Accident Severity Model

Would it be possible to predict for a car driver the severity of an eventual impacting accident he would have?

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Index

1. Introduction to business needs

Unfortunately, car accidents happen.

Therefore we will try to answer the following question: would it be possible to understand/predict the severity of an eventual accident for a car driver if ever happening? We will use easy to have variables to develop the model so that anyone can use it before driving it's car.

Such a predictive model could be interesting for instance for:

- *Insurance companies* to set a final price for products based on customer/drivers characteristics.
- *For government authorities* to forecast casualties that may occur during a year based on vehicles registered and drivers records and plan measures to reduce those casualties numbers.
- *To generate awareness in individuals* so that they are aware of the need of replacing their car, be even more careful when it rains or when it's a foggy day, etc.

We will be exploring the feasibility of creating such a predictive model based on variables that could be stored into the following categories:

- *Driver data*: age, etc.
- *Time, road and environmental conditions*: visibility, weather conditions, moment of the year, etc.
- *Car specifications*: engine capacity, driver side, etc.
- *Parameters of the accident*: speed, point of impact, etc.

Based on those variables the model would predict if the driver ever has an accident if it's going to be "fatal" or "Serious/Slight" with a certain confidence (binary classification problem).

To proceed we will be using the database published on Kaggle.com called "UK Accidents 10 years history with many variables" that collects accidents that took place from 2005-2014 in UK roads. Data are stored in 3 tables: accidents, vehicles and casualties and can be found in the following link:

https://www.kaggle.com/benoit72/uk-accidents-10-years-history-with-many-variables

Important to note that this database is likely to give insights and a prediction model to be used only for countries like the United Kingdom, Japan, Australia, India (more than 50 countries) where traffic happens from the left side.

2. Dataset information, definition and understanding

As already mentioned we will be using the database published on Kaggle.com called "UK Accidents 10 years history with many variables" that collects accidents that took place from 2005-2014 in UK roads. Data are stored in 3 tables: accidents, vehicles and casualties and can be found in the following link:

https://www.kaggle.com/benoit72/uk-accidents-10-years-history-with-many-variables

- *Accidents file*: main data set contains information about accident severity, weather, location, date, hour, day of week, road type, etc.
- *Vehicles file*: contains information about vehicle type, vehicle model, engine size, driver sex, driver age, car age, etc.
- *Casualties file*: contains information about casualty severity, age, sex social class, casualty type, pedestrian or car passenger, etc.

All available variables are presented in Table 1.

Table 1. All variables.

Accidents	Vehicles	Casualties
Accident Index	Accident Index	Accident Index
Police Force	Vehicle Reference	Vehicle Reference
Accident Severity	Vehicle Type	Casualty Reference
Number of Vehicles	Towing and Articulation	Casualty Class
Number of Casualties	Vehicle Manoeuvre	Sex of Casualty
Date (DD/MM/YYYY)	Vehicle Location-Restricted Lane	Age of Casualty
Day of Week	Junction Location	Age Band of Casualty
Time (HH:MM)	Skidding and Overturning	Casualty Severity
Location Easting OSGR (Null if not known)	Hit Object in Carriageway	Pedestrian Location
Location Northing OSGR (Null if not known)	Vehicle Leaving Carriageway	Pedestrian Movement
Longitude (Null if not known)	Hit Object off Carriageway	Car Passenger
Latitude (Null if not known)	1st Point of Impact	Bus or Coach Passenger
Local Authority (District)	Was Vehicle Left Hand Drive	Pedestrian Road Maintenance Worker (From 2011)
Local Authority (Highway Authority - ONS code)	Journey Purpose of Driver	Casualty Type
1st Road Class	Sex of Driver	Casualty IMD Decile
1st Road Number	Age of Driver	Casualty Home Area Type
Road Type	Age Band of Driver	
Speed limit	Engine Capacity	
Junction Detail	Vehicle Propulsion Code	

