trees (Random Forest) will produce a better classification accuracy compared to K-Nearest Neighbors and Support Vector Machine when applied to the data to predict accident severity.
- Adding a seasonality factor to the model developed for monthly fatality will help explain peaks in fatalities and better outlier detection.

Data

- FARS - Reporting system by the NHTSA for fatal accidents - now provided for public use in the form of CSV files and SAS database with additional information about specific environment variables.
- Bias in the data: Data might not accurately represent all crashes, another layer of non-fatal accidents would have given more ground threshold in terms of the importance of factors and severity of an accident. The lack of familiarity and understanding with the reporting system might have lead to unintentional human errors (missing data, incomprehensible values, duplication, etc.).

Methods

- Random Forest, K-Nearest Neighbors and Support Vector Machine for classification of the accident severity level.
- Time Series Modeling for total fatal crashes prediction.

- Mostly only Exploratory Data Analysis has been done on traffic data and so there are not enough resources to tell if any of the above methods have been applied to make predictions. We aim to explore all the methods learnt in class and pick the method with the best outcome.

Evaluation Setup

- Using Random Forest we perform feature selection and identify the most important variables that contribute to higher numbers of fatalities.
- Using time series forecasting, we will predict the number of fatal crashes annually and compare the result for 2018 when the FARS data is released.
- We will use cross-validation to check for misclassification error while predicting accident severity (ROC curves, TPR and FPR trade-off).
- Ideally, we would have liked to classify severity into an extra level - a non-severe accident, but dataset does not have that level because measurement by FARS is only for fatal accidents.
- Given that all methods work with minimal error, the models should be good predictors of the outcome and, serve our initial intentions of contributing to understanding the factors leading to fatal crashes.

5. Approach and Results

Problem

There are many factors that may influence the number of fatalities in each crash, as a result, historical data from past crashes is collected by FARS in order to identify these factors. Vehicle crashes can be reduced by studying the crash data and detailing the factors behind traffic fatalities. Nonetheless, since specific combinations of these variables result in different levels of crash severity, it is difficult to anticipate all these factors to come into play all at ones. In this project, we try to identify the most important factors that contribute to fatal crashes and try to predict such results for future accidents.

Data

We worked with the data from FARS ranging from 2015-2017. The data came from three separate datasets for each year - accident cases, vehicles involved in the accident and person records for fatalities. We discovered that all three datasets had the same number of unique accident cases for each year and combined the data based on Year and Case Number. The total number of accidents over a span of three years is 101533. The response variable selected was the number of fatalities per accident. The number of fatalities per accident in our data ranged from 1-13. We converted this response variable to a categorical variable - accident severity with three levels: low, medium and high. Low corresponds to one fatality per accident, medium corresponds to two fatalities per accident and high corresponds to over two fatalities per accident. We discovered that the distribution of levels in the categorical response suffered from severe class imbalance - Low severity (93%), Medium severity (6%) and High severity (1%).

