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Predicting Road Accident Severity Using Machine Learning Models

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Abstract

The project developed a machine learning model to predict accident severity based on road accident statistics in the United Kingdom. The analysis shows that there is no single determinant factor that may lead to severe or fatal injuries during an accident, but there are rather a number of factors and their parallel prevalence that can increase the likelihood of such outcomes. Therefore, it is crucial to analyse the relationship between each factor to determine the most common causes of road accidents and then deploy tangible solutions on the ground to mitigate the risks of road fatalities and severe injuries. While the United Kingdom has one of the safest roads in the European Union and on the globe, the number of road accidents and road fatalities have stabilised since 2010 and authorities are struggling to find long-term solutions to further decrease these numbers. This project is meant to find the best fit machine learning model that may assess some of the most common factors and assist decision-makers in making the roads of the United Kingdom even safer.

I.Business Understanding

Global Context and Relevance

Road accidents have been in the spotlight due to the increasing number of global traffic accidents recorded each year. According to the World Health Organisation (WHO), there were 1.35 million road traffic deaths in 2016 and road traffic injuries became the leading cause of death for children and young adults (aged 5-29) in recent decades. This shows that it is crucially important to study the factors leading to severe or fatal road accidents and having a better understanding of the circumstances may allow to further improve preventive measures and develop new safety technologies.

Case Selection

The United Kingdom (UK) ranks among the top countries for road safety with the second lowest road accident fatality per million inhabitants in the European Union. (European Commission, 2017) There were more than 122 thousand road accidents recorded in 2018 with 25,511 reported severe injuries and 1,784 deaths in the UK. Until 2010, fatality rates had been constantly declining and were stabilised on its current rate in the past decade. According to the Department of Transport, extreme weather events have slightly influenced the annual figures, but the overall trends have not changed significantly in this period.

The Department of Transport claims that the highest fatality rate is observed among vulnerable road user groups - namely pedestrians, pedal- and motorcyclist, as they are more exposed in an event of colliding with other vehicles or objects. Although, there is no single underlying factor that drives road casualties, instead there are several influences can be observed. These are mostly distance travelled per driver, the mix of transport modes used, driver's behaviour, the mix of groups using the road (young inexperienced and older drivers) and external effects, such as weather and road conditions.

Application and Target Audience

With each accident being unique and several factors are hard to measure (e.g. fatigue) it is challenging to develop a generalised machine learning (GML) model that can predict accident severity with a high precision. However, this project may demonstrate a GML model that can predict road accident severity based on a number of features, including weather, road conditions, driver characteristics' and the type of road users involved in the accident. The model can be used to develop an early warning system for road users, which could be of high interest for government officials, local authorities (hospitals and law enforcement), as well as for car manufacturing companies wishing to further develop the drivers' assistance features of their models.

II.Data Understanding

About the Dataset

For this project the latest road accident and safety statistics is used from 2018, covering the territory of Great Britain. The dataset is published annually by the Department of Transport, obtaining the data through the reporting system used by local authorities and also self-reported data by drivers. In the case of severe and fatal accidents, most of the data are recorded by authorities, while slight accidents are usually reported by the drivers.

Considering that the database includes various features regarding the environment, drivers' and casualties' characteristics[1], it is suitable to develop a machine learning model. It provides a comprehensive description of the circumstances, making it fit to examine the relationship between the selected predictors and the target variable.

The data is published in three datasets annually:

1. The first dataset describes the accidents, the number of casualties and in terms of our target variable, which is accident severity, it records, whether at least one party was severely injured or died. In cases, when no such outcome was observed, it is indicated as slight injury. The dataset also doesn't include accidents with property-damage only, only ones, where at least one party was injured.
2. The second dataset describes the driver's behaviour, age, gender and the vehicle's manoeuvre and condition. Unfortunately, there is no record of substance abuse or exceeding the speed limit for 2018, which could significantly improve the accuracy of the model.
3. The third dataset describes the casualties, their mode of transport, as well as their behaviour during the accident (e.g. crossing road, loitering on central carriageway refuge, etc.).