Junction Control	Age of Vehicle (manufacture)	
2nd Road Class	Driver IMD Decile	
2nd Road Number	Driver Home Area Type	
Pedestrian Crossing-Human Control		
Pedestrian Crossing-Physical Facilities		
Light Conditions		
Weather Conditions		
Road Surface Conditions		
Special Conditions at Site		
Carriageway Hazards		
Urban or Rural Area		
Did Police Officer Attend Scene of Accident		
Lower Super Ouput Area of Accident_Location (England & Wales only)		

Those tables have been joined in order to build a larger dataset using the key parameter Accident_Index of the accident that is common to all tables. Then, most likely variables to be useful a priori for building the model have been conserved

Note: during the *Data analysis* section, those variables will be studied to conserve, transform or even remove them.

Preselected variables are shown in Table 2.

Table 2. Preselected variables.

Variable Name	Table of origin	Initial data type	Definition
Age_Band_of_Driver	Vehicles	Categorical	The age of the driver is stored in ranges (i.e. 0-10, 10-20, etc.).
Sex_of_Driver	Vehicles	Categorical	Sex of the driver (i.e. male of female).
Age_of_Vehicle	Vehicles	Integer	Age of the vehicle (i.e. 5, 9, 14, etc.)
Light_Conditions	Accidents	Categorical	Was there daylight or not?
Road_Surface_Conditions	Accidents	Categorical	Dry, wet, snow, ice on road?
Urban_or_Rural_Area	Accidents	Categorical	Where did the accident takes place (i.e. city, small city or rural)?
Date	Accidents (from Date variable)	Categorical	Date of the accident.

Casualty class	Casualties	Categorical	Is it the driver, a passenger or a pedestrian?
1st_Point_of_Impact	Vehicles	Categorical	Where did the impact took place (i.e. no impact, front impact, etc.).
Speed limit	Accidents	Integer	Speed limit of the street/highway in which the accident took place (30, 50, etc.).
Casualty Severity	Casualties	Categorical	Severity of the accident based on casualties table information (i.e. fatal, severe, slight).
Day of week	Accidents	Categorical	If it’s happening on Monday, Tuesday, etc.
Vehicle Type	Vehicles	Categorical	If it’s a car, a bus,a bike, etc.
Accident Severity	Accidents	Categorical	Severity of the accident based on accidents table (i.e. fatal, severe, slight).

3. Methodology

The following actions are done in order to get the initial dataset prior Data analysis that will be called df_cars. Afterwards, data analysis for each specific variable will happen before using Machine Learning methods and calculate metrics of the created model.

1. The tables *Accidents*, *Vehicles* and *Casualties* are joined using *Accident_Index* variable common to all tables. Afterwards we can drop *Accident_Index* column. Moreover, multiple variables are removed because not apparently helping to solve the problem.

   Dataset contains now (4287593, 16)

2. We analyze missing data, note that some variables have it signaled as -1 and are transformed into *NaN* values previously. We get:

```
Accident_Index                  0
Vehicle_Type                  554
1st_Point_of_Impact          2418
Sex_of_Driver                  46
Age_of_Driver              405664
Age_Band_of_Driver         405664
Age_of_Vehicle            1155488
Casualty_Class                  0
Casualty_Severity               0
Accident_Severity               0
Date                            0
Day_of_Week                     0
Speed_limit                     0
Light_Conditions                0
Road_Surface_Conditions      4824
Urban_or_Rural_Area             0
dtype: int64
```

   We are therefore removing the columns *Age_of_Driver*, *Age_Band_of_Driver* and *Age_of_Vehicle*. We also drop the *Accident_Index* column and duplicates that would existe. Afterwards we remove all the rows that would have NaN values.

   We have the following dataset (4279897, 12).

3. From *Casualty_Class* we keep values “1” that refer to drivers as casualty and from *Vehicle_Type* we select only cars whose value is ‘1’ and we get a dataset containing (2158083, 10).

4. For integrity of data we checked that *Casualty_Severity* and *Accident_Severity* not always have the same values. We will keep only the events that have the same value. We now have a dataset of (2015253, 9).