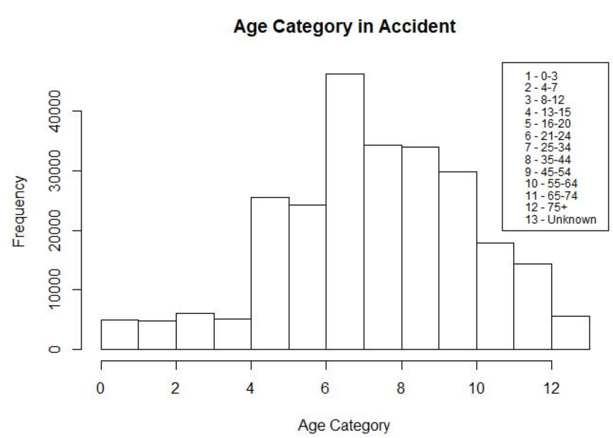
Exploratory Data Analysis

The main datasets that we used were accidents data, to which we appended persons and vehicles data aggregated on year and case number. When performing exploratory data analysis we checked trends in response variable in relation to individual regressors. We discovered that more accidents (and more fatalities) were happening during the weekdays and at night time. There are also more fatalities that happened in an urban setting and close to main roadways. Most fatalities are recorded to have occurred in crashes that were not classified as collisions with other motor vehicles in transport, nonetheless, when another vehicle was involved, there were significantly more crashes and more fatalities in two-vehicle accidents. We could also observe that there were more accidents and fatalities in crashes that involved young drivers (under the age of 24) and senior drivers (over the age of 65). To observe the patterns in the causes of crash data we created a table that summarized accidents and fatalities per cause and saw that most fatalities happened on roadways, in speeding crashes, on junctions or intersections, and involved driving under intoxication. However, when we sorted these values by the ratio of the number of fatalities and accidents we saw that most fatalities per crash occurred in crashes involving police pursuit, large trucks, interstate crashes, and drowsy or intoxicated drivers.

	Accidents	Fatalities
rd	52354	57698
spcra	26712	29731
roll	24064	26897
intsec	24909	26796
junc	24909	26796
posbac	22839	25423
ped	17461	17813
mc	15311	15795
inter	12709	14282
lt	11756	13225
dist	9374	10182
hr	5699	5879
pedal	2472	2499
drowsy	2190	2459
polpur	1033	1204

	Accidents	Fatalities	Ratio
polpur	1033	1204	1.165537
lt	11756	13225	1.124957
inter	12709	14282	1.123771
drowsy	2190	2459	1.122831
roll	24064	26897	1.117728
posbac	22839	25423	1.113140
spcra	26712	29731	1.113020
rd	52354	57698	1.102074
dist	9374	10182	1.086196
intsec	24909	26796	1.075756
junc	24909	26796	1.075756
mc	15311	15795	1.031611
hr	5699	5879	1.031584
ped	17461	17813	1.020159
pedal	2472	2499	1.010922

In exploring data from the vehicles datasets we have observed that the passenger cars formed the majority of the fatal accidents with front-end collisions. Drivers of the commercial vehicles in the accidents had an invalid commercial driving license and ten percent of drivers overall had invalid license compliance to the specific type of vehicle they were driving, among which 50% of the motorcycle accidents involved a driver with an invalid license type. Around 25% of our data involved accidents that resulted from speeding.



From the dataset on persons involved in each accident, we have seen that the majority of the accidents distributed by age were clustered around young drivers (particularly 20-24 years old). In addition, 50% of the drivers involved in an accident were tested for intoxication and out of these drivers, 33% were identified as positive. We also see that in fatal motorcycle accidents the majority of drivers did not wear a helmet.

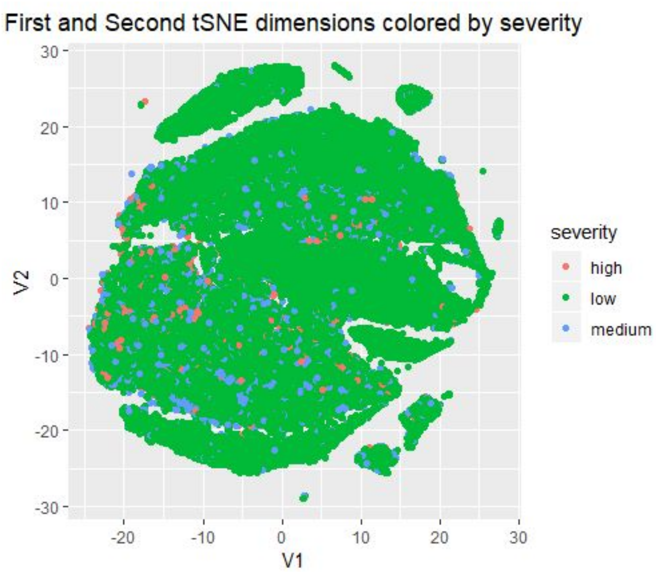
Most of the results that were discovered from data exploration were expected on the onset of the project, in particular, factors such as the size of the vehicle, age, and intoxication of the drivers were important.

