1. Introduction

Car accidents or on road collisions and something we witness daily on the news. The vehicle count on road today is much larger than it used to be 10 years ago.

The predictive analysis performed here aims towards analyzing the “Severity” of the accident/collision based on road conditions, lighting conditions, area of collision, number of people involved and many more factors as such. Knowing the severity of any such collision beforehand will lead to prevention and prompt action.

2. Data

All the collision data used in this analysis is taken from ArcGIS, which was provided by Seattle Police Department and recorded by traffic records. The data provided is that of collisions which took place in the city of Seattle, from year 2004 till present.

Mentioned below is list of features that was available in the raw data:

SEVERITYCODE	Target Column (1: Property Damage Only Collision, 2: Injury Collision)
SEVERITYCODE.1	Copy of Target Column
SEVERITYDESC	Description of Target Column
SDOTCOLNUM	A number given to the collision by SDOT
JUNCTIONTYPE	Category of junction at which collision took place
X, Y	Coordinate of accident
LIGHTCOND	The light conditions during the collision
WEATHER	A description of the weather conditions during the time of the collision
ROADCOND	The condition of the road during the collision
ST_COLCODE	A code provided by the state that describes the collision
ST_COLDESC	A description that corresponds to the state's coding designation
COLLISIONTYPE	Collision type
UNDERINFL	Whether or not a driver involved was under the influence of drugs or alcohol
LOCATION	Description of the general location of the collision/address
ADDRTYPE	Collision address type (Alley, Block, Intersection)
SDOT_COLCODE	A code given to the collision by SDOT
SDOT_COLDESC	A description of the collision corresponding to the collision code
SEGLANEKEY	A key for the lane segment in which the collision occurred
CROSSWALKKEY	A key for the crosswalk at which the collision occurred
VEHCOUNT	The number of vehicles involved in the collision
INCDTTM	The date and time of the incident
INCDATE	The date of the incident
PEDCYLCOUNT	The number of bicycles involved in the collision
PEDCOUNT	The number of pedestrians involved in the collision
PERSONCOUNT	The total number of people involved in the collision
STATUS	(Matched, Unmatched)***
REPORTNO	Report identifier
COLDETKEY	Secondary Key for incident

INCKEY	Unique key for incident
OBJECTID	ESRI unique identifier
HITPARKEDCAR	Whether or not the collision involved hitting a parked car
EXCEPTRSNCODE	***
EXCEPTRSNDESC	***
PEDROWNOTGRNT	Whether or not the pedestrian right of way was not granted
SPEEDING	Whether or not speeding was a factor in the collision
INATTENTIONIND	Whether or not collision was due to inattention
INTKEY	Key that corresponds to the intersection associated with a collision

*** Column details not available.

Feature List

There are in total 38 data columns in the dataset including the 3 target related columns. We will keep various aspects in mind

while deciding the importance of a particular column or the transformation it may need before we feed it to the model.

Some of the given data columns are features related to or identifying a single particular accident, thus may not be very much useful for our predictive analysis. These features include:

SDOTCOLNUM, Coordinates, LOCATION, INCDTTM, INCDATE, REPORTNO, COLDETKEY, INCKEY, OBJECTID.

There are some description columns for a given code. Columns *ST_COLDESC, SDOT_COLDESC and EXCEPTRSNDESC* are description columns for code which is already specified in the given dataset.

There are also data columns which has missing data in abundance. *Column EXCEPTRSNCODE,* EXCEPTRSNDESC, *PEDROWNOTGRNT, SPEEDING, INATTENTIONIND* and *INTKEY* have more than 50% of data missing. Although few of these columns can be very crucial indicator of collision severity, it would be misguiding to use it with so many missing rows and very difficult to fill in these categorical values.

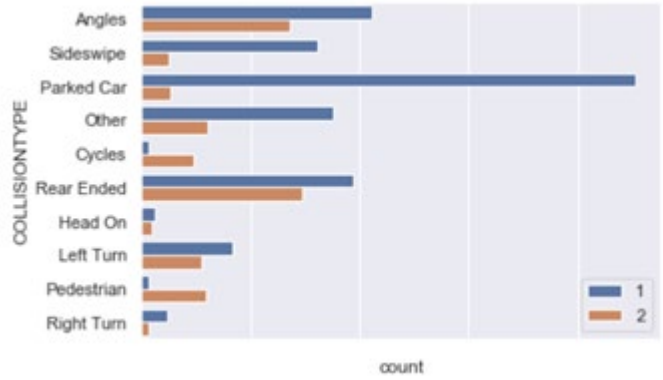
Columns mentioned in all the three categories above will not be used in the model that we are going to build. Most of the columns that remains are categorical and will require one-hot and label encoding before we can use them as a feature for our model.

