Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

Roads are considered one of the most common ways to travel and transport material in Brazil. Nevertheless, Brazilian roads are considered extremely dangerous and unsafe. According to OMS, Brazil is the fifth country with deaths in traffic accidents, with more than 47 thousand deaths per year.

There are three main types of road in Brazil: local, regional (by state) and national roads. National roads are monitored by the Federal Highway Police (Polícia Rodoviária Federal, aka, PRF), which keeps records on time, place and type of accidents that happened in these highways per year. The dataset are publicly available on the PRF website.

This project used the data from the PRF in an attempt to predict the type of victims an accident can have based on the characteristics of the highway, the moment of the accident and main characteristics of the accident. The main goal is to define if that accident will likely have no victims, injuries victims or death victims.

Problem Statement

The main goal is try to predict whether an accident will have no victims, injured victims or dead victims. We considered information on the time of the accident (moment of the day, day of week, etc), on the place the accident happened (road number, kilometer, state, etc) and the accident characteristics (such as cause of the accident, and type of accident).

If we can predict, with a certain amount of confidence, the type of victims based solely on the local and time of the accident, one can assume that there is a problem on Brazilian Roads, and one can predict most dangerous areas. Even if this is not possible, the predictions could help identifying most problematic areas and help on prevention measures.

One possible approach if this 3 class scenario is not viable, is to create a model identifying if an accident will have victims (deaths or injured) or not or if an accident will have dead victims or not.

Metrics

The main metrics used throughout the project was the accuracy score, which can handle multi class classification problems. The formula considered by Sklearn is the following:

$$\texttt{accuracy}(y, \hat{y}) = \frac{1}{n_\text{samples}} \sum_{i=0}^{n_\text{samples}-1} 1(\hat{y}_i = y_i)$$

I also used the classification report for detailed observation of recall and precision for each class. The classification report give three metrics for each class and for all classes: precision, recall and

For a better visualisation of the model performance, I used the confusion matrix_to visualize the results, using the script suggested on this page.

$$f1score = 2 * \frac{(precision * recall)}{(precision + recall)}$$

Where:

$$precision = \frac{TP}{(TP + FP)}$$

$$recall = \frac{TP}{(TP + FN)}$$

Given:

- TP - True positives
- FP - False positives
- FN - False negatives

It is my believe that all these metrics together, gives a good ideia of where the model is failing, where is it doing it right and how can we improve it. Nevertheless, I always prioritise the **recall** metrics instead of any other, since for the purpose of this study, we want the minimum number of false negatives.

II. Analysis

Data Exploration

The datasets contained the following features:

Feature Name	Feature Meaning	Feature Type	Values
Id	accident identification	-	-
data_inversa	accident date	Categorical	-
dia_semana	weekday of the accident	Categorical	-

Feature Name	Feature Meaning	Feature Type	Values
horario	accident hour	-	00 - 23
uf	state	Categorical	MG, PR, SC, RS, SP, RJ, BA, GO, PE, MT, ES, CE, MS, PB, RO, PA, RN, MA, PI, DF, AL, TO, SE, AC, RR, AP, AM
br	highway number	Categorical	E.g.: 101, 116, 381…
km	Kilometer	Numerical	E.g: 1, 2, 4…
municipio	city	Categorical	E.g.: Curtiba, Brasília, São José
causa_acidente	accident cause	Categorical	lack of attention to driving, lack of attention, other, incompatible speed, alcohol ingestion, unsafely distance, disobedience to the rules of transit by the driver, mechanical problem, driver asleep, animal in the road, improper overshoot, slippery track, defect on the road, lack of attention of the pedestrian, problems on the tire, sudden onset, visibility restriction, static object on the dockable bed, excessive cargo, nature phenomena, insufficient or inadequate road signs, no lights on the vehicle, drugs ingestion, external offensive

Feature Name	Feature Meaning	Feature Type	Values
tipo_acidente	accident type	Categorical	rear collision, lateral collision, transversal collision, carriage bed outlet, out of road, collision with static object, rollover, tipping, frontal collision, pedestrian trampling, vehicle fall, animal trampling, vehicle occupant fall, fire, bike collision, pestle, collision with moving object, cargo spill, eventual damage
classificacao_acidente	accident classification (target variable)	Categorical	injured victims, no victims, dead victims
fase_dia	moment of the day	Categorical	day, night, nightfall, dawn
sentido_via	road way	Categorical	crescent, decrescent, not informed
condicao_meteorologica	Climate	Categorical	Clear sky, cloudy, rain, sun, drizzle, foggy, snow, hail, windy
tipo_pista	road type	Categorical	simple, double, multiple
tracado_via	road layout	Categorical	straight, curve, not available, intersection, temporary detour, roundabout, viaduct, bridge, return, tunnel, straight, curve, crossing
uso_solo	soil use	Categorical	yes, no, urban, country
pessoas	Number of people	Numerical	-
mortos	Number of deaths	Numerical	-
feridos_leves	Number of light injured	Numerical	-
feridos_graves	Number of severe injured	Numerical	-
ilesos	Number of people not harmed	Numerical	-
ignorados	Number people that we don’t have information about	Numerical	-
feridos	Total number of injured	Numerical	-
veiculos	Number of cars	Numerical	-
Latitude	Latitude	Numerical	-