[1] The variable lookup is available through the following link.

The final dataset used for the analysis is merged from these three datasets and the selected variables are transformed into binaries.

Data Characteristics

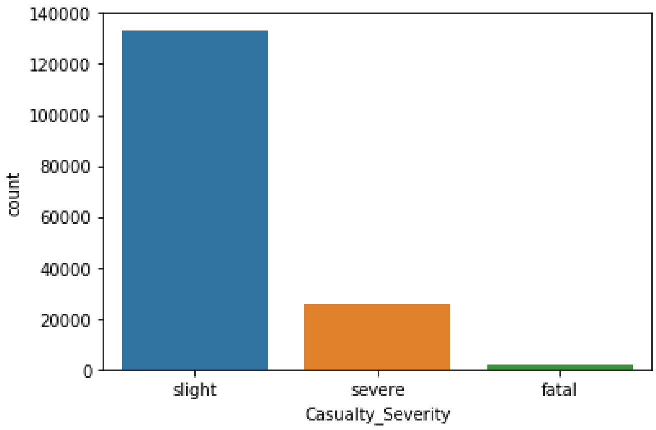
Variable name	Type	No. of Categories
Accident Index	Unique Identifier	–
Vehicle Type	Nominal	20
Vehicle Leaving Carriageway	Nominal	9
Age Band of Driver	Nominal	11
Pedestrian Location	Nominal	11
Accident Severity	Nominal	3
Number of Casualties	Numeric	–
Number of Vehicles	Numeric	–
1st Road Class	Nominal	6
Road Type	Nominal	7
Speed limit	Numeric	–
Junction Detail	Nominal	9
Light Conditions	Nominal	5
Weather Conditions	Nominal	9
Road Surface Conditions	Nominal	7
Urban or Rural Area	Nominal	3
Casualty Type	Nominal	21
Day of Week	Numeric	7

1. Figure: List of Variables

Figure 1 lists the variables, which are used for the model development. Most of the variables are on a nominal scale, where each number corresponds to a class. The difference between each value cannot be interpreted on a nominal scale, therefore, they need to be transformed into binary variables. In order to determine the classes, the one hot encoder was used, and several categories were merged, when they shared certain characteristics. For instance, in the case of vehicle classes, motorcycles are distinguished in 5 categories, so they were merged into one. In other cases, only some classes were kept as binary variable to describe the accident and the others were simply dropped (e.g. vehicle leaving carriageway).

Casualty Severity

The target variable is casualty severity, which is split into three categories – slight, severe and fatal. Figure 2 below shows the distribution of these categories from the casualty dataset.

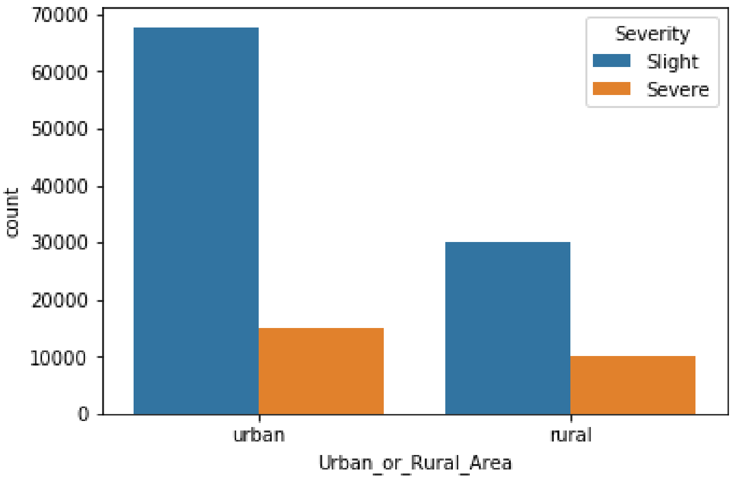


2. Figure: Distribution of Casualty Severity

Having a peek at the above figure, it becomes visible that the distribution of accident severity is extremely skewed. This is also referred to as Poisson distribution, when one category has a high number of observation and the frequency of observation rapidly drops in further categories.

