IBM Capstone Project: Car accident severity

Introduction

Background:

Annual Global Road Crash Statistics

- Approximately 1.35 million people die in road crashes annually, on average 3,700 people lose their lives every day on the roads.
- An additional 20-50 million suffer non-fatal injuries, often resulting in long-term disabilities.
- More than half of all road traffic deaths occur among vulnerable road users—pedestrians, cyclists, and motorcyclists.
- Road traffic injuries are the leading cause of death among young people aged 5-29. Young adults aged 15-44 account for more than half of all road deaths.
- On average, road crashes cost countries 3% of their gross domestic product.

Annual United States Road Crash Statistics

- More than 38,000 people die annually in crashes on U.S. roadways. The U.S. traffic fatality rate is 12.4 deaths per 100,000 inhabitants.
- An additional 4.4 million are injured seriously enough to require medical attention.
- Road crashes are the leading cause of death in the U.S. for people aged 1-54.
- The economic and societal impact of road crashes costs U.S. citizens $871 billion.
- Road crashes cost the U.S. more than $380 million in direct medical costs.
- The U.S. suffers the most road crash deaths of any high-income country, about 50% higher than similar countries in Western Europe, Canada, Australia and Japan.

Target Audience:

1. The Seattle administration: By targeting areas prone to areas to speeding accidents, interventions such as speed bumps, stop signs etc. can be put in place to reduce accidents.

2. Car Insurance Companies: Areas where parked cars are prone to getting damaged. Owners in those localities may be asked to pay more premium on their car insurance.

3. Health-care workers and emergency services in Seattle: By having enough data on the crash one can predict the severity and therefore take action more quickly potentially saving lives.

Practical Uses of the Model:

- Speed reduction measures in areas prone to accidents due to speeding
- More accurate calculation of risk premiums by Car Insurance companies
- Proactive actions taken by Health-care by predicting severity of the accident.

Future Use Case: AI in self-driving cars can use such models to assess risk of accidents and change routes or ask the driver to be vigilant during auto-pilot.

Data:

The Accident data (provided by seattle.gov: Link) will be used to predict the Severity of an accident given certain features (Metadata). The data is for Accidents occurring in the city of Seattle from 2004 to 2020.

Label = y = SEVERITYCODE

Total Number of features: 37

Features selected (X):

Feature	Description	Reason for Selecting
ADDRTYPE	Collision at Alley, Block, Intersection	Gives the likelihood of collision at these places
PERSONCOUNT	Number of people involved in the collision	Gives an indication of severity
PEDCOUNT	Number of pedestrians involved in the accident	Gives an indication of severity
PEDCYLCOUNT	Number of cyclists involved in the accident	Gives an indication of severity
VEHCOUNT	Number of vehicles involved in the accident	Gives an indication of severity
INCDTTM	The date and time of the incident	Time of accident: midnight/ day time
INATTENTIONIND	Whether the person was not paying attention	Not paying attention can result in accident
UNDERINFL	Whether the person was driving under influence	DUI can cause accidents
WEATHER	Weather conditions	Bad weather can cause accidents
ROADCOND	Road conditions	Wet roads can cause skidding
LIGHTCOND	Light conditions	Light conditions affect visibility
PEDROWNOTGRNT	Pedestrian right of way was granted or not	
SPEEDING	Whether speeding or not	Speeding causes accidents
COLLISIONTYPE	Collision Type	Type of collision gives severity of accident
HITPARKEDCAR	Whether or not the collision involved hitting a parked car.	Hitting a parked car causes property damage

Features dropped:

Feature	Description	Reason for Dropping
X	Latitude	Can't be modelled in classification
Y	Longitude	Can't be modelled in classification
OBJECTID	ESRI unique identifier	ID not relevant
INCKEY	Secondary key for the incident	ID not relevant
COLDETKEY	Identifying key	ID not relevant
LOCATION	Description of Location	ADDRTYPE captures this
REPORTNO	Report Number	ID not relevant
STATUS	Matched/Unmatched	ID not relevant
INTKEY	Intersection key for collision	ID not relevant
EXCEPTRSNCODE	Blank	No data
EXCEPTRSNDESC	Blank	No data
SEVERITYCODE	Label	Label to be predicted
SEVERITYDESC	Description of Severity	Label to be predicted
INCDATE	The date of the incident.	INCDTTM captures this
SDOT_COLCODE	Collision code	Collision type captures this
SDOT_COLDESC	A description of the collision corresponding to the collision code.	Collision type captures this
SDOTCOLNUM	A number given to the collision by SDOT.	Collision type captures this
SEGLANEKEY	A key for the lane segment in which the collision occurred.	ID not relevant
CROSSWALKKEY	A key for the crosswalk at which the collision occurred.	ID not relevant

Features after Feature Engineering:

SL No.	Feature	Description	Reason for Selecting
1	ADDRTYPE	Collision at Alley, Block, Intersection	Gives the likelihood of collision at these places
2	PERSONCOUNT	Number of people involved in the collision	Gives an indication of severity
3	PEDCOUNT	Number of pedestrians involved in the accident	Gives an indication of severity
4	PEDCYLCOUNT	Number of cyclists involved in the accident	Gives an indication of severity
5	VEHCOUNT	Number of vehicles involved in the accident	Gives an indication of severity
6	INATTENTIONIND	Whether the person was not paying attention	Not paying attention can result in accident
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8	WEATHER	Weather conditions	Bad weather can cause accidents
9	ROADCOND	Road conditions	Wet roads can cause skidding
10	LIGHTCOND	Light conditions	Light conditions affect visibility
11	PEDROWNOTGRNT	Pedestrian right of way was granted or not	
12	SPEEDING	Whether speeding or not	Speeding causes accidents
13	COLLISIONTYPE	Collision Type	Type of collision gives severity of accident
14	HITPARKEDCAR	Whether or not the collision involved hitting a parked car.	Hitting a parked car causes property damage
15	Year	Year of accident	Did one year have a lot of accidents
16	Month	Month of Accident	Does month affect number of accidents
17	Day	Day of accident	Day of month
18	Hour	Time of accident	Are accidents caused majorly at night
19	Weekday	What day of the week accident happened	Are accidents caused more on certain days of the week

Data Analysis:

- Plotting factors on the map to get density of areas where accidents were caused by the features in question:
    1. Speeding:
    2. Under Influence (DUI)
    3. Inattention
    4. Hitting a parked car

- Using the following classifiers to get the prediction whether given certain attributes (features), the severity of the accident (label)
    1. K Nearest Neighbours
    2. Logistic Regression
    3. Decision Tree Classifier
    4. XGBoost Classifier
    5. Random Forest Classifier
    6. Support Vector Machine