We save this dataset as *'carsPriorDataAnalysis.csv'*. Now we will analyze each conserved variable.

5. We remove events that have no value for *Sex_of_Driver*, getting now dataset of (1918837, 9).

6. We recategorize *Light_Conditions* in a way that we only differentiate between Light (1) and darkness (0) conditions. Dataset remains (1918837, 9).

7. For Road_Surface_Conditions we will recategorize in a way that we only differentiate between dry (1) and wet/ice/snow (2). Dataset remains (1918837, 9).

8. For *Urban_or_Rural_Area* we recategorize so that we only differentiate between big cities (0) and small cities/rural area (1). Dataset remains (1918837, 9).

9. For *1st_Point_of_Impact* we will only consider situations in which there is indeed an impact therefore we remove events having value '0'. Dataset is now (1859852, 9).

10. Concerning *Speed_limit* we differentiate between accidents with speed limit equal or below 30 (0) and above 30 (1). Dataset is now (1859852, 9).

11. Concerning the *Date* we extract the Month, but we don't really see an impact of it. Dataset is now (1859852, 9).

12. We finally differentiate *Day_of_Week* between weekend (Friday, Saturday and Sunday = 0) and the rest of the week (Monday, Tuesday, Wednesday and Thursday = 1). Dataset is now (1859852, 9).

13. We binarize Accident_Severity and we will have 'Fatal' = 1 and 'Severe/Slight' = 0.

We save the obtained dataset into *'carsForModeling.csv'*.

We finally check the correlation of retained and transformed variables with *Accident_Severity*, presented in Table 3.

Table 3. Correlation of variables with *Accident_Severity*.

	Sex_of_Driver	Light_Conditions	Road_Surface_Conditions	Urban_or_Rural_Area	Speed_limit	Day_of_Week	Accident_Severity
Sex_of_Driver	1.000000	0.082586	0.003862	-0.006513	-0.015494	0.043430	0.042699
Light_Conditions	0.082586	1.000000	-0.185675	0.018758	0.000178	0.038032	0.045380
Road_Surface_Conditions	0.003862	-0.185675	1.000000	0.103964	0.100384	0.015135	0.004397
Urban_or_Rural_Area	-0.006513	0.018758	0.103964	1.000000	0.639037	-0.004701	-0.065206
Speed_limit	-0.015494	0.000178	0.100384	0.639037	1.000000	0.001049	-0.053038
Day_of_Week	0.043430	0.038032	0.015135	-0.004701	0.001049	1.000000	0.021133
Accident_Severity	0.042699	0.045380	0.004397	-0.065206	-0.053038	0.021133	1.000000

We will use the following Machine Learning techniques to address this binary classification problem and present its metrics:

- Binary classification using Logistic regression
- Decision tree

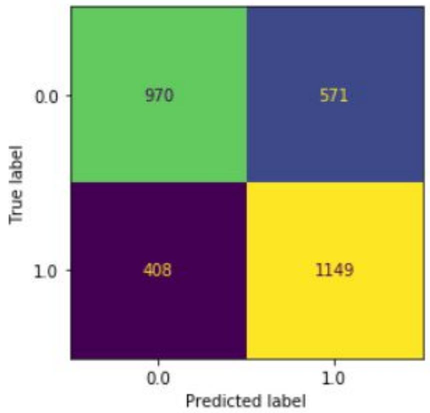
We need to precise that since the dataset is unbalanced, meaning we have much more events that are Accident_Severity = ‘Severe/Slight’ that Accident_Severity = ‘Fatal’, this last one is a limitant. Therefore since now in our dataset we have 7744 ‘Fatal’ events we will select a random subset of data of 7500 events having Accident_Severity = ‘Severe/Slight’ and Accident_Severity = ‘Fatal’.