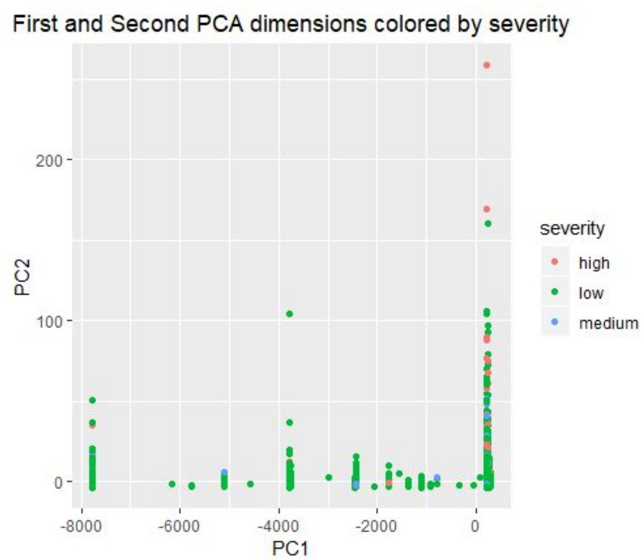
Data Cleaning

The data that was downloaded from the FARS website was sufficiently cleaned and had no missing values, however, we noticed that there were several columns with different breakdowns of the same variable. For instance, the dataset on the persons involved in the accident had nine different classifications for age. We only kept one of these classifications, the one that had the most categories. In addition, we aggregated the number of people involved in each crash by counting the number of rows per crash number (since each row is descriptive of one person involved). In the vehicles dataset, we removed the vehicle number (given that it is unique for each row and does not provide significant information in the analysis) and aggregated the rest of the data on year and case number (averaging out the year of the vehicle model for all the vehicles involved into the crash). Similarly, from the main accidents dataframe, we removed additional variables for age and variables for region and county, which had a large number of classifications and did not show to be significant. After the initial cleaning steps, we performed one-hot encoding on all three datasets and allocated a separate column for each category of each variable. In the end, all three datasets aggregated of year and case number had the same number of rows and we column-merged them based on these parameters. This gave us a dataframe with 101533 observations and 185 variables, which we used for further analysis.

Exploring the high-dimensional Data

To understand and explore the relationships between the features and to look for patterns in the data, we performed Dimensionality Reduction - Principal Component Analysis and t-Distributed Stochastic Neighbor Embedding and visualized the outputs for the two methods.





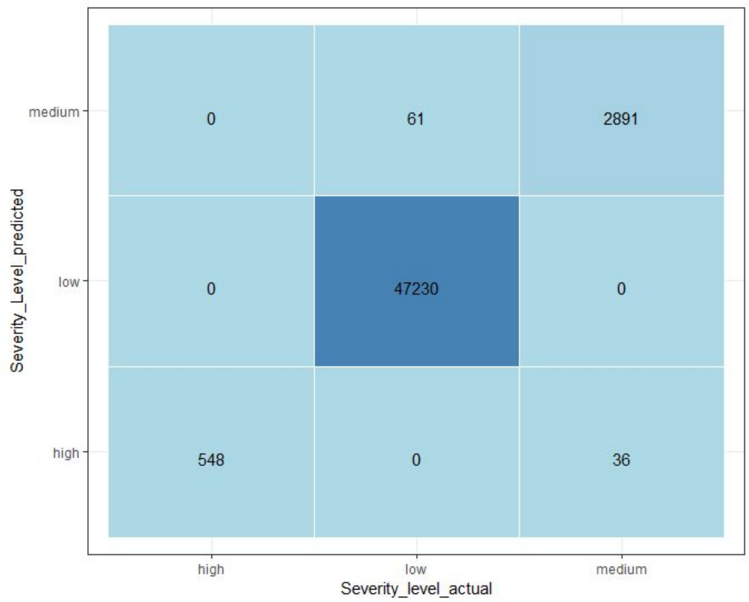
We noticed that t-SNE has tried to separate the different points confirming that the data is separable and the classification methods should work well for the data.