Since there are relatively few fatal accidents observed in the dataset, it is reasonable to merge severe and fatal categories into one category. This will allow better visualisation and a more balanced sample for further statistical analysis. Also, having a binary target variable is more suitable to be used for the selected GML models.

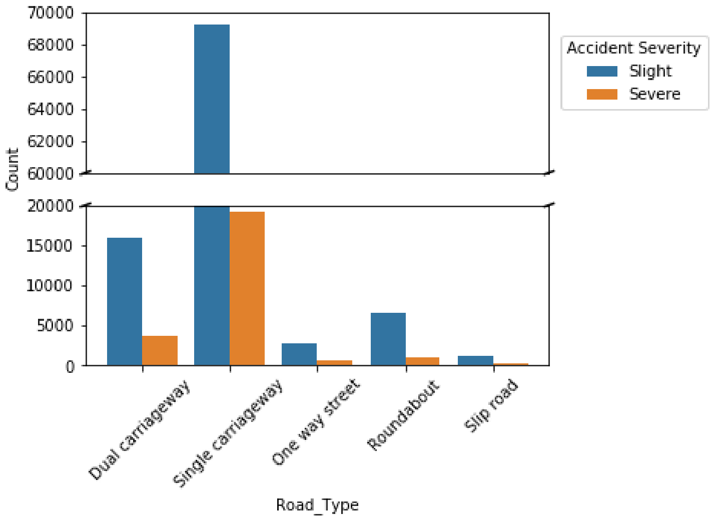
Accidents in Rural and Urban Areas



3. Figure: Accident severity in rural and urban areas

The figure 3 shows that while there are more accidents in urban areas, they less likely have a severe or fatal outcome than the ones in rural areas. This can be explained by higher traffic, but lower speed limits. In rural areas due to lower traffic, cars may less likely collide, but there will be a higher chance of sever or fatal outcome due to higher speed limits.

Accidents by Road Type



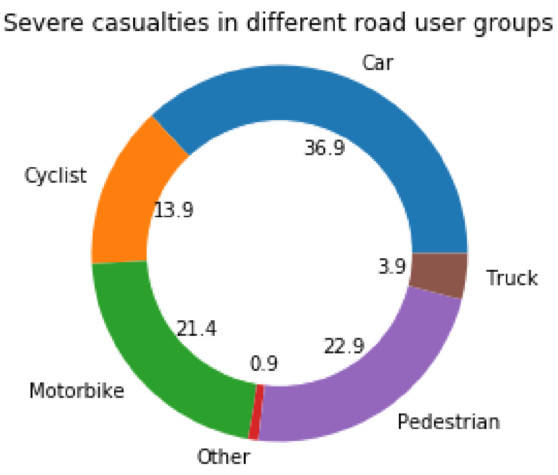
4. Figure: Accident severity by road type

The above figure shows that single carriageway roads have the most accidents observed. However, road type is not necessarily a good predictor per se, but it might be fit as joint predictor when examining its relations with other variables. For instance, if a car encounters an unexpected event (e.g. the car slip on the slippery road) it might more easily hits an object or another car in the opposing traffic, as there are no physical barriers to stop it.

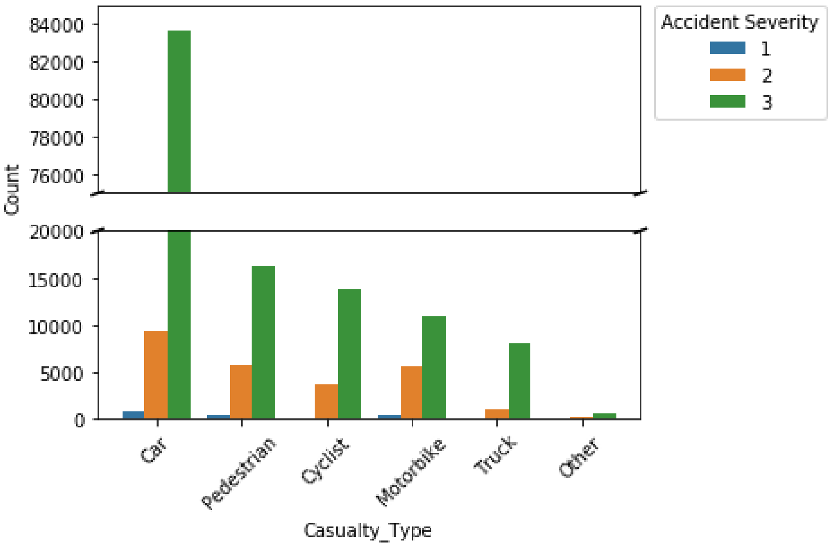
Also, it should be noted that most roads in the urban setting are single carriageway roads, therefor the sample may be biased. But if the relationship between the road type, weather conditions are measured in a rural area, it might provide a more accurate description of a severe or fatal accident.

Casualty Type

As other sources claim, vulnerable road users are the ones, who will most likely have serious injuries, when they collide. A pedestrian hit by a car may more likely to have severe injuries than the car driver and a motorcyclist may also have a severe accident, if they hit an object or another car with high speed.



5. Figure: Severe or fatal accidents among different road users.



6. Figure: Distribution of accident severity by casualty types

Figure 5 shows that the overall distribution of severe and fatal accidents among different road users. It is visible that among fatal and severe accidents, car passengers were exposed the most to such outcomes. However, figure 6 shows that there is a significantly higher number of observations among car drivers and overall, car passengers are less likely exposed to severe or fatal accidents than vulnerable road users.

Concluding Data Understanding

While evidence shows that road accidents cannot be defined by a simple set of characteristics, some variables tend to show a greater impact on the target variable than others. The most significant variables so far are area type – urban or rural area – and the participation of vulnerable road users in an accident. It is important to note that none of these conditions can determine the outcome of an accident per se, but correlating them with other factors may provide more precision and helps to develop an accurate model.

III.Data Preparation

Replacing Missing Values and Binarization

Following the conclusion of the data understanding, the next step is to clean the data from missing values and narrow down the predictors to binary variables – in the case of nominal scales – for the modelling. First, the missing values were converted into NaN values in each category, so that the algorithm can recognise them. This step is essential to avoid potential bias and to clean the data from outliers – missing values are marked by -1 in the original dataset.

The threshold for removing variables with missing values was thirty percent, and following this principle, only junction control was removed from the dataset, where closely half of the values were either missing or out of range. Where the number of missing values were below the threshold, they were replaced by the median or average values, where applicable.

In the following steps, several categories were merged into one and new variables were created describing the basic characteristics of the accidents. For instance, data for road condition was split into one category – dry or wet – and light conditions were also merged into full darkness and daylight. Following the binarization, numeric scales were also applied , such as counting the number of victims from vulnerable road user groups and so on.

Balanced Sampling and Normalisation

Following the data cleaning the selection of the final variables to be used in the model, the data was split into a training set and a testing set, by randomly splitting the data. In this step, 80% of the data was used for training the model and the remaining 20% for testing, leading to a 98,000 and 25,000 sized sample respectively. As the distribution of accident severity is skewed and the sample is imbalanced towards slight injuries, the imbalanced learn packages was used from the scikit-learn library on the training set.

The sampler applies a statistical approach to balance the two categories to an equal distribution by finding their nearest neighbour considering all independent variables. It is important to note that the test set sample was not balanced, as it would seriously affect the reliability of the model and lead to potential bias. The balanced sample has a size of 38,000 observations with a balanced number of observations in both severe and slight categories. As a final step before the model development, both the balanced training data and the test sets were normalised using the pre-processing functions from the scikit-learn library.

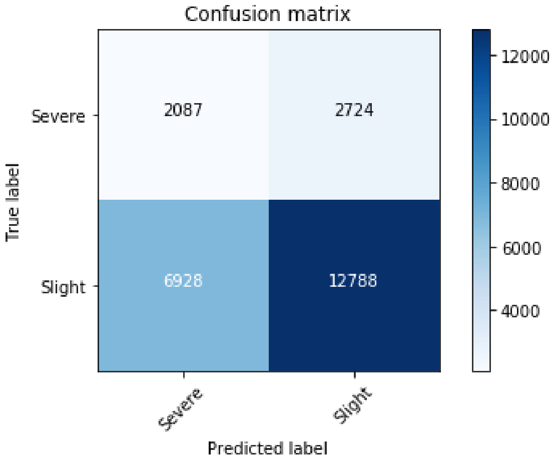
IV.Modelling

With each accident being unique and a number of factors are hard to measure (e.g. fatigue) it is challenging to develop a generalised machine learning (GML) model that can predict accident severity with a high precision. Traditionally, statisticians may use the ordered probit (OP) model, ordered logit (OL) model, multinomial logit (ML) model, and logistic regression (LR) model.

In recent years, there have been a wider application of GML models in the field, in particular the Bayesian network (BN) model, regression tree, and artificial neural networks (ANN). In this project, two common GML models will be used, namely the Support Vector Machine (SVM) and the classification tree. Classification models are the most suitable in this case, as they can operate with both numeric and categorical variables.

V.Evaluation

The Support Vector Machine had an overall lower accuracy, but could predict that under a given set of circumstances, every 5th accident will likely to be severe or fatal. Unfortunately, it also misdiagnosed severe accidents and classified them as slight. This is also reflected by the weighted precision and F1 scores, which are 0.71 and 0.64 respectively. The Support Vector Machine doesn't seem suitable for the given circumstances, when the distribution of the target variable is skewed.



7. Figure: Support Vector Machine Confusion Matrix

Based on the results from the two models, the classification tree has the highest accuracy with 80% and a F1 score of 0.87. In other words, it could accurately predict the outcome of 4 out of 5 accidents. In sum, the classification tree seems the most accurate model for deployment. The dependent variables involve characteristics of the casualties, drivers and the environment, which may give a better understanding of the circumstances leading to a severe or fatal accident.

The dependent variables involve characteristics of the casualties, drivers and the environment, which may give a better understanding of the circumstances leading to a severe or fatal accident.

Training and Testing Variables	**Type**	**Description**
Risk_Group	numeric	number of casualties from vulnerable road user groups
Number_of_Vehicles	numeric	number of vehicles involved in the accident
Number_of_Casualties	numeric	overall number of casualties from all groups
Speed_limit	numeric	speed limit at accident location
Fog_or_Mist	binary	–
Precipitation	binary	–
Single_Carriageway	binary	–
Wet	binary	road surface wet or dry?
Bicycle	binary	cyclist involved in accident?
Motorbike	binary	motorcyclist involved in accident?
Truck	binary	truck involved in accident?
Crossroads	binary	accident at crossroads?
Darkness	binary	complete darkness or daylight?
Distributor_Road	binary	accident on secondary road (not motorway or urban road)
Rural	binary	–
Median_Age (26-35)	binary	driver below or above median age?
Irregular_Crossing	binary	did pedestrian cross the road at zebra crossing?
Vehicle_Staying_in_Carriageway	binary	vehicle leaving carriageway
Saturday	binary	accident on Saturday

8. Figure: Final list of variables after preprocessing

VI.Deployment and Conclusions

The presented classification model may be used for deployment either by integration into an early warning system for authorities or for car manufacturers to further develop safety equipment in their models. The potential applications for the model could lead to a number of precautionary measures in given circumstances, for instance:

- Increased ambulance preparedness near dangerous road sections,
- Temporary speed limits or rerouting traffic,

- Enhanced driver inspections by law enforcement (blood alcohol level testing and deploying speed traps),
- Installing information screens to drive attention to potential hazards,
- Installing streetlamps by unpredictable road sections,
- Physical separation of car and bicycle traffic,
- Placing zebra crossings and central carriageway refuge at dangerous road sections,
- Deploying traffic lights or building roundabouts at dangerous intersections.

VII.Bibliography

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