Driver Injury Severity Prediction: Machine Learning Analysis in Montgomery County, Maryland

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Date of submission: July 16, 2023

Github link: https://github.com/catherine12jiang/CIND820\_capstone

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# Abstract

The problem is to develop a predictive model with the concentration on the injury severity of drivers in traffic collisions occurring on county and local roadways within Montgomery County. As for the theme, the researcher decides to choose classification and regression learning methods.

To be more specific regarding research problems, the researcher plans out 4 main research questions based on the summary of research questions listed above. Initially, what factors contributed to the injury severity in traffic collisions in Montgomery County? Secondly, how could a predictive model be effectively developed in order to forecast the injury severity level of drivers involved in traffic collisions? Lastly, how could the local policy makers, law enforcers, and the other potential stakeholders from Montgomery, Maryland utilize this model for enhancing road safety and reduce the injury severity of the drivers from traffic accidents?

The data used by the researcher is named as “Crash Reporting - Drivers Data” published by Montgomery County Government of Maryland, which can be sourced from the U.S. Government’s Open Data (data.gov). According to data.gov, this dataset provides detailed information on drivers involved in traffic collisions in Montgomery County, and the data was collected via the Automated Crash Reporting System (ACRS) of the Maryland State Police. (Data.gov, 2023) The raw data contains 159,357 rows and 41 columns. The data type of most columns can be converted to categorical data type, such as “Route Type”, “Collision Type”, “Weather”, “Surface Condition”, and “Light”.

## The researcher proposes the following methodologies and techniques to tackle down each question listed from the second paragraph of this abstract. For the tech stack of this research project, Python and Jupiter Notebook are chosen considering the rising popularity among industrial practitioners, especially in the data science field. Before conducting the research, the researcher suggests that there is a pressing need for data cleaning during data preparation considering the data is not in the well-maintained condition because of the inconsistencies occurred in several columns. Therefore, the researcher is implementing the following techniques in the data preprocessing stage: removing data columns with too many missing values, reducing highly correlated columns, balancing class attribute, feature selection, and processing PCA - Principal component analysis for Dimensionality Reduction.

# Literature review

Over years, there are numerous studies have been conducted based on vast variety of methodologies to investigate the relationship between traffic incident severity and its contributing factors. During the literature review stage, the author has read 19 journal articles, and the findings are as follows. 1. The researchers generally tend to define several categories for the contributing factors and group the factors under the defined categories. In this way, the data exploration is illustrated in an organized format. The common categories are driver, environment, road, vehicle, etc. 2. For the methodologies and tools used in those 19 studies, the author would like to address the modeling algorithms used in the studies. Firstly, modeling algorithms that commonly used in the investigation of the traffic accidents contributing factors are K-NN, Naïve Baye, logistic regression, and Decision Tree. However, several researchers from the Asia and South America used the Support Vector Machine (SVM) and a relatively new approach called Gradient Boosting Machines, in which the author has limited knowledge. During the next stage, the author will attempt to utilize these two relatively less popular methods and review the performances accordingly. At the same time, the author found out that multiple journals demonstrated quite robust methodology and strong statistical knowledge, but the conclusion from them are perfectly aligned with ordinary people’s common sense. For example, one of the journal studies used SVM and other modeling tactics to build a machine learning model. For their conclusions and recommendations, they suggested the driver to be more careful when driving with limited light condition, which seems pointless for conducting a multi-stage research study because most ordinary people already know very well about this fact.

In following paragraphs, the author selected 6 journals which are either strongly related to the research questions of this study or demonstrated an extremely detailed implementation tactics during each step of implementation. Moreover, a relatively summary was also generated for each chosen article.

In the study carried out by the Kongju National University in South Korean, the researchers aimed to investigate the relationships between major factors and types affecting the injury severity in the traffic accidents in Seoul city. This research is particularly significant in the literature review section considering it has a quite similar research objective with the author’s study. According to Jeong, Kim, and Han, the study derived several critical factors that were found to affect the severity of traffic accidents via supervised learning methods (i.e., ensemble-based and regression-based algorithms) and discovered dominant accident types via unsupervised learning methods. (Jeong et al., 2022). According to the research team's findings, the conclusion contrasts with conventional mindset as it reveals that factors such as season, day of the week, and even weather have been determined to lack a significant influence on the severity of traffic accidents in Seoul city. The value of the journal written by the South Korean research team extends beyond the methodologies and implementations. In particular, the significance lies in the fact that the conclusion drawn from the machine learning model contradicts the common beliefs or intuitive expectation, which encourage the other researchers to explore the other unconventional factors involved in this research field.

