Applied Data Science Capstone
Final Assignment

Car Accident Severity

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Car Accident Severity (Business Understanding)

Car accidents are very common in every part of the world. Car accidents can cause injuries, disabilities, property damage and can result in death, so, trying to minimize or get the needed medical assistant in the proper way is very important.

There are a lot of factors that can contribute to the severity of the accident like the speeding, the road, if there are multiple cars, alcohol, drugs, street racing, lack of maintenance, unfamiliar with the road, lack of visibility, distractions, traffic safety culture, etc.

The National Safety Council of USA says that in 2019, an estimated 38,800 people lost their lives because of car crashes. In 2018, an estimated 39,404.

In my country, Guatemala, the government estimates more than 10,000 car accidents in a year and more than 1,700 people lost their lives.

In 2013, more than 54 million people worldwide sustained injuries from car accidents and an estimated of 1.4 million lost their lives. The effects of Car accidents can be physical and psychological, so car accidents are a serious problem and we have to minimize its effects.

Because of the car accidents is a very common type of event, it is necessary to try to estimate the severity of the result of an accident to know how to take actions to reduce the severity and to give the proper medical care in the proper time and to control the traffic to reduce the accumulation of cars (like long lines of cars or the car barely moving).

If we can predict the possibility of a car accident, we can warn us and take actions to avoid them. The possibilities can be predicted with factors like the weather, road, etc.

In this document, we are going to analyse a data set with data of car accidents with a variety of labels and observations and the severity, that represents the fatality of an accident, of the car accidents of every case.

Data Understanding

For this project, we are going to use the Dataset “Example Dataset” and we can find it in the next link: [Dataset]

We can find the metadata for the dataset in the next link: [Metadata]

In this document we are going to use a IBM Cloud Notebook, you can find it in the next link: [Notebook]

The label that we want to predict is the label “severity” that describes the fatality of a car accident. In total there are a total of 37 attributes of features but not all of them are useful, we are going to analyze them to find the proper features to utilice.

The data will be used to train a model and the model will give predictions of the severity of the car accidents. For that purpose, we are going to normalize the features, apply features engineering and we are going to split the data in groups, one for train and one for testing the trained model. The proportion of each group will be 80% for training and 20% for testing. Because we are going to predict a categorizing variable, we are going to train various categorizing models and we are going to choose the one with best accuracy.

Just inspecting the data we can see that there are son features that do not add value to the model like the description, ObjectID, IntKey, increment of identifiers of the incident, etc. The ignore features with the initial analysis are the following:

- X
- Y
- OBJECTID
- INCKEY
- COLDETKEY
- REPORTNO
- STATUS
- INTKEY
- EXCEPTRSNDESC
- SEVERITYDESC
- INCDATE (Because, there is a timestamp of the incidente with INCDTTM)
- SDOT_COLDESC
- SDOTCOLNUM
- ST_COLDESC

After removing the features that do not add value to the model. The goal of the project is to predict the Car Accident Severity using the remaining features. Now we can analyse the remaining features:

Data Summary:

	SEVERITYCODE	SEVERITYCODE.1	PERSONCOUNT	PEDCOUNT	PEDCYLCOUNT	VEHCOUNT	SDOT_COLCODE	SEGLANEKEY	CROSSWALKKEY
count	194673.000000	194673.000000	194673.000000	194673.000000	194673.000000	194673.000000	194673.000000	194673.000000	1.946730e+05
mean	1.298901	1.298901	2.444427	0.037139	0.028391	1.920780	13.867768	269.401114	9.782452e+03
std	0.457778	0.457778	1.345929	0.198150	0.167413	0.631047	6.868755	3315.776055	7.226926e+04
min	1.000000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000e+00
25%	1.000000	1.000000	2.000000	0.000000	0.000000	2.000000	11.000000	0.000000	0.000000e+00
50%	1.000000	1.000000	2.000000	0.000000	0.000000	2.000000	13.000000	0.000000	0.000000e+00
75%	2.000000	2.000000	3.000000	0.000000	0.000000	2.000000	14.000000	0.000000	0.000000e+00
max	2.000000	2.000000	81.000000	6.000000	2.000000	12.000000	69.000000	525241.000000	5.239700e+06

Missing data

The missing data is as follows (bold columns have missing data):
SEVERITYCODE
False 194673
Name: SEVERITYCODE, dtype: int64

ADDRTYPE
False 192747
True 1926
Name: ADDRTYPE, dtype: int64

LOCATION
False 191996
True 2677
Name: LOCATION, dtype: int64

EXCEPTRSNCODE
True 109862 ← have a lot of missing data
False 84811
Name: EXCEPTRSNCODE, dtype: int64