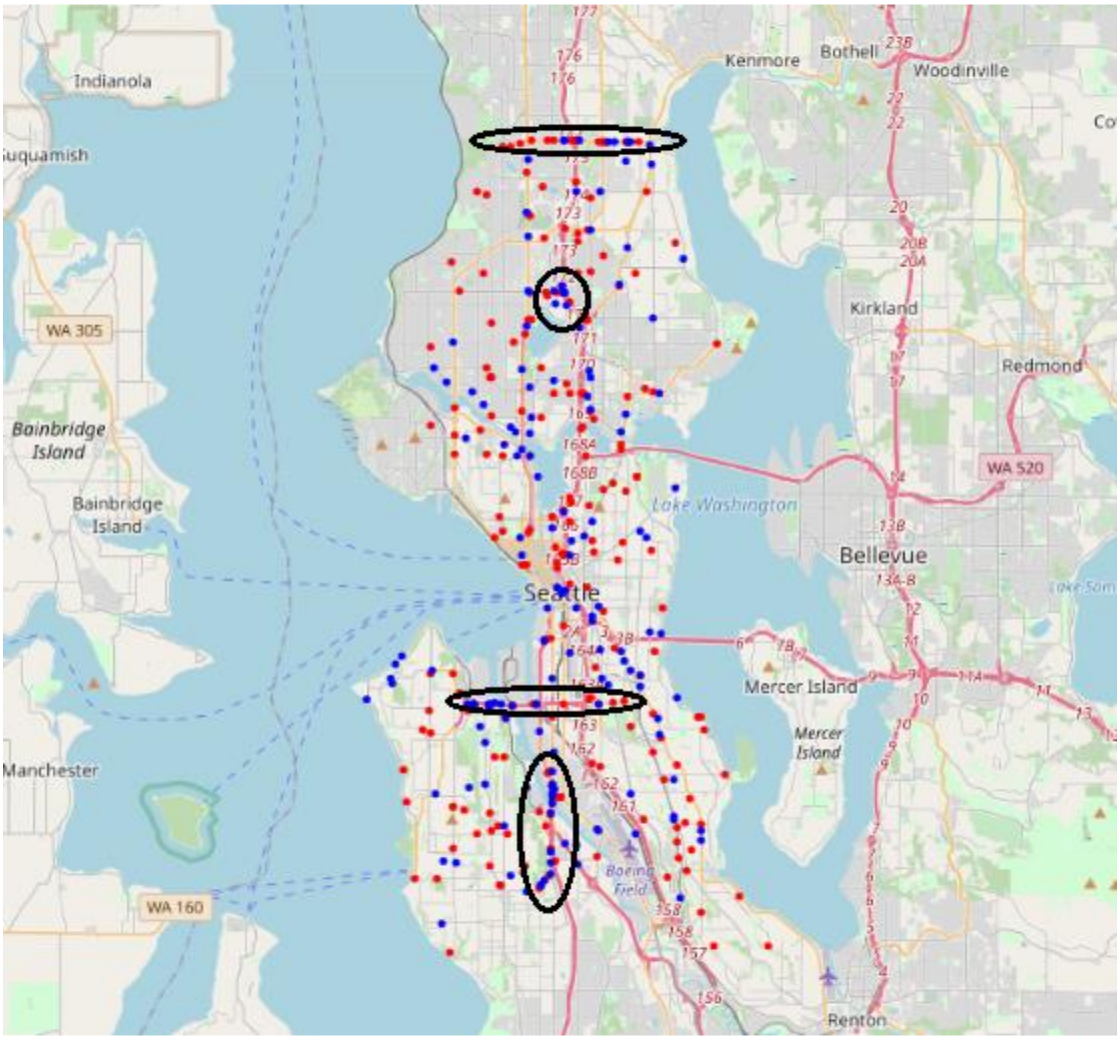
Methodology:

A. Plotting density of accidents sorted by Severity caused by the following features:

Following convention followed in plots:

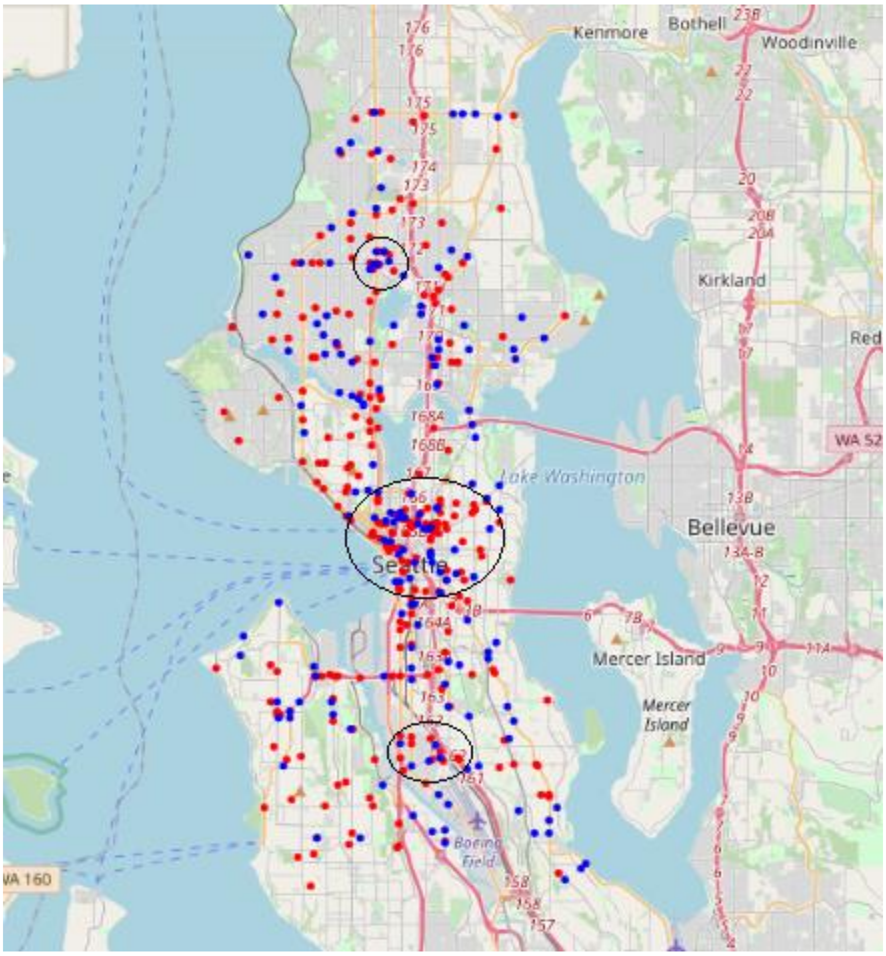
- Severity value of 1 shown by **RED** circle
- Severity value of 2 shown by **BLUE** circle
- Data plotted is for years 2017 – 2020 for all graphs except for feature: Hitting Parked Car
- Data plotted for Hitting Parked car for the year of 2020.

I. Speeding



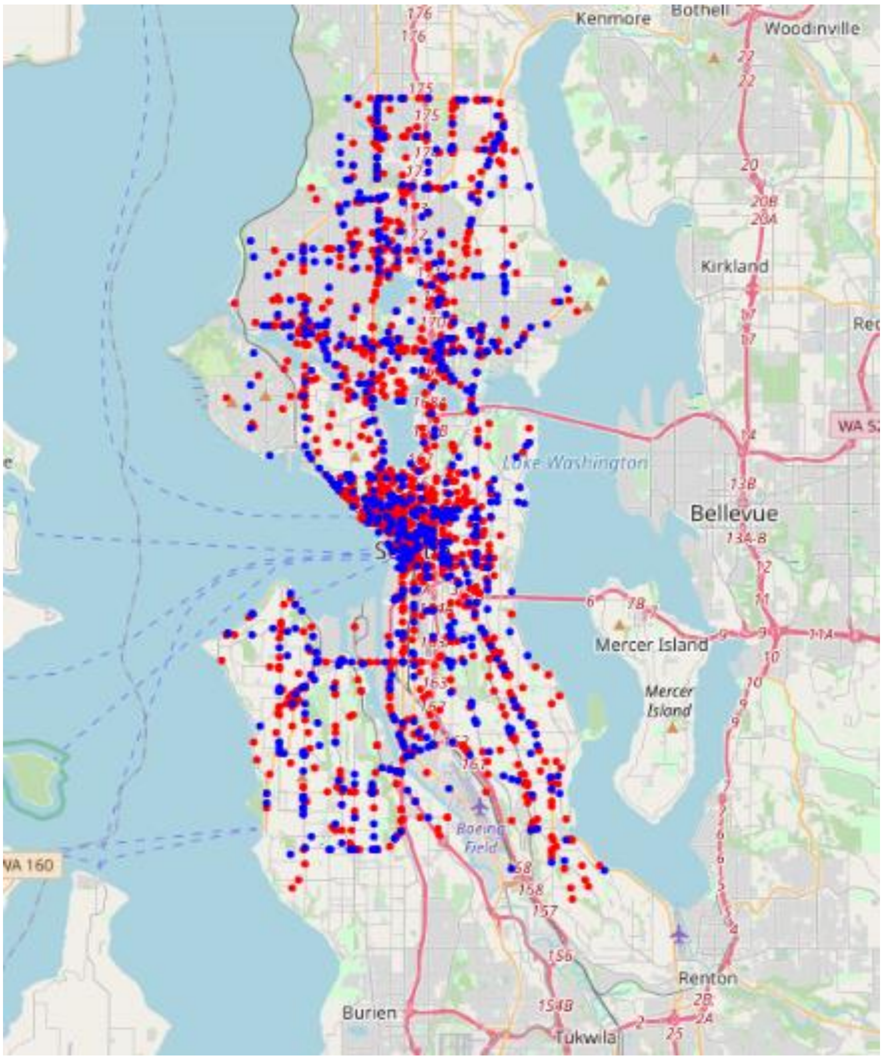
Certain roads have a lot of accidents which occur on them due to speeding (*As shown by the circles figure above)*
The government of Seattle can introduce proper traffic management in the form of speed restricting interventions (e.g. speed bumps). This can cause reduction in accidents due to speeding.