Methods

To predict the severity of an accident, we built three classification models - Random Forest, K-Nearest Neighbors and Support Vector Machine.

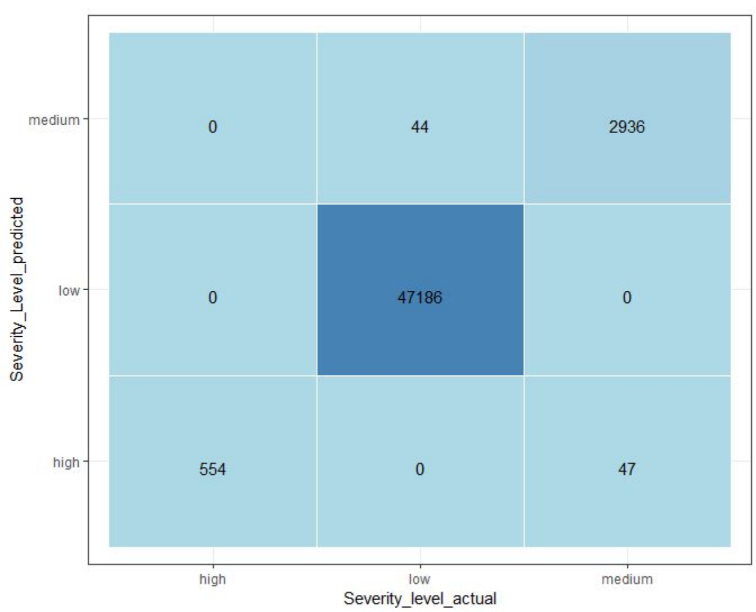
- H2O library was used for the random forest algorithm. We randomly split the data into train and test, ran the algorithm of train data with 50 trees and performed 10-fold validation when running the code. The resulting accuracy from random forest was 99.81% with only 61 observations in low severity and 36 observations in medium severity misclassified. All high severity accidents were predicted with 100% accuracy.

Confusion Matrix for Random Forest



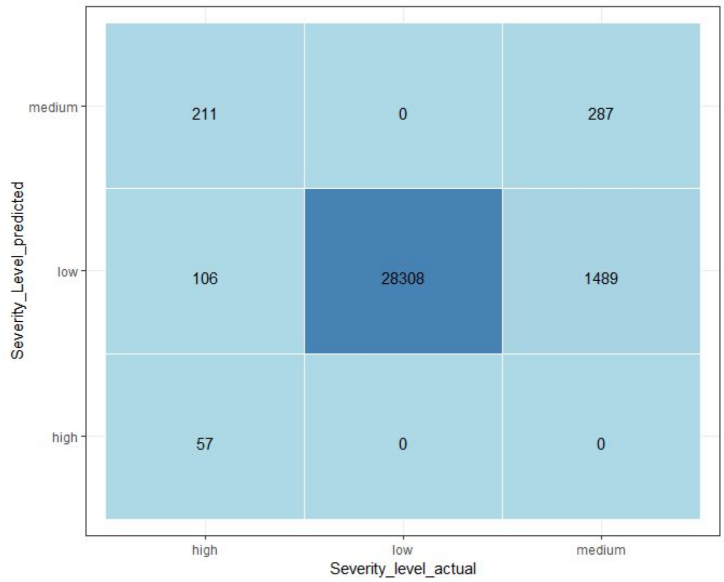
- Similarly, we used the gbm library to run boosting algorithm on the data. We split the data into test and train sets of equal length, ran the gbm model with multinomial distribution and chose the result that gives us the highest classification probability. This model was also run on 50 trees and produced the accuracy of 99.82%, misclassifying only 44 observations with low severity, 47 observations with medium severity, and predicting high severity observations with perfect accuracy.