There was another study regarding machine learning models related to road traffic accidents conducted by the researchers from University of Johannesburg. According to Bokaba, Doorsama, and Paul, the study aimed to assess prediction model designs for RTAs (road traffic accidents) to assist the local transport authorities and policy makers. (Bokaba et al., 2022) Indeed, the study utilized the dataset collected from Gauteng Province in South Africa and employed several classic supervised machine learning methods. Although the study conducted in South African is not directly relevant to the injury severity, the research team extensively demonstrated the use of various tools such as K-NN, naïve Bayes, logistic regression, etc. It is also valuable that the research team dedicate numerous pages on describing the dimension reduction and machine learning model performance evaluation. The methodologies are commonly used in every step of the data science project life cycle and could potentially be adapted or applied in the author’s own study.

The study carried out by the collaboration between the scholars from China and United States of America has a concentration of investigating the factors affecting passenger car and truck drivers’ injury severity in the traffic collisions, which has a strong connection related to the author’s study. Moreover, the research team adopted a method to reset the levels for the categorical variables in order to avoid an excessively large number of levels. As a result, each attribute has meaningful and manageable categories, which sets a solid step for the further development of the machine learning model. Meanwhile, the class variable – injury severity is highly imbalanced in the dataset where the no injury is significant dominant than others. To cope with imbalanced data, the researchers used four unique methods to conduct the proper treatments in order to enhance the performance of classifier, which inspires the author to a great extend because the dataset from Montgomery, Maryland is significantly imbalanced as well. However, the findings from this journal were limited in their significance due to their alignment with common knowledge. Despite the differing perspectives regarding the study’s findings, the author found value and relevance in the methodologies and approaches used by the research team.

The researchers from Chang'an University conducted a study that focused on driving experiences and other potential factors contributing to traffic collision severity. Unlike other journals in the literature review section, the research team utilized various modeling and data cleaning techniques that are not commonly mentioned by industrial practitioners. In particular, they employed techniques such as SMOTE (Synthetic Minority Over-Sampling Technique), ENN (Edited Nearest Neighbor), and Tomeklink for data resampling. This was necessary because the dataset they used had imbalanced injury severity categories. By applying these techniques, they aimed to address the data imbalance issue and improve the reliability of their results. Additionally, the researchers dedicated significant efforts to the boosting algorithm in order to further improve the performance of their model. This approach inspired the author to include a section on boosting algorithms in their future study. Based on the result of the machine learning process, the researching team illustrated that the pavement surface conditions, overload condition, and gender have the least impact on the accident severity, which contradicts from ordinary people’s common perceptions.

One of the journals that related to the author’s study is carried out by a researching team from United Kingdom. The focus of this study is laid on building a machine learning model to analyze the accident severity’s contributing factors. The UK team obtained a raw data with 60 columns and 135453 rows, and after data preprocessing, there were only 16 attributes left. The author was in the same dilemma during the data cleaning process, and this study from UK provided insightful opinions when the data scientists must decide which attributes needs to be trimmed off. Meanwhile, the study’s tech stack is 90% aligned with the author’s decision. Especially, there are several parts contain comprehensive information about using Scikit Learn and Pandas during the data modelling and evaluation stages. For the conclusion of the journal, the UK team pointed out that the vehicle factor is the most significant contributing factor to the traffic accident severity in UK.

Also, there is another journal focused on developing a machine learning model to investigate the car accident severity and casualties. What makes this study stand out is that the researchers did not simply remove the null value rows. Instead, the data was imputation by a using method named as Hot-deck imputation, which is quite beneficial to the author of this study. At the same time, another data cleaning method called interquartile method was applied to clean the numeric attributes from the dataset. During the implementation of the data modeling, the researchers used three different machine learning algorithms naïve baye, multinomial logistic regression, and random forest classifier to build a global model. This approach potentially enhanced the accuracy of the model. However, the data generated by naïve baye algorithm was taken off from the global model due to its low accuracy during the evaluation stage. As for the conclusion, apart from the points can align perfectly with common sense, the machine learning model is suggesting that Snowing with high winds weather is least likely to cause serious traffic accidents. It is quite exciting to review journals that contain conclusions which are challenging ordinary people’s common perception.

Although there are numerous studies have been conducted regarding similar research questions as the author proposed, the research is still worth pursuing because of the following reasons.