3. Methodology

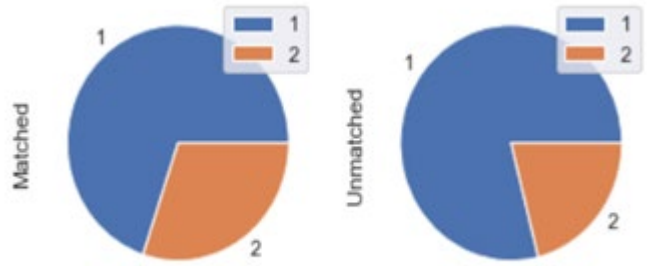
3.1 Exploratory Data Analysis

First part of the process will be to explore the data and understand that how a particular data column is distributed.

Most of our data columns are categorical and we need to know that how affect the severity of the accident.



Frequency of Property Damage Only Collision and Injury Collision with respect to collision type feature



Class distribution of ‘Matched’ and ‘Unmatched’ categories of status variable

There are low cardinality categorical variables with 6–7 categories, moderate cardinality categorical variables with 40–70 categories and very high cardinality categorical variable with 1500+ categories.

3.2 Feature Engineering

Mostly all the variables (except the features which defines the number of people, vehicles etc.) are nominal features; i.e., features where the categories are only labelled without any order of precedence. Preferred encoding for these categories is One-Hot encoding. However, One-Hot encoding will generate around 1500 data columns for just one high cardinality categorical variable, which will be very expensive to work with.

We can get over this hurdle by using feature hashing. Feature hashing is an encoding technique which is used to encode high cardinality feature by hashing them. By this we can pull down the number of encoded data columns to 32–64 even for variables with >1500 categories.

Distribution of all missing data in the training set was found to be:

```
Total distribution of training data:
1    95539
2    40732
Name: SEVERITYCODE, dtype: int64

Total distribution of missing data we are planning to drop:
1    7151
2    1086
Name: SEVERITYCODE, dtype: int64
```

Distribution of all missing data in the training set

As the class proportion is not getting much affected by dropping these data rows, we will proceed to do so.

After the process of feature hashing and one-hot encoding, we obtain in total 208 feature columns. We are using Random Forest to get the feature importance, eliminating 40 least important features and correlation matrix to detect >90% correlations.

After removing the least important and highly correlated features we are left with 160 features to train the model with.

3.3 Modelling

As it was clear from above analysis that we have had a skewed dataset. This resulted in a low recall on class 2 and as a result low F1 score.

To solve this problem, we used smote to oversample the rare class and generated the cross-validation score again. While doing oversampling we have to keep in mind that oversampling should be done on each iteration of cross-validation and not on the whole training set.

As a result, we observed that although the recall on class 2 and F1 increased a little bit, it decreased the accuracy too. Considering the increase in computational expense due to increased data, oversampling didn't prove to be worth the effort in this case.

We used the XG Boost Classifier to start with and plotted the learning curve to see if the model is overfitting the training data.

We observed that converged training and validation error were close to each other, which means that we can use high variance algorithms like Random Forest, XG Boost and Support Vector Machine, and we can also use the high number of features that we are using.

Algorithm	Accuracy	Weighted Precession	Weighted Recall	Weighted F1
Random Forest	0.74	0.73	0.74	0.72
XG Boost	0.75	0.75	0.75	0.73

Cross-validation results for both the algorithms

As expected, we got the best performance from XG Boost Classifier. We will further try hyperparameter tuning to improve the performance.

4. Results

For final prediction we have to preprocess the whole test data-set. While encoding the feature columns we made sure that the one-hot encodings are same as the train set and feature hasher transformer used should be fitted on train data.

Following are the Final result on the test data:

Accuracy	0.76
Weighted Precession	0.77
Weighted Recall	0.76
Weighted F1	0.71
Jaccard Score	0.74

Final Evaluation on Test data

5. Discussion

Many more analysis and methodologies can be added to this project as a future work. We haven't used the coordinates. Those coordinates could result in some unforeseen clusters which could exponentially improve the study.

Further other encoding techniques can be used in place of feature hashing or feature hashing with different feature count can be used. The performance of these changes can be evaluated using cross-validation.

6. Conclusion

The results are satisfactory but expectations were much higher. A lot of improvement can be done on class 2 predictions. Overall a lot of improvement can be observed from the basic model.