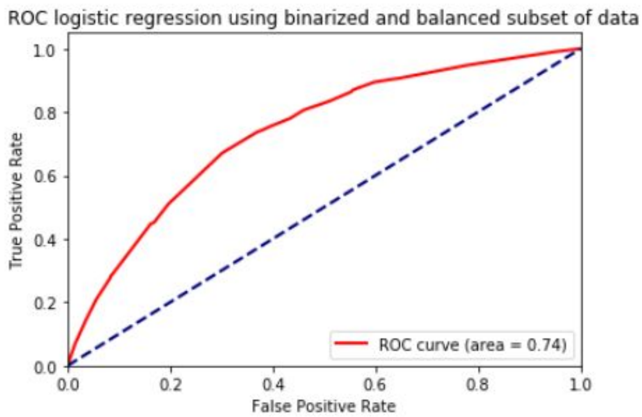
This will cause our models to converge better and be more accurate/realistic but also note that each time we run the model the metrics could slightly from one time to the other.

4. Results

4.1. Binary Logistic Regression

We run a Binary Logistic regression model with 15000 events (7500 with 'fatal' severity and 7500 with 'Severe/Slight' Severity) and using 80% of the events for training and 20% of the events for testing. We obtain the following results:



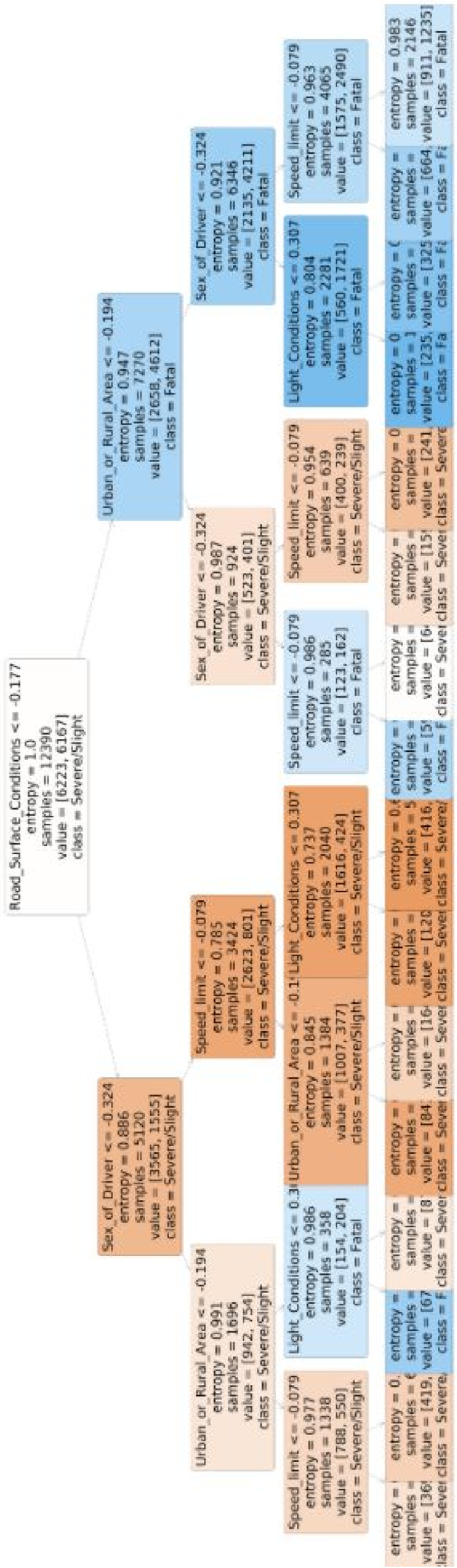


The model has a ROC AUC = 0.74, F1_Score = 0.672 and accuracy = 0.670.

4.2. Decision tree

Same subset of data is used to run a decision tree algorithm with depth = 4, and we obtain the following results:

F1_Score = 0.670 and accuracy = 0.670.