1. Continuously evolving methodologies: The field of research methodologies, specifically in the machine learning field, is continuously changing and advancing. By comparing the journals from 2013 and 2023, there are numerous differences between the researcher’s implementations. By adapting to the new methodologies, there could be more findings uncovered by the researchers even when it comes to the same topic.
2. Enhancing of machine learning frameworks: The machine learning packages and frameworks are evolving at the same time. There are cases where certain functions are only supported only supported from specific version codes onwards. Therefore, the author’s study is worth for the whole data science community for serving as a reference about utilizing the latest version of a machine learning framework like scikit-learn.

In summary, although the study could potentially have certain parts overlapped with the previous research, conducting this study does hold the value and the relevance because of the continuously evolving methodologies and machine learning frameworks.

# Data Cleaning

The original dataset contains 43 columns including 4 numeric columns and 39 object columns. The columns names from raw data are appropriate and meaningful, therefore, the author will keep original columns names.

During the data cleaning process, the author found out there are multiple columns consist over 90% of null values. Therefore, the columns were removed because of too many missing values. Also, there are many rows containing records such as unknown and others. Depending on the column name and the nature of the traffic collision, the rows were either removed from the dataset or imputed by using forward fill tactics. Moreover, several columns contain large number of unique values, and the author decided to convert them into a manageable size by grouping them with less levels. For time variable, it is a special case because the author decided to convert it into two new columns named “Day of Week” and “Time of Day” and dropped the original date column due to the excessive number of levels.

After the removal of unrelated columns, meaningless columns, and columns with too many missing values, all the columns are converted to categorical type since object type would consume more resources during the data modeling stage.

# Data Description

After data cleaning, this is adjusted data frame’s dictionary. This data set totally consists of 105,379 rows and 14 columns. As for the target variable, the chosen attribute is “Injury Severity” based on the research questions from the abstract section. It is also noticeable that the class variable is significantly imbalanced due to the nature of traffic collisions.

|  |  |  |
| --- | --- | --- |
| Column Name | Description | Variable type |
| Route Type | Type of the Roadway at crash location. | Categorical |
| Collision Type | Type of traffic collision | Categorical |
| Weather | Type of the weather at collision location | Categorical |
| Surface Condition | Condition of roadway surface | Categorical |
| Light | Condition of lighting | Categorical |
| Traffic Control | Signage or traffic control devices | Categorical |
| Driver Substance Abuse | Substance abuse detected for drivers involved | Categorical |
| Driver At Fault | Whether the driver was at fault | Categorical |
| Injury Severity | Severity of injury to the driver | Categorical |
| Speed Limit | Local area posted speed limit | Categorical |
| Location | Exact location of the collision | Categorical |
| Day of Week | The day of week when collision happened | Categorical |
| Time of Day | The time of day when collision happened | Categorical |
| Driver Distracted By | Whether the driver was distracted | Categorical |

As for each column’s value distribution, the author plotted following frequency bar charts. The charts themselves are relatively self-descriptive.

A picture containing text, screenshot, diagram, plot

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Additionally, the spearman correlation analysis was completed after the author generated a new data frame that was converted from the cleaned data set to numeric values on basis of the index of the levels. Because Spearman correlation coefficients does not require the data to be normally distributed and based on the ranks of the values instead of the actual values. By using seaborn and matplot, the heatmap of Spearman correlation analysis results are presented in a well-organized approach.

A close-up of a graph

Description automatically generated

The analysis of the provided table reveals two notable correlations. First of all, the positive correlation between "Route Type" and "Speed Limit" indicating that certain types of routes tend to have higher speed limits. This finding implies that the nature of the route may influence the designated speed limits in the specific area. Additionally, a positive and significant correlation between "Weather" and "Surface Condition" implying that specific weather conditions are associated with particular surface conditions. This correlation suggests that certain weather patterns, may impact the condition of the road surface, potentially affecting driving conditions and safety considerations.

# Research Methodology

As for the research methodology, the author aims to employ an iterative data science development cycle to conduct the entire research. This methodology is inspired by the popular software development philosophy named Agile, which involves a flexible and iterative approach that allows adaptation, changes, and improvements throughout the entire research process.

By adopting this methodology, the author could break down the entire research into smaller manageable iterations. Each iteration involves data preprocessing, data modeling, and performance evaluations. After each iteration, the author can make the adjustments in order to enhance the performance of the modeling and ensure the research strictly aligned with the research questions and objectives.

To provide a more visualized approach for understanding the methodology of this research, the author created a flow chart that serves as a visual roadmap to guide the research process.

A diagram of a flowchart

Description automatically generated with low confidence

# Data Modelling

Due to the nature of traffic accidents, the class attribute – Injury Severity’s distribution is significantly imbalanced. The following table presents the exact counts of accidents falling into the respective categories.

|  |  |
| --- | --- |
| No Injury | 84376 |
| Minor Injury | 19981 |
| Serious Injury | 1022 |

Considering the imbalance data could cause the models to be biased and neglect the pattern of the minority class, the need of data balancing was recognized by the researcher.

There are multiple approaches to conduct the data balancing, and Synthetic Minority Over Sampling Technique was chosen because of its effectiveness in handling imbalanced data. The researcher used “make\_classification()” method to generate synthetic data based on the original dataset, and then applied the over sampling onto the synthetic data set. As a result, the data is balanced and prepared for the final data modelling.

After data balancing was completed, the researcher implemented Stratified K-fold Cross Validation as the study design. Stratified K-fold Cross Validation provides a quite robust evaluation of the model performance by averaging the result from each iteration, which potentially enhances the model’s generalizability and reduced its bias.

There were 5 machine learning models conducted by utilizing distinct classification algorithms. In the following paragraphs, the author will elaborate further and provide detailed explanations regarding the models individually.

**Logistic Regression:**

Logistic regression is normally considered as the base line for the classification machine learning modelling by the industrial practitioners. Therefore, the researcher decided to conduct the first model by using logistic regression algorithm. Meanwhile, Newton-Cholesky was chosen as the optimization algorithm for logistic regression. Although the execution time was reduced from 5.3 seconds to 0.6 seconds after applied Newton-Cholesky, the memory consumption and CPU usage surged during the execution. As for model evaluation, the accuracy and F1 score were chosen as the metrics to benchmark the performance of the models. F1 score is commonly used in the classification tasks due to its comprehensiveness by considering both precision and recall.

**Naïve Bayes:**

The preprocessed dataset from this research contains 13 categorical columns, and Naïve Bayes is better suited for categorial input variables than numerical variables. Based on this fact, the author decided to develop a machine learning model utilizing the Naïve Bayes algorithm. The model efficiency was the highest amongst all 5 models, but the accuracy and F1 score were the lowest from the group.

**KNN:**

Considering KNN does not make strong assumption about the underlying data distribution, it is selected to build the third machine learning model. For the number of neighbors in the KNN algorithm, the author found out that the rule of thumb is the square root of total number of samples, so the value was calculated and rounded to 500. And to improve the speed of the KNN modeling, the n\_jobs was set as 8 because the CPU of the device has 8 threads. The accuracy and the F1 score were quite promising and reached 0.9, but the efficiency is not very ideal.

**Decision Tree:**

Decision Tree is a classification algorithm known for transparency and easy to understand by the non-technical background readers. However, this algorithm also requires a lot of manual fine-tuning by manipulating the options like max depth unlike KNN known for lazy learning. After several rounds of attempts, max depth was determined as 8 to prevent overfitting and underfitting. The F1 score and accuracy were above average, and the efficiency was also above average compared to other models.

**Gradient Boosting:**

This algorithm was relatively new compared with the other algorithms mentioned above, and it is famous for the high accuracy of the machine learning model. The algorithm used several weak learners into a strong model. Also, it sometimes can capture very complex relationships between each feature. The effectiveness of the model is second best, which reaches 0.81. However, it took the researcher’s laptop 9 minutes and 33.7 seconds to finish the whole training and testing process.

# Findings

## Traffic accident injury severity machine learning model:

The table below records each algorithm’s execution time and its performance measured in F1 score and accuracy.

|  |  |  |  |
| --- | --- | --- | --- |
| Algorithm Name | Execution Time | F1 Score | Accuracy |
| Logistic Regression | 0.6 seconds | 0.66 | 0.66 |
| Naïve Bayes | 0.1 seconds | 0.66 | 0.65 |
| KNN | 36.7 seconds | 0.90 | 0.90 |
| Decision Tree | 2.8 seconds | 0.77 | 0.76 |
| Gradient Boosting | 9 minutes and 33.7 seconds | 0.81 | 0.81 |

Researcher’s laptop specs: CPU: I7 1165G7 , 12 GB RAM (8GB ram soldered on the motherboard)

From the table above, it is very straight forward that KNN outperformed compared with other algorithms used in this research. It took a moderately long time but accuracy and F1 score reached around 90% which are the highest amongst the five algorithms. As for the second most robust algorithm - Gradient Boosting, the author was warned by the data science community that the GB algorithms generally require a long time to execute and a significant large number of resources during the run time. Indeed, Gradient Boosting algorithm is probably the least environmentally friendly algorithm which could potentially leave a huge carbon foot print compared with other algorithms. Naïve Bayes and Logistic Regression, on the other hand, did not perform well and the metrics are lower than the average amongst the 5 selected algorithms. Also, it is noticeable that the execution time of these two algorithms is significantly lower than the others. As for the decision tree, the performance indicators are exactly sitting on the average, same as the execution time. Also, since the size of the synthetic data set after balance is massive, the decision tree lost one of its advantages – visualized decision-making process because of the unreasonable number of nodes and edges.

## Contributing factors of traffic accidents:

As for the investigation of the contributing factors regarding injury severity in traffic accidents, the author used Random Forest algorithm to build a model first, however only the importance of each feature was extracted and sorted.

|  |  |
| --- | --- |
| Feature Name | Importance |
| Driver Distracted By | 0.068601184713805 |
| Light | 0.07145062589908156 |
| Day of Week | 0.073614156825297 |
| Traffic Control | 0.07427376158019805 |
| Time of Day | 0.0763123672446986 |
| Speed Limit | 0.07737299323404966 |
| Route Type | 0.07991461127291333 |
| Weather | 0.08113449507280751 |
| Driver Substance Abuse | 0.08249730213612899 |
| Collision Type | 0.08769162477568253 |
| Driver At Fault | 0.0937420022083293 |
| Surface Condition | 0.13339487503700848 |

By using the results from Random Forest algorithm, the quantified importance of each contributing factor is illustrated at last part of the previous section. “Surface Condition” is ranked as the most significant contributing factor of the traffic collision injury severity. The importance is slightly over as twice much as the importance of the last ranked feature – “Driver Distracted By”. This finding obviously does not align well with ordinary people’s mindset, which the author will discuss further in the conclusion and recommendation section. Although the weather is only ranked as the 5th most significant contributing factor, the surface condition is highly positively correlated with weather, which was described in the initial analysis section of this research. The same theory also applies onto the features — Driver Distracted By” and “Driver At Fault” due to the moderate positive correlation. At the same time, numerous factors are not as significant as the author expected prior to the research such as “Light”, “Time of Day”, and “Speed Limit”.

# Conclusions, Suggestions and Limitations

This research has investigated the contributing factors of the traffic collision injury severity in Montgomery County, Maryland, US. In order to enhance the effectiveness and efficiency during the data modelling process, the author reorganized and sanitized the data from the public open database. Meanwhile, the data was significantly imbalanced due to the nature of the traffic accidents. Therefore, the author decided to use SMOTE to balance the data set and further enhance modelling performance. During the modelling stage, the author selected 5 machine learning algorithms including Logistic Regression, Naïve Bayes, Decision Tree, KNN, Gradient Boosting, and Random Forest was used to investigate which factors are more significant than the others.

Some results from Random Forest model are quite different from the people’s common sense. First of all, the lighting condition and time of the day might not be very important, and this is quite understandable because the lighting features from most vehicles nowadays are capable of providing the driver and passengers with a safe experience despite the lighting condition. Also, the speed limit and traffic control are not as important as ordinary people expected according to the results from this research, which could encourage more future researchers to investigate and further prove it. As for the top 5 factors, they are Surface Condition, Driver At Fault, Collision Type, Driver Substance Abuse, Weather, which leads to the suggestions to the local authorities. First of all, road surface condition is a vital factor to prevent serious injury in an accident. Thus, the MTO needs to be more responsive and resilient while the event changes road conditions occurred because road condition recovery could save lives. It is also important for drivers to focus and raise the alert when the road condition starts changing. There are two factors related to the drivers. As a result, the local authorities might be interested in investing more efforts onto educating the drivers about DUI and the traffic rules. If there are less mistakes made by the drivers, the accidents severity might be able to reduce to a lower level.

The key contributions of this research are stated as follows.

* The previous researches conducted in Montgomery County are focused on using GIS and other tools with an concentration of descriptive statistics or pattern analysis. But this research could be the first attempt to develop a machine learning model in order to forecast the injury severity of the traffic accidents based on the given parameters.
* Certain conclusions from this research could be very controversial because they are not aligned with the ordinary people’s mindset, which could further encourage more researchers to either prove or disprove the conclusions.

Although the data cleaning stage was conducted by using several strategies and tactics, an unsupervised machine learning methodology can be employed during pruning the missing values. As a result, there would be less rows removed from the dataset, and the model performance could be further enhanced. Also, the location column which contains a specific GPS coordination for each recorded traffic accident was removed from the raw data set during the data preprocessing stage. Due to the complexity of GIS analysis, the author stopped the attempt to plot the accident locations onto the GIS map layer in order to investigate the distribution patterns. The future researcher could follow this path go elevate the research into another level by combining the power of machine learning and GIS analysis.

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