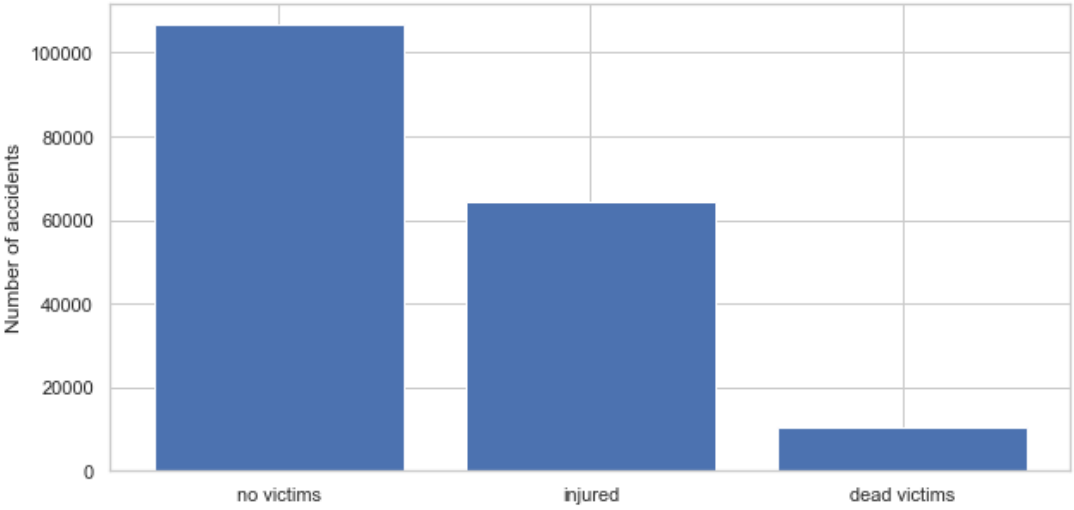
Feature Name	Feature Meaning	Feature Type	Values
Longitude	Longitude	Numerical	-

The datasets from 2016 and 2017 had inconsistencies so a cleanup was necessary. The common problem found was that the categorical features had differences on names. On the cleanup, the names of categorical features were standardised and translated to english. The target variable, *classificacao_acidente*, was changed to values from 0 to 2 (no victims, injured victims and dead victims, respectively) and renamed as *target*.

Records that did not have information on moment of day, climate or had no information on the target variable, were removed. From a initial total of 184225 records, 180991 records were available after the cleanups.

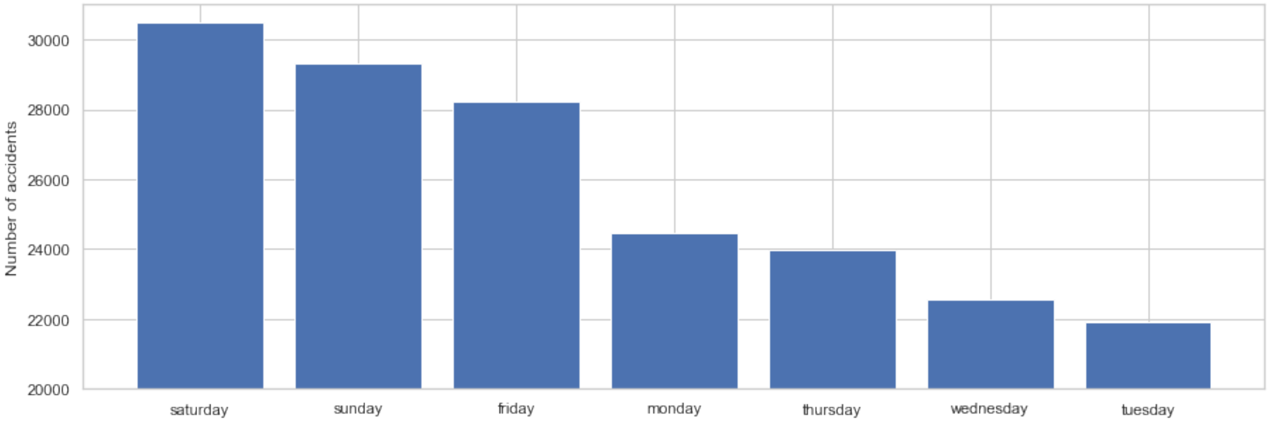
All cleanups were made on a single notebook and the cleaned dataset was exported and this was the dataset used on all analysis.

From all the 180991 records, 58.8% had no victims, 35.4% had injured victims and only 5.6% had dead victims. So we have a clear case of unbalanced classes:

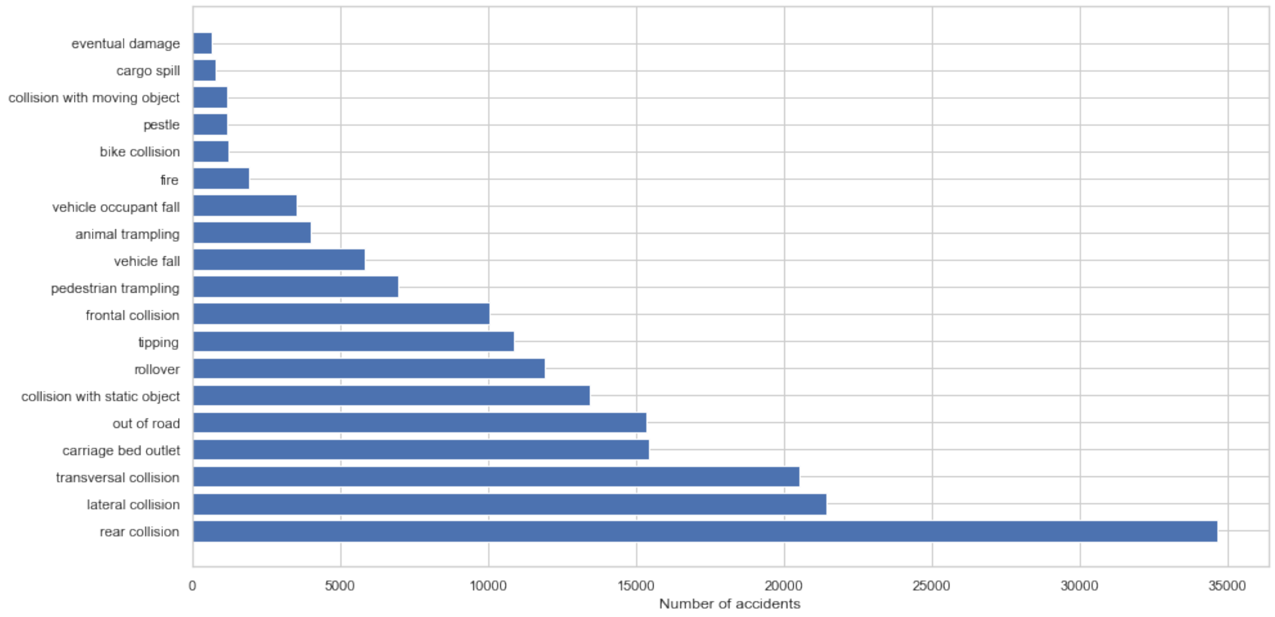


Exploratory Visualization

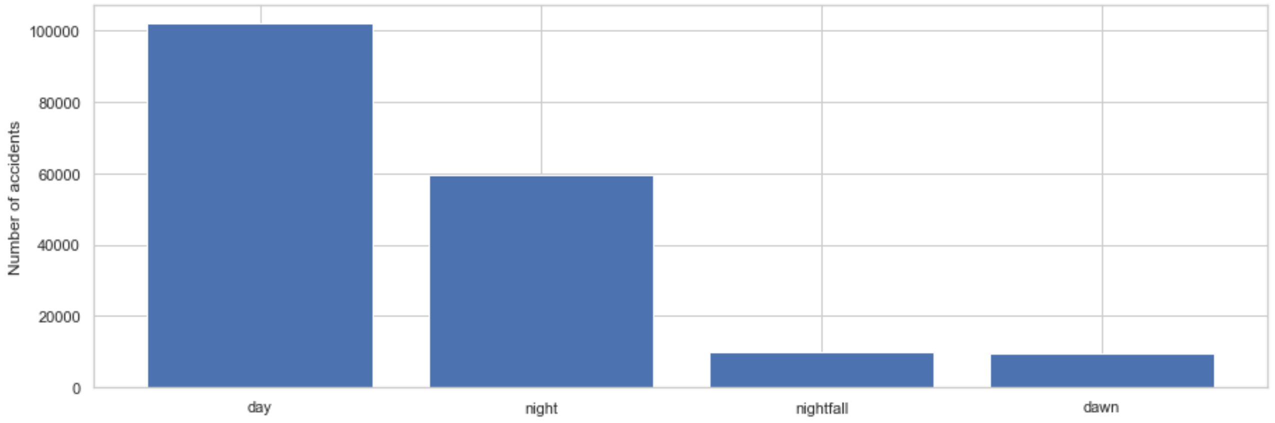
Most of the accidents happens during the weekends, being Saturday the day with higher number of accidents. Monday is the weekday with higher number of accidents, while Tuesday is the day with less number of accidents:



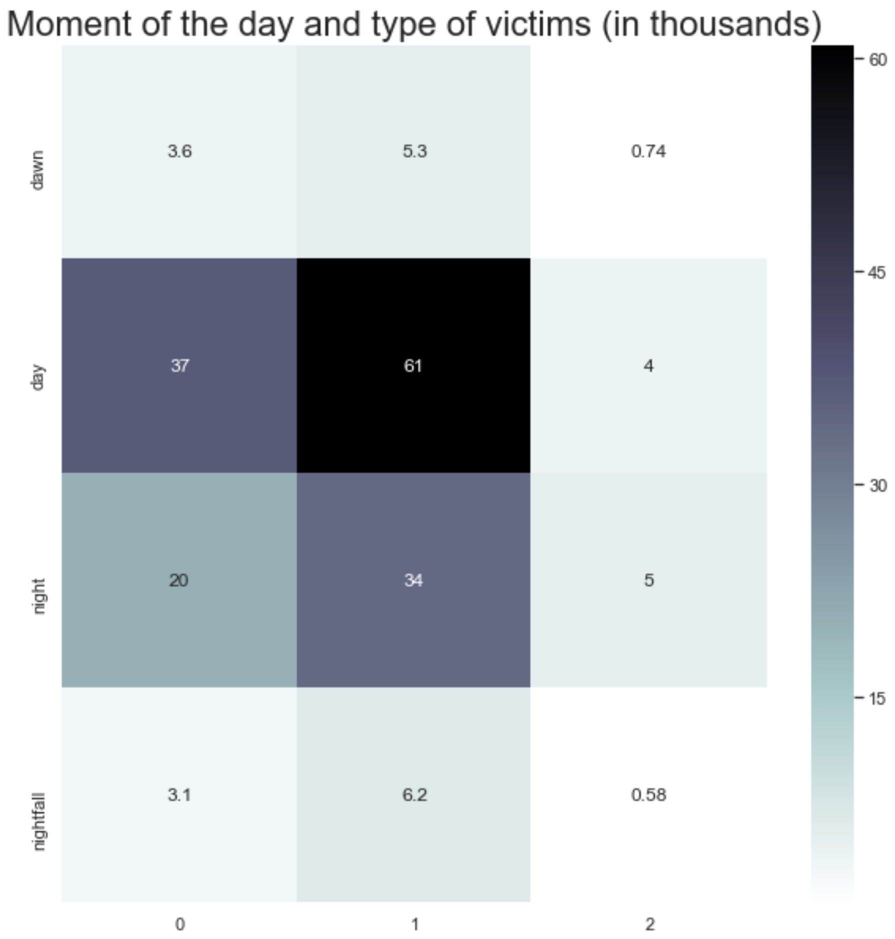
Rear collision are the most common type of accident, with almost 35000 accidents registered. Lateral and transversal collision are the second and third more common cause of accidents, with more than 20000 records.