II. Driving Under Influence:



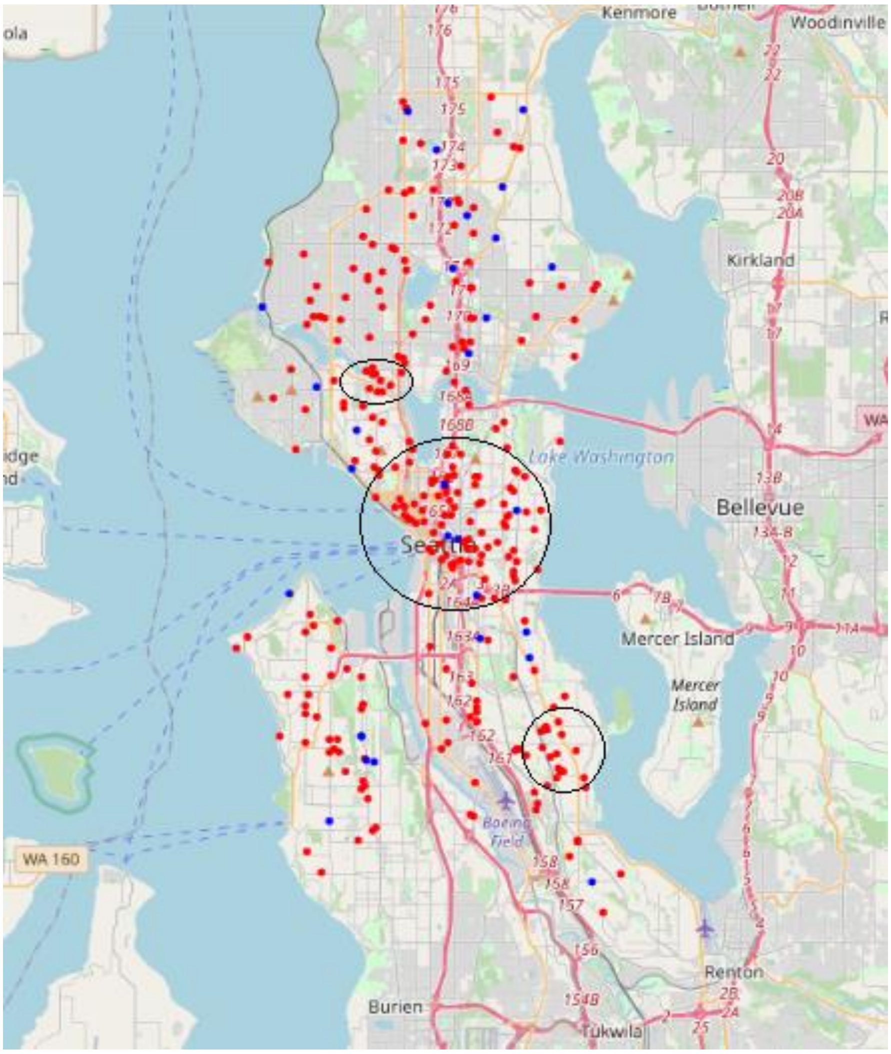
The above map shows, the points where accidents are caused due to DUI. The Seattle government can introduce Police check-ups on vehicles which are entering nodes where one has high density of accidents caused by DUI (*shown in black circles*). This can reduce potential accidents before they happen.

III. Inattention:



The above map shows, the points where accidents are caused due to Inattention. The figure filled with circles represents an accident, it just goes to show that a huge majority of accidents are caused by inattention. Perhaps a product monitoring the attention of drivers can be developed/marketed citing this data.

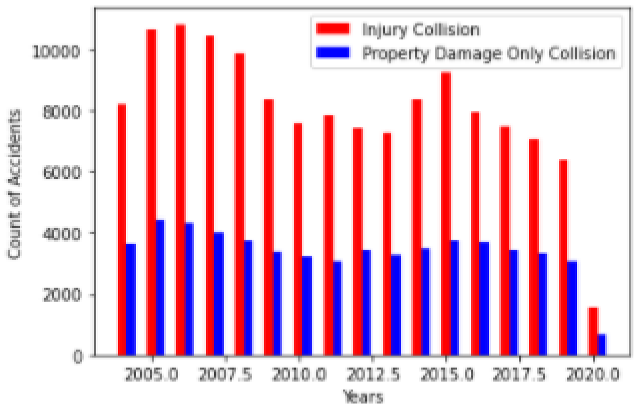
IV. Hitting Parked Cars



The above figure shows where accidents in which parked cars were hit. The areas marked by black circles can be used by Insurance companies to tweak their car insurance premiums for individuals living in those areas.

B. Plotting count of accidents based on the following factors:

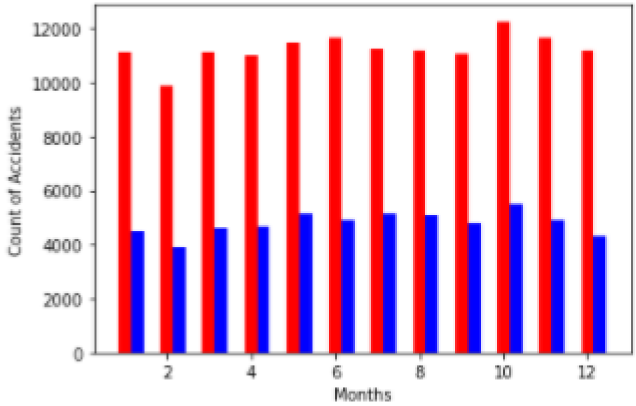
1. Year:



1. The Number of accidents in both the Severity classes have been decreasing over the years.

2. The drastic drop in 2020 is due to there being data for part of the year.

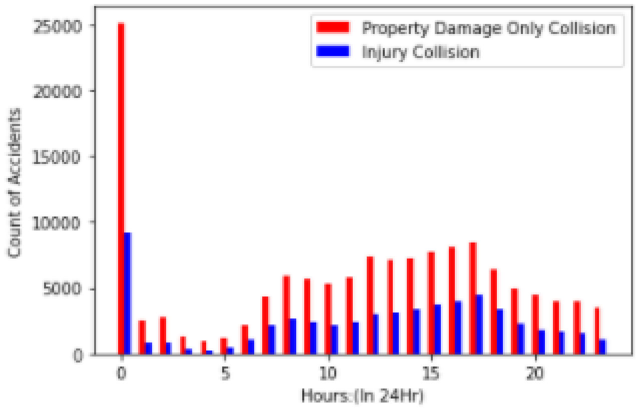
2. Months



October has the most number of crashes in the year.

