# Predicting Accident Severity with Different Factors

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## 1. Introduction

### 1.1 Background

Traffic accidents have different level of severity and cause different levels of traffic jam and delayed in the transportation. The severity of traffic accidents depends on different factors such as the location of the accident occurred, the number of vehicles or people involved. The objective of this project is to develop a classification model to predict the severity of traffic accidents so that based on the traffic accidents attribute the model can alert travelers on the severity and the potential delays in the traffic.

### 1.2 Problem

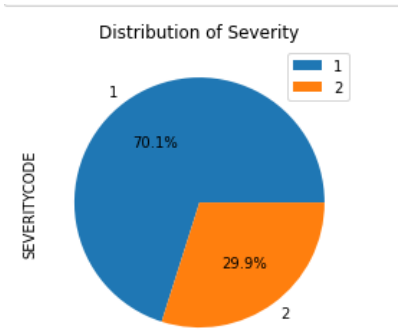
The problem is to determine the severity of traffic accidents using the traffic accidents data in Seattle city in United States.

## 2. Data acquisition and cleansing

2.1 Data sources

The traffic accidents data is obtained for the Seattle city in this link. The metadata description of the columns of the data is available in this link. The data period is from January 1, 2004 to May 20, 2020.

The column 'SEVERITYCODE' is target label that the model would predict. It is notated as 1 and 2 which represent prop damage and injury respectively. The distribution of the severity level of the data is presented as follow. About 70.1% of accidents were with level 1 and 29.9% were with level 2. Note that the distribution between level 1 and level 2 are not even and additional adjustments to the data might be required later to avoid biased classification model.




### 2.2 Data cleansing

There are in total 194,674 rows of data. Most of the data columns are categorical and some of them are numerical. The following columns are removed as they are the index of map objects or the reporting number of the accident which has no value for the classification problem.

- OBJECTID
- INCKEY
- COLDETKEY
- REPORTNO
- SEGANKEY
- CROSSWALKKEY

The column INCDATE is converted to date object in the data set in order to identify the date of the data.

Some categorical features with blank values were replaced with the label ‘UNKNOWN’

### 2.3 Features selection

The following 16 features were selected for the classification problem as they are potentially related to the accident severity, including:

Categorical:

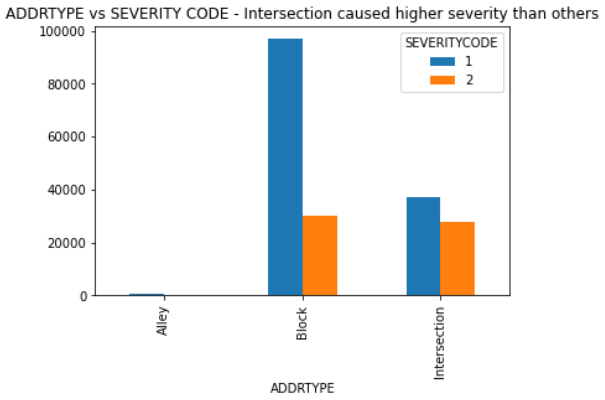
- ‘ADDRTYPE’
- 'EXCEPTRSNDESC',
- 'COLLISIONTYPE',
- 'JUNCTIONTYPE',
- 'SDOT_COLDESC',
- 'INATTENTIONIND',
- 'UNDERINFL',

- 'WEATHER',
- 'ROADCOND',
- 'LIGHTCOND',
- 'SPEEDING',
- 'ST_COLDESC',
- 'HITPARKEDCAR',

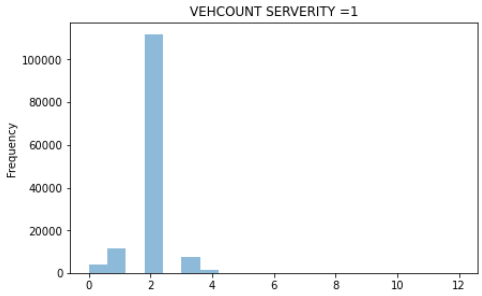
Numerical:

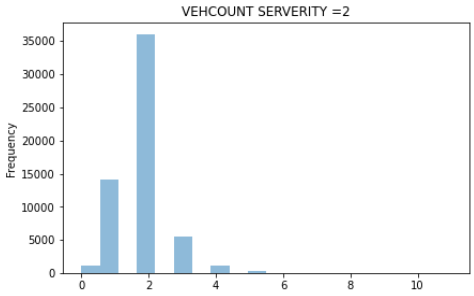
- 'PERSONCOUNT',
- 'PEDCOUNT',
- 'VEHCOUNT',
- 'PEDCYLCOUNT'

For categorical feature, we try to analyze whether the category has any relation to the severity. For example, the below is the ADDRTYPE category and the number of accidents with different severity. Obviously, ADDRTYPE of Intersection has a high chance of level 2 accident and the other two categories. We repeatedly plotting the relation of each categorical feature versus the severity to try to identify if any potential relationship exists.




For numerical feature, the histogram is plotted for the frequency of accidents' severity level for each feature. For example, the below shows the number of vehicle count involved in the accident and the frequency of the severity. However, there is no obvious relationship found.




## 3. Modeling

Since most of the features selected are categorical attributes, a decision tree model is more appropriate for the machine learning classification for this problem.

Also, the level 2 severity accidents are much less than level 1 accidents, we have duplicated the data set of level 2 accidents and append to the original data set to avoid the over-biasing of the classification towards level 1.

The categorical label of the categorical features is converted to numerical label using the preprocessing hot encoding method.

The numerical values are than normalized to avoid over-biasing to any one of the features.

## 4. Evaluation

The following metrics are used to evaluate the original model using the original data set.

```
Test set accuracy score:  0.7488099722612239
Test set percision score:  0.6431193570790753
Test set recall score:  0.36923953289661066
Test set F1 score:  0.4691322284142723
```

The F1 score is low at 0.46 for the model using the original data because the level 2 severity rate is much lower than level 1, causing the recall ratio is only 0.36.

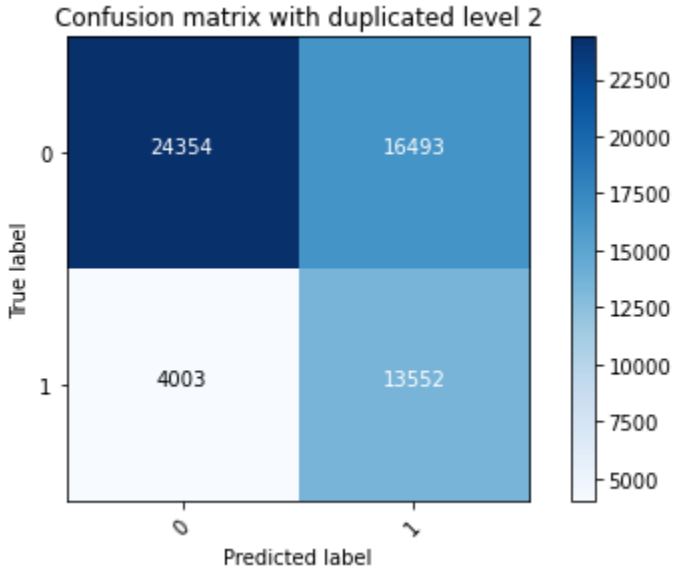
To improve the recall ratio and F1 score, we try to duplicate the data set of level 2 and train the model again. The metrics of the duplicated model is below:

```
Test set accuracy score:  0.644823807403856
Test set percision score:  0.4475036227111053
Test set recall score:  0.7740244944460267
Test set F1 score:  0.567123687889981
```

The recall ratio is improved to 0.77 and the F1 score is now 0.56. It is important for this model because it is more critical to tell the driver the potential severity of the accidents and ask them to

prepare. The high recall ratio is better with high false positive than a higher accuracy score with false negative.

Below is the confusion matrix for the duplicated model:




## 5. Conclusion

The report describes a classification model of the traffic accident severity using different attributes of the traffic accidents in Seattle from January 1, 2004 to May 20, 2020. The F1 score of the model is 0.57 with a recall ratio of level 2 severity of 0.77. The accuracy of the mode is still need to be improved.