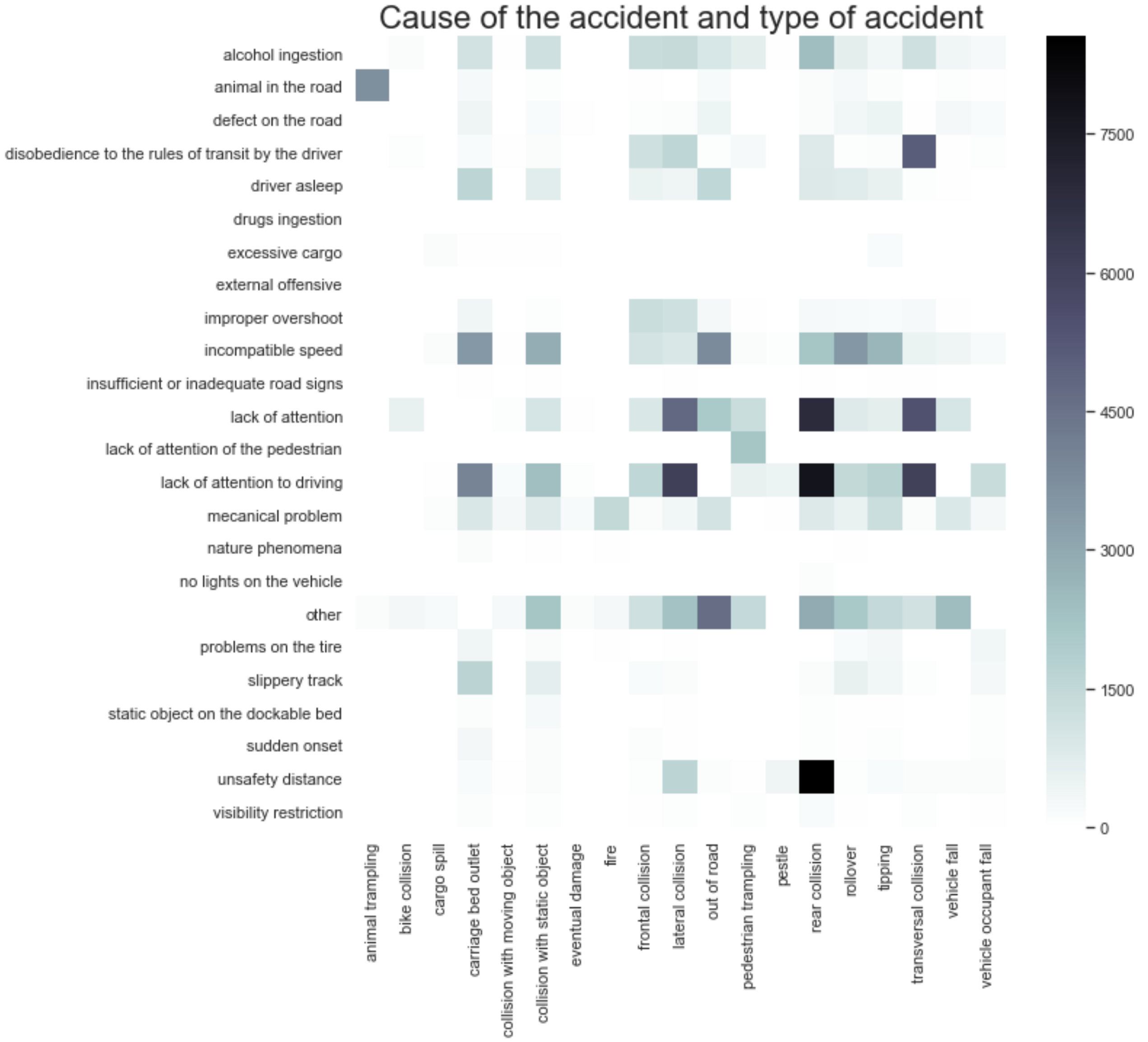
Most accidents happened during the day (56.3%), while a third happened at night (32.8%) and ~11% happened in the transition between day and night.



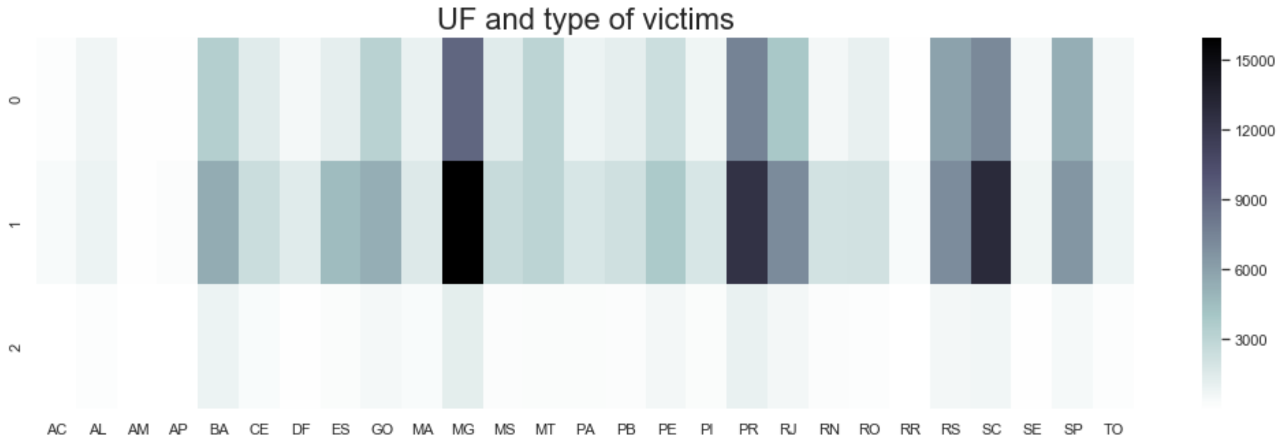
While most of the accidents with injured victims occurred during day time (61 thousand), accidents during the night with dead victims were higher than during the day, probably due to worse visibility causing accidents with more fatal victims.



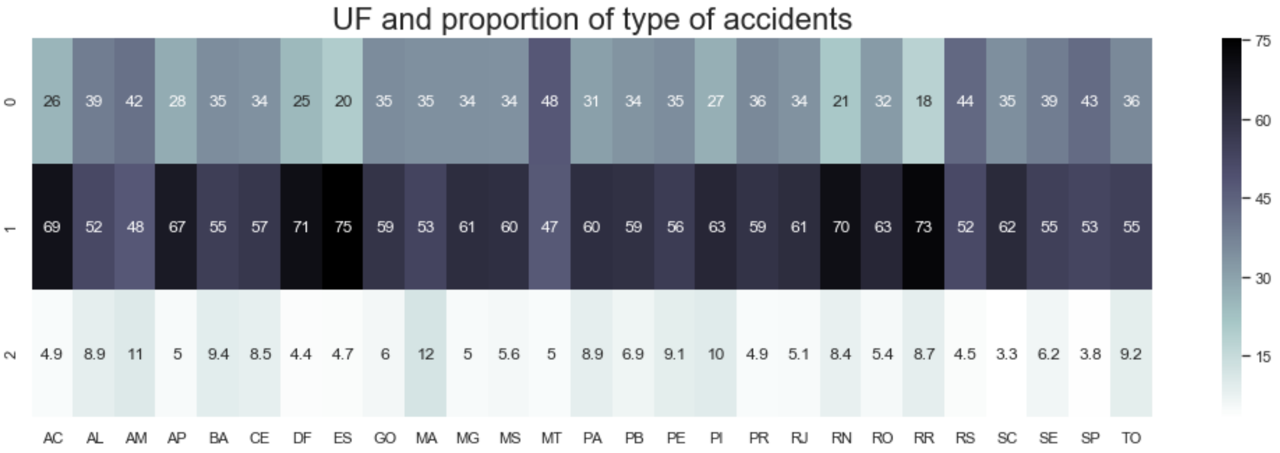
It is possible to see that some causes of accidents are highly correlated to the type of accident caused. For instance, rear collision are highly associated with unsafely distance and incompatible speed can be associated with the vehicle being out of the road.