SEVERITYCODE.1
False 194673
Name: SEVERITYCODE.1, dtype: int64

COLLISIONTYPE
False 189769
True 4904
Name: COLLISIONTYPE, dtype: int64

PERSONCOUNT
False 194673
Name: PERSONCOUNT, dtype: int64

PEDCOUNT
False 194673
Name: PEDCOUNT, dtype: int64

PEDCYLCOUNT
False 194673
Name: PEDCYLCOUNT, dtype: int64

VEHCOUNT
False 194673
Name: VEHCOUNT, dtype: int64

INCDTTM
False 194673
Name: INCDTTM, dtype: int64

JUNCTIONTYPE
False 188344
True 6329
Name: JUNCTIONTYPE, dtype: int64

SDOT_COLCODE
False 194673
Name: SDOT_COLCODE, dtype: int64

INATTENTIONIND
True 164868 ← have a lot of missing data
False 29805
Name: INATTENTIONIND, dtype: int64

UNDERINFL
False 189789
True 4884
Name: UNDERINFL, dtype: int64

WEATHER
False 189592
True 5081
Name: WEATHER, dtype: int64

ROADCOND
False 189661
True 5012
Name: ROADCOND, dtype: int64

LIGHTCOND
False 189503
True 5170
Name: LIGHTCOND, dtype: int64

PEDROWNOTGRNT
True 190006 ← have a lot of missing data
False 4667
Name: PEDROWNOTGRNT, dtype: int64

SPEEDING
True 185340 ← have a lot of missing data
False 9333
Name: SPEEDING, dtype: int64

ST_COLCODE
False 194655
True 18
Name: ST_COLCODE, dtype: int64

SEGLANEKEY
False 194673
Name: SEGLANEKEY, dtype: int64

CROSSWALKKEY
False 194673
Name: CROSSWALKKEY, dtype: int64

HITPARKEDCAR
False 194673
Name: HITPARKEDCAR, dtype: int64

Because **EXCEPTRSNCODE, INATTENTIONIND, PEDROWNOTGRNT and SPEEDING** has a lot of missing data and there's no description in the metadata file, we are going to drop the column.

Detailed information of the values of the features with missing data are as follow:

Block 126926
Intersection 65070
Alley 751
Name: ADDRTYPE, dtype: int64

BATTERY ST TUNNEL NB BETWEEN ALASKAN WY VI NB AND AURORA AVE N
276
BATTERY ST TUNNEL SB BETWEEN AURORA AVE N AND ALASKAN WY VI SB
271
...
41ST AVE SW BETWEEN SW 102ND ST AND SW 104TH ST 1
8TH AVE NE AND NE 90TH ST 1
40TH AVE S AND S WEBSTER ST 1
Name: LOCATION, Length: 24102, dtype: int64

Parked Car 47987
Angles 34674
Rear Ended 34090
Other 23703
Sideswipe 18609
Left Turn 13703
Pedestrian 6608
Cycles 5415
Right Turn 2956
Head On 2024
Name: COLLISIONTYPE, dtype: int64

Mid-Block (not related to intersection) 89800
At Intersection (intersection related) 62810
Mid-Block (but intersection related) 22790
Driveway Junction 10671
At Intersection (but not related to intersection) 2098
Ramp Junction 166
Unknown 9
Name: JUNCTIONTYPE, dtype: int64

N 100274
0 80394

Y 5126
1 3995
Name: UNDERINFL, dtype: int64

Clear 111135
Raining 33145
Overcast 27714
Unknown 15091
Snowing 907
Other 832
Fog/Smog/Smoke 569
Sleet/Hail/Freezing Rain 113
Blowing Sand/Dirt 56
Severe Crosswind 25
Partly Cloudy 5
Name: WEATHER, dtype: int64

Dry 124510
Wet 47474
Unknown 15078
Ice 1209
Snow/Slush 1004
Other 132
Standing Water 115
Sand/Mud/Dirt 75
Oil 64
Name: ROADCOND, dtype: int64

Daylight 116137
Dark - Street Lights On 48507
Unknown 13473
Dusk 5902
Dawn 2502
Dark - No Street Lights 1537
Dark - Street Lights Off 1199
Other 235
Dark - Unknown Lighting 11
Name: LIGHTCOND, dtype: int64

32 27612
10 23427
14 16883
32 16809
10 11247

```
50    9089
14    8888
11    8636
28    6925
13    5363
```
4886
```
50    4465
      ...
4       20
7       18
54       1
87       1
60       1
Name: ST_COLCODE, Length: 115, dtype: int64
```

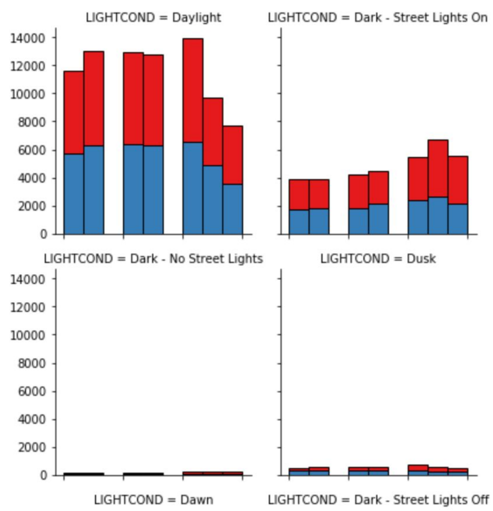
I have put in bold the data that we have to deal with for the next step.

Now, we need to check the current data types:

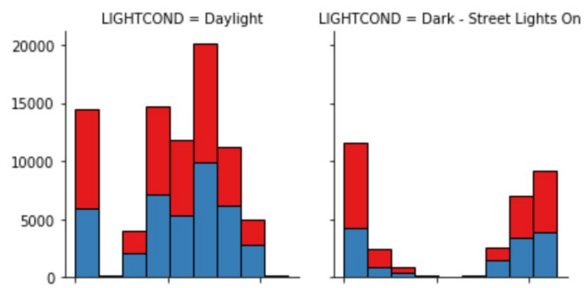
```
SEVERITYCODE      int64
ADDRTYPE          object
SEVERITYCODE.1    int64
COLLISIONTYPE     object
PERSONCOUNT       int64
PEDCOUNT          int64
PEDCYLCOUNT       int64
VEHCOUNT          int64
INCDTTM           object
JUNCTIONTYPE      object
SDOT_COLCODE      int64
UNDERINFL         object
WEATHER           object
ROADCOND          object
LIGHTCOND         object
ST_COLCODE        object
SEGLANEKEY        int64
CROSSWALKKEY      int64
HITPARKEDCAR      object
```

So, we need to change INCDTTM to datetime and visualize the data to find some util patrons. First we will inspect if there's some importance if the accident occurs in the weekend and then we are going to examine the incident in some hours of the day:

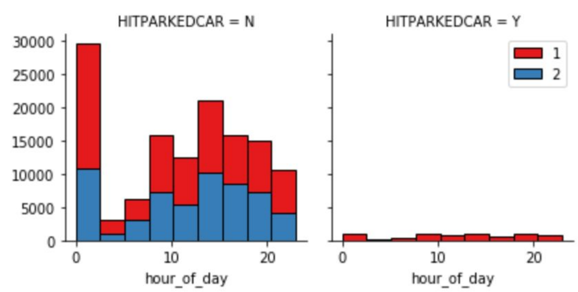
Data Visualization



Day of the week



Hour of the day



Hour of the day (hit parked car)

Data Transformation (For details, checkout the Notebook)

First, we are going to deal with the unknown values changing then to NaN. In this case we need to change the features: JUNCTIONTYPE, ROADCOND, ST_COLCODE and ST_COLCODE has a blank space as value.

After analyzing the data, we can see that the location is not relevant (there are too many values and there is no direct influence over the severity) and for that case, we are going to drop it.

In most of the cases we have less than 5% of the rows with missing values (In statistical language, if the number of the cases is less than 5% of the sample, then the researcher can drop them), so we are going to drop the values that match that rule and deal with the other missing values. In this case we drop the values for COLLISIONTYPE.

We also need to drop the duplicated column SEVERITYCODE.1.

We need to change categorical values to numerical values, in this case for: UNDERINFL, CROSSWALKKEY and HITPARKEDCAR. Then we need to correct the type of the columns. All of the steps to clean, fill missing values and transformation can be found in the Notebook, they're not included here to try keep this document simple for the non technical people and reduce the complexity of the document.

Now, we need to transform the categorical values to binary variables with hot encoding techniques and in this case we are going to use the get_dummies function of Pandas to encode the following features: **ADDRTYPE, COLLISIONTYPE, JUNCTIONTYPE, WEATHER, ROADCOND and LIGHTCOND.**

After all the data transformations, we have the final shape of (189769, 58) and the only thing missing is to normalize the data to reduce bias.

Check all the required steps in the Notebook that is in the Github repository.

Modelling

In this phase, we are going to train 4 basic models with the dataset. The models that we are going to train are: SVM, KNN, Logistic Regression and a Decision Tree.

First of all, we need to split the dataset into Train and Test data with a 80% and 20% proportion (Train and Test respectively). We do that with the train_test_split function.

The training models can be found in the Notebook for more details.

Evaluation

In this phase, we use the test set to evaluate the trained models in the previous step and we get the following accuracy table (the details of the calculation can be found in the Notebook):

Algorithm	Jaccard	F1-score	LogLoss
KNN	0.75115	0.72525	NA
Decision Tree	0.71059	0.70013	NA
SVM	0.76108	0.72098	NA
LogisticRegression	0.75815	0.72177	0.47582

Conclusion

So, in conclusion, we can say that the best model for the car incident severity model is the SVM model with a 0.76108 accuracy. The model can take several hours to train in the IBM Cloud with the free plan.