Confusion Matrix for Boosting



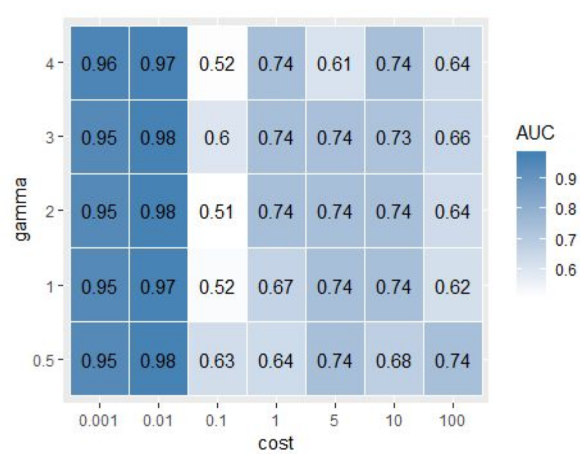
- A KNN model was then used to perform classification with the important variables as found from the results of Random Forest Algorithm. Data splitting - train and validation sets was carried out to evaluate the model performance. The KNN algorithm was fit to the train data with a repeated 10-fold cross-validation and the optimum k value (k = 23) was chosen using the Log Loss metric since the response variable suffered from severe class imbalances. The chosen model was tested on the validation data and the classification accuracy obtained was 94.07%

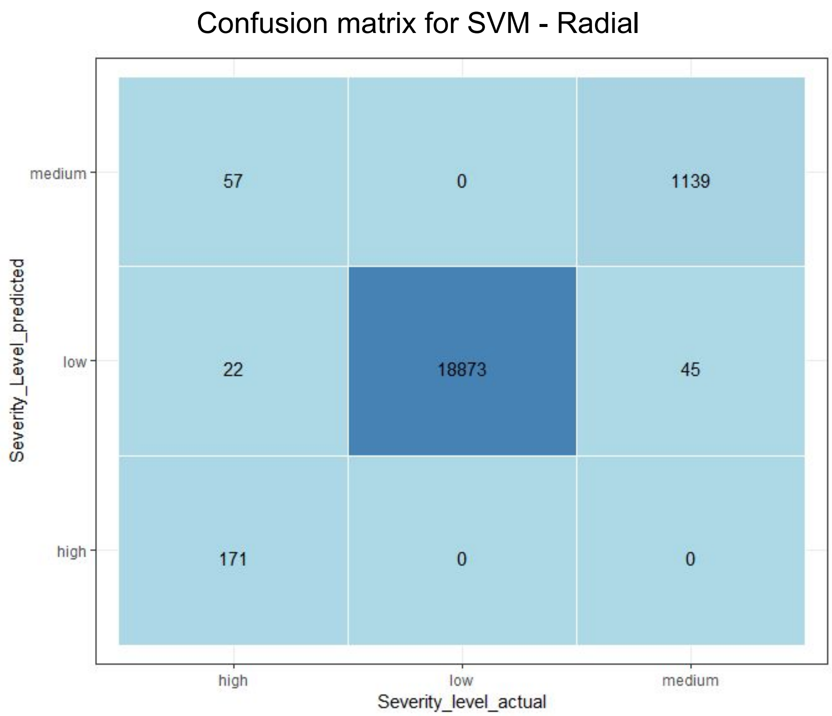
Confusion Matrix for KNN



- We used support vector machines to perform classification of severity level of fatalities using the 59 variables we found significant by performing random forest importance function. We used the e1071 library + parallel processing using doparallel and foreach packages whereas for radial kernel we used the parallelSVM package. We tried the linear kernel with cost values of (0.001, 0.01, 0.1, 1, 5, 10, 100) for each of gamma varying from (0.5, 1, 2, 3, 4) and performed 4-fold cross validation. We found the most optimum results with cost value of 0.01 and gamma making little difference in the area under the ROC curve (maximum being for gamma =2) at 0.978. While running svm cross validation for radial kernel, we could not do it for a lot of values as the system was not able to perform operation on this big a dataset. We did 80:20 split to form the train and test dataset. We found out that the radial kernel performed much better than the linear kernel at cost =1 and gamma = 1 with 99.39% accuracy.