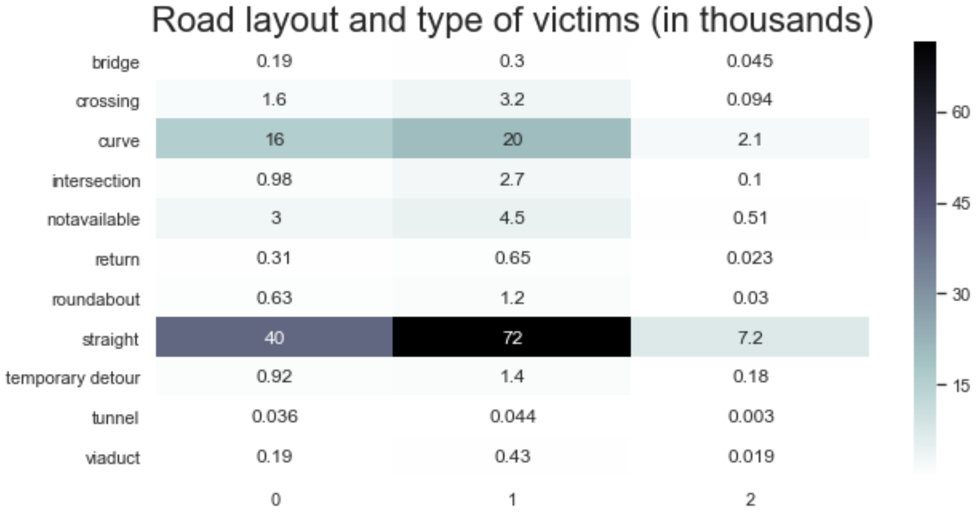
We can see that the state of MG, PR and SC are the states that have more accidents, followed by SP, RS and RJ. Although having a small number of accidents (2961), MA is the state with the highest number of accidents with dead victims in proportion (12.2%). SC, for instance has 10 times the number of accidents than MA but only 3.3% of them had dead victims.



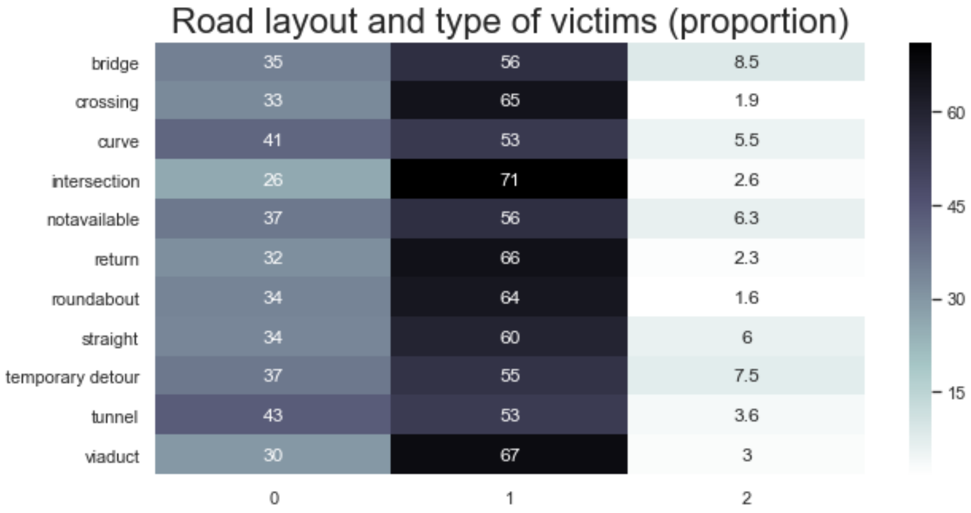
AM, MA and PI are the states with more than 10% of accidents resulting in dead victims while AC, DF, ES, PR, RS, SC and SP have less than 5% of accidents resulting in dead victims. Almost 50% of accidents in MT have no victims, which makes it the most secure state, considering this prerogative.



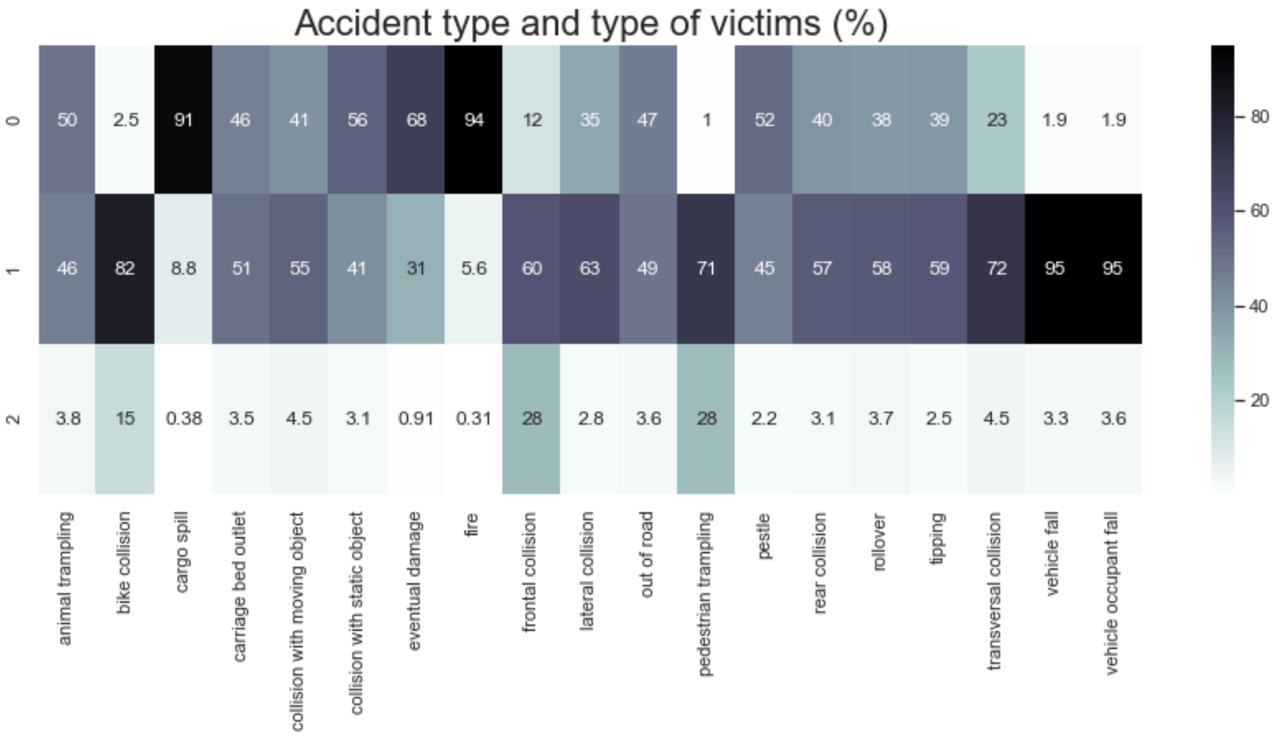
Most accidents occur in straight highways followed by accidents in curves. In general, one every 10 accidents with victims have dead victims.



Accidents in bridges have a higher chance to have dead victims (8,5%), followed by accidents in temporary detours (7,5%) while accidents in roundabout have the lowest chance of dead victims (1.6%). Be the other hand, accidents in tunnel have the higher percentage of accidents with no victims (43%) followed by accidents in curves (41%).



It is possible to observe in the next figure, that accidents involving fire and cargo spill has a high chance of having no victims (> 90%). Accidents with vehicle fall, vehicle occupant fall and bike collision have a high chance of having injured victims (> 80%). Frontal collision and pedestrian trampling have a huge chance of having dead victims (28%) while bike collision has a 15% chance of having dead victims. Thus, we can say that pedestrian trampling, frontal collision and bike collision are the most dangerous type of accidents.



Algorithms and Techniques

All main classifier from the *sklearn* library were used in order to identify the best one for the present study. The idea was to start with simpler models, such as Logistic Regression, go further deep with ensemble models (Random Forest and Gradient Boosting) up to more complex models, such as Neural Networks. The following models were used on the present study:

- Random Forest Classifier - An ensemble model that uses multiple decision trees made with random samples of the dataset. This model usually gives a good perfomance and is harder to overfit. However, it is usually a slow model that doesn't scale well. It is a good option specially with smaller datasets, such as the ones with undersampling.
- Gaussian Naive Bayes - It is a model that need less training data and in highly scalable, thus it could be a good fit for the present study, specially with large data.
- Logistic Regression - It is a model that doesn't worry about features being correlated, although it needs more data to train, it is a good choice.
- Support Vector Machines (SVM)
- KMeans - It is a fast model that works well with multi class datasets.
- Gradient Boosting - It is similar to random forest, but this model consider the error of the previous decision tree on the next one.
- Neural Networks - A more complex model in case a simpler approach won't work.

The models Logistic Regression, Random Forest, Gradient Boosting and SVM were applied using the GridSearchCV method for optimising the hyper-parameters. The other models were used in their default configuration.

The techniques used were:

- Configuring hyper-parameters using GridSearchCV
- Under-sampling: selecting the same number of records for each class to avoid unbalanced classes
- Reducing classes: instead of trying to estimate 3 classes of victims, try to predict whether there would be a victim or not (binary output)
- Change the output from a categorical variable (type of injured) to a numerical parameter (number of victims)
- Changes in the input variables
- Use three simple models to predict each one of the three main classes (binary outputs) and use the probability results as features to a more complex model to predict the three classes

Benchmark

Chong, Abraham & Paprzycki, 2005 did a similar study, where they used neural network for trying to classify victims degree of injuries on traffic accidents. On this study, they had 5 classes of injures, including no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury. The features where based both on road and driver's characteristics. The road characteristics were similar to what we found in the datasets of National Road Police. The authors found a ~60% accuracy on predicting the type of victims.

III. Methodology

Data Preprocessing

The fixes made on the dataset were:

- Fix the date to the pattern yyyy-mm-dd
- Removed values that did not have the target variable
- Add columns for hour, year, month and day of the accident

- Change the name of the target variable to classes 0, 1 and 2
- Renamed and standardized weekdays to English
- Renamed and standardized accident type to English
- Added a simplified accident type column - many of the accident type were variation of a similar type. A column with a simplified type was added for testing. For instance: all columns of lateral collision, frontal collision, etc became a single class collision.
- Renamed and standardized accident cause to English
- Renamed and standardized accident type to English
- Renamed and standardized climate to English
- Renamed and standardized moment of day to English
- Rounded the km variable - the km variable was a float variable indicating which part of the road the accident took place. The decimals would be a precision not necessary for this study, so everything was rounded to integers.
- Define the br variable as object
- Renamed and standardized road type to English
- Renamed and standardized road layout to English
- Renamed and standardized road way to English
- Removed 3232 datasets were climate were not available, since many records were available, no attempt on fulfilling this was made
- Removed 1 datasets were moment of day were not available

Implementation

The first step was to construct a quick and dirt model (notebook 01) using Logistic Regression. An accuracy of 0.63 was achieved. However, the recall of class 2 (dead victims) was only 0.01, which is not nearly good enough. After that, all other models were compared with this baseline in an attempt to achieve the best model.

Techniques used:

- GridSearchCV - Is a technique of model optimization and parameter tunning. It permits to pass several values of parameters to a model and it evaluates, based on a metric you defined, which set of parameters gives better performance.
- Undersampling - Sample classes with higher number of records so they end up with the same number of records as the smallest class.
- Binary output - Elements of class 2 (dead victims) were considered of class 1, thus the model would have to predict whether victims existed or not (no matter if they were dead or injured victims).

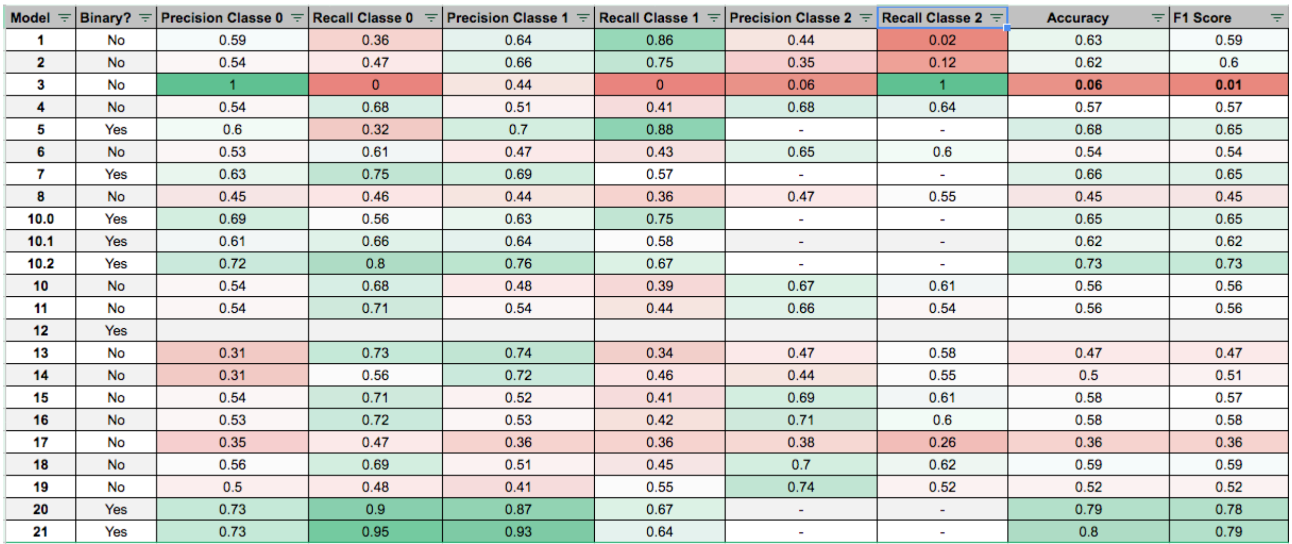
Implementation table:

ID	Num. classes	Model	Techniques	Num of records considered	Features
1	3	Logistic Regression	GridSearchCV	180991	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout

ID	Num. classes	Model	Techniques	Num of records considered	Features
2	3	Random Forest	GridSearchCV	180991	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
3	3	Gaussian Naive Bayes	None	88038	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
4	3	Logistic Regression	GridSearchCV and undersampling	31365	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
5	2	Logistic Regression	GridSearchCV and binary output	180991	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
6	3	Random Forest	GridSearchCV and undersampling	31611	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
7	3	Logistic Regression	GridSearchCV, binary output, under sampling	129333	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
8	3	Logistic Regression	GridSearchCV and undersampling	31365	weekday, uf, br, km, moment_of_day, climate, road_layout
9	0	Random Forest	GridSearchCV and numerical output	88038	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
10	3	Logistic Regression	GridSearchCV, model composition and undersampling	88038	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
11	3	Logistic Regression	GridSearchCV and unbalanced undersampling	42291	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
12	2	Random Forest	GridSearchCV, binary output and undersampling	128332	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
13	3	Gaussian Naive Bayes	Unbalanced undersampling	51455	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout

ID	Num. classes	Model	Techniques	Num of records considered	Features
14	3	SVM	GridSearchCV and undersampling	30873	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout
15	3	Logistic Regression	GridSearchCV and undersampling	30873	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout, month, hour, day, year
16	3	Random Forest	GridSearchCV and undersampling	30873	weekday, uf, km, accident type , climate, month, hour, day, year
17	3	KMeans	Undersampling	30873	weekday, uf, br, km, accident cause, accident type , moment_of_day climate, road_layout, month, hour, day, year
18	3	Gradient Boosting	GridSearchCV and undersampling	30873	weekday, uf, km, accident type , climate, month, hour, day, year
19	3	Neural Network	Undersampling	30873	weekday, uf, km, accident type , climate, month, hour, day, year
20	2	Neural Network	Unbalanced undersampling, binary output	41166	weekday, uf, br, km, accident cause, accident type, climate, road_layout, month, hour, day, year
21	2	Gradient Boosting	GridSearchCV, binary output and undersampling	41166	weekday, uf, br, km, accident cause, accident type, climate, road_layout, month, hour, day, year

For each implementation described above, the result of precision and recall and the general accuracy and F1 score were collected to define which model was best. The table below sums up the results found:



Model	Binary?	Precision Classe 0	Recall Classe 0	Precision Classe 1	Recall Classe 1	Precision Classe 2	Recall Classe 2	Accuracy	F1 Score
1	No	0.59	0.36	0.64	0.86	0.44	0.02	0.63	0.59
2	No	0.54	0.47	0.66	0.75	0.35	0.12	0.62	0.6
3	No	1	0	0.44	0	0.06	1	**0.06**	**0.01**
4	No	0.54	0.68	0.51	0.41	0.68	0.64	0.57	0.57
5	Yes	0.6	0.32	0.7	0.88	-	-	0.68	0.65
6	No	0.53	0.61	0.47	0.43	0.65	0.6	0.54	0.54
7	Yes	0.63	0.75	0.69	0.57	-	-	0.66	0.65
8	No	0.45	0.46	0.44	0.36	0.47	0.55	0.45	0.45
10.0	Yes	0.69	0.56	0.63	0.75	-	-	0.65	0.65
10.1	Yes	0.61	0.66	0.64	0.58	-	-	0.62	0.62
10.2	Yes	0.72	0.8	0.76	0.67	-	-	0.73	0.73
10	No	0.54	0.68	0.48	0.39	0.67	0.61	0.56	0.56
11	No	0.54	0.71	0.54	0.44	0.66	0.54	0.56	0.56
12	Yes								
13	No	0.31	0.73	0.74	0.34	0.47	0.58	0.47	0.47
14	No	0.31	0.56	0.72	0.46	0.44	0.55	0.5	0.51
15	No	0.54	0.71	0.52	0.41	0.69	0.61	0.58	0.57
16	No	0.53	0.72	0.53	0.42	0.71	0.6	0.58	0.58
17	No	0.35	0.47	0.36	0.36	0.38	0.26	0.36	0.36
18	No	0.56	0.69	0.51	0.45	0.7	0.62	0.59	0.59
19	No	0.5	0.48	0.41	0.55	0.74	0.52	0.52	0.52
20	Yes	0.73	0.9	0.87	0.67	-	-	0.79	0.78
21	Yes	0.73	0.95	0.93	0.64	-	-	0.8	0.79

The model 9, which tried to compute the number of people injured instead of the type of victims, was not added to this table, since it is not a classification approach. Nevertheless, this model had a perfomance not much better than predicting the mean number of injured people and was discarded as an inadequate model.

We can observe that the model 10, which is a combination of 3 models into a fourth model, did not have a better perfomance than the other more simple models.

Undersampling was a technique much more efficient than changing algorithms or trying more or less variables. Some variables, such as the number of the road or the accident cause, initially thought as important features, actually weren't as important. We ended up with 2 models: a model with a binary output (with out without victims) with an accuracy of 0.8 and a model with a multi class output, with accuracy of 0.59.

The main idea of this project was to create a model that could help prioritise resources of attendance in case of accidents. Thus, the best model was the model 20, with a binary output and where both recalls were higher than any other models.

Refinement

The solution was not ideal (over 0.6 of accuracy), as define in the benchmark session, for the three class model, but close enough to define de model as a good enough. However, the model with a binary class got an accuracy of 0.79, which is very good.

We could try to improve the multi-class model with adding more records, since the under sampling made a huge decrease in the number of records processed.

IV. Results

Model Evaluation and Validation

Even though the original proposition (multiclass model) had a similar accuracy to the benchmark model, a binary model had a better accuracy and better recall, that was chosen as the best model.

The database was divided between train and test samples, so we could test the model with a dataset that would not be known to it previously.

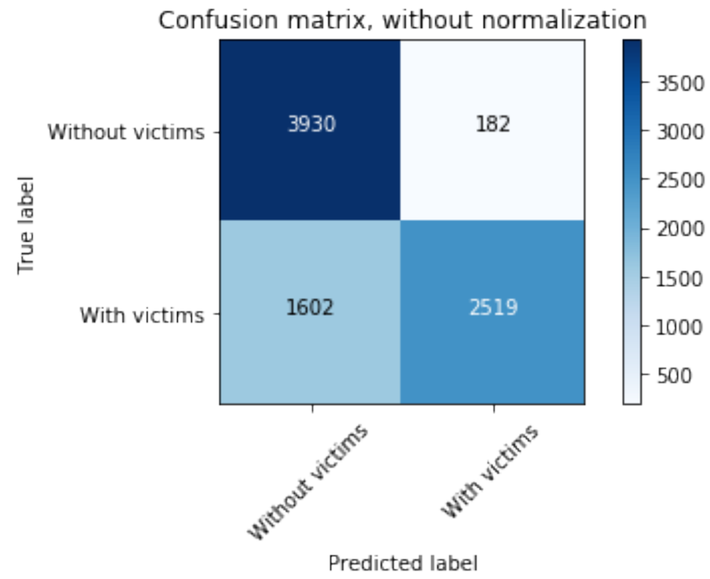
The best model was the Multi-layer Perceptron Classifier (Neural Network), was optimised with the following parameters:

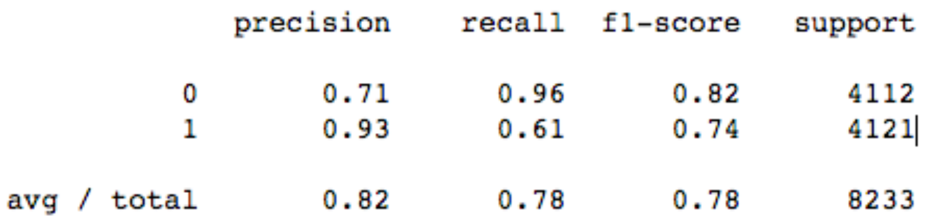
Parameter	Values Tested	Value Optimal
activation	identity, logistic, tanh, relu	Logistic

Parameter	Values Tested	Value Optimal
solver	lbfgs, sgd, adam	adam
hidden layer sizes	50, 100, 200	100
learning rate	constant, invscaling, adaptive	invscaling

The results here presented are a combination of the best algorithm and variables, but this were small changes compared to the change that could be achieved only by under sampling.

On the figure below we can see the confusion matrix of the best binary model (notebook 20). We can see that only 182 accidents that had not victims were classified as with victims, while 1602 with victims were classified as without victims. The table below has the results of precision, recall and f1-score for each class.





```
             precision    recall  f1-score   support

          0       0.71      0.96      0.82      4112
          1       0.93      0.61      0.74      4121

avg / total       0.82      0.78      0.78      8233
```

V. Conclusion

Reflection

I believe that the models had a good result, similar to those found on the study define as the benchmark. This study could improve defining priority of ambulance attendance, specially in places where the recurses are limited. I would like to try new approaches to increase the accuracy of them. Some approaches that could be viable are: increase number of records, test different algorithms and try to gather more information about the accidents.

It was really difficult working with multiclass models, since it is more intuitive the possible approaches that could be done. I believe that the binary model achieved a good performance that could help places were recurses are scarce, but the recall of the class of injured should be increased to prevent putting people in risk with such a model.