Road_Surface_Conditions <= -0.177
entropy = 1.0
samples = 12390
value = [6223, 6167]
class = Severe/Slight
Sex_of_Driver <= -0.324
entropy = 0.886
samples = 5120
value = [3565, 1555]
class = Severe/Slight
Urban_or_Rural_Area <= -0.194
entropy = 0.947
samples = 7270
value = [2658, 4612]
class = Fatal
Urban_or_Rural_Area <= -0.194
entropy = 0.991
samples = 1696
value = [942, 754]
class = Severe/Slight
Speed_limit <= -0.079
entropy = 0.785
samples = 3424
value = [2623, 801]
class = Severe/Slight
Sex_of_Driver <= -0.324
entropy = 0.987
samples = 924
value = [523, 401]
class = Severe/Slight
Sex_of_Driver <= -0.324
entropy = 0.921
samples = 6346
value = [2135, 4211]
class = Fatal
Speed_limit <= -0.079
entropy = 0.977
samples = 1338
value = [788, 550]
class = Severe/Slight
entropy = 0.986
samples = 358
value = [154, 204]
class = Fatal
entropy = 0.845
samples = 1384
value = [1007, 377]
class = Severe/Slight
Light_Conditions <= 0.307
entropy = 0.737
samples = 2040
value = [1616, 424]
class = Severe/Slight
Speed_limit <= -0.079
entropy = 0.986
samples = 285
value = [123, 162]
class = Fatal
Speed_limit <= -0.079
entropy = 0.954
samples = 639
value = [400, 239]
class = Severe/Slight
Light_Conditions <= 0.307
entropy = 0.804
samples = 2281
value = [560, 1721]
class = Fatal
Speed_limit <= -0.079
entropy = 0.963
samples = 4065
value = [1575, 2490]
class = Fatal
entropy = 0.983
samples = 2146
value = [911, 1235]
class = Fatal

5. Discussion

The obtained results are similar for each Machine Learning technique used. Far from being perfect, the results obtained for those models represent a good start for building such a predictive model. Metrics results are sum-up in Table 4.

Table 4. Metrics obtained for used Machine Learning Algorithms

Model	Logistic regression	Decision tree
F1 score	0.672	0.670
Accuracy	0.670	0.670
ROC AUC	0.731	

It's quite surprising how by setting a few parameters (accidents for cars, driver as casualty and accidents having an impact), and using some easy to access variables (*Sex_of_Driver*, *Light_Conditions*, *Road_surface_Conditions*, *Urban_or_Rural_Area*, *Speed_limit* and *Day_of_Week*) it's possible to assess with an acceptable degree of certainty when a car driver is about to start his journey, if ever having an accident it would be fatal or severe/slight for him.

That said, due to its simplicity of usage and no need of computation, decision trees would be more appealing for individuals while logistic regression and SVM could be more adequate for companies or authorities.

Moreover, even if those models have been developed using UK data from 2005-2014, a country where traffic happens from the left side, it is very likely that the important variables remain the same for countries where traffic happens from the right side, and therefore those models could be also applicable.

In order to improve the results of the models, it could be advisable to:

- Have more events containing the age of the driver, so that we don't have to drop *'Age_of_Driver'* or *'Age_Band_of_Driver'*.
- Have a classification of the car concerning its size (i.e. small, medium or big car).
- We have an unbalanced dataset, meaning we have more events Accident_Severity = 'Severe/Slight' rather than Accident_Severity = 'fatal'. Therefore, the metrics of the models are ('unfortunately') likely to be improved if ever having more 'fatal' events with all required information.

6. Conclusions

The above mentioned models would represent a good start to develop a much more accurate model.

That said, the presented results allow to pull out the following conclusions:

- a few easy to assess variables enable to generate initial models that can be accessible by individuals, companies and/or authorities.
- authorities / car companies / assurance companies could work together to reduce fatality of the accidents by acting on three major axes:
    - improve visibility of the roads either because of the weather (fog, rain, storm, snow, etc.) or because it’s night.
    - improve the roads surface or car wheels surface and/or design so that when the road is wet or has ice or snow, this doesn’t influence a fatal accident.
    - improve roads in small cities/villages and rural roads.

7. Bibliography

- https://www.kaggle.com/benoit72/uk-accidents-10-years-history-with-many-variables
- IBM Data Science professional certificate documents and notebooks.