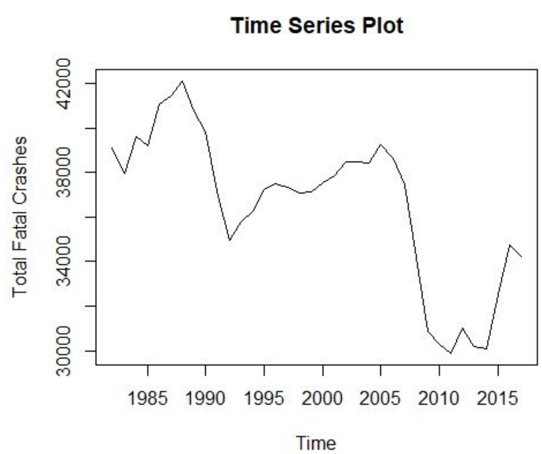
AUC variation for SVM - linear kernel



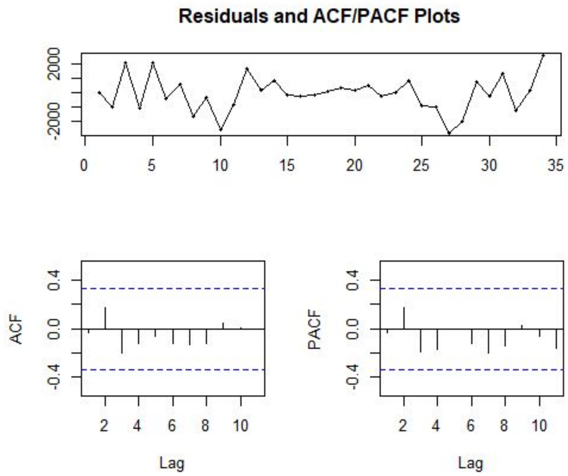


Time Series Forecasting

To project the total fatal crashes for the year 2018, we performed a time series analysis of the total fatal crashes from the year 1982 to 2017.



Fitting an ARIMA model requires the series to be stationary. A series is said to be stationary when its mean, variance, and autocovariance are time invariant. The Augmented Dickey-Fuller Test (ADF test) was used to test for stationarity. The null hypothesis assumes that the series is non-stationary and was not rejected, confirming that the time series was not stationary. The non-stationary series can be corrected by differencing the series while fitting the ARIMA model. An ARIMA model was fit for the years 1982-2015 and was evaluated for the years 2016-2017. The optimal parameters for the fitted ARIMA model were differencing of degree one and autoregressive of lag one. We checked for the model adequacy by examining the ACF and PACF plots for model residuals and found that there was no significant autocorrelations present.



The RMSE after evaluating the model was found to be 885.0426. The ARIMA was refit for the entire data and forecasting was done for the year 2018. The total fatal crashes will decrease to 34046 for the year 2018 according to the prediction made by the ARIMA model.

Conclusions

The factors that were identified by the Random Forest model such as Non-Helmeted, Positive BAC in Alcohol Testing, Unrestrained and Size of the vehicle (Truck) confirmed with our initial hypotheses. Factors such as Head-on Collision, Front Initial Impact, Urban setting, Week of the day and Time confirmed with the results obtained from the exploratory data analysis. In addition to this, the model also identified factors such as Invalid License Status, No Roadway Departure and a particular roadway function class (Principal arterial). The age group though was not an important factor as hypothesized from the Exploratory Analysis.

Being able to predict the determining factors of the severity of this crash will help in reducing the number of crashes with high severity and the number of fatal crashes overall. We believe we were able to successfully identify the main parameters resulting in high levels of fatalities given the data that was collected by FARS. Nonetheless, predicting the existence of the conditions contributing to main factors presents the challenge of its own - this data was not a part of out dataset and, as a result, was not in the scope of this project. However, we believe that analysing such data could be a significant contributing factor in achieving the desired outcome in practice.

References

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Link to the data used in the project:
ftp://ftp.nhtsa.dot.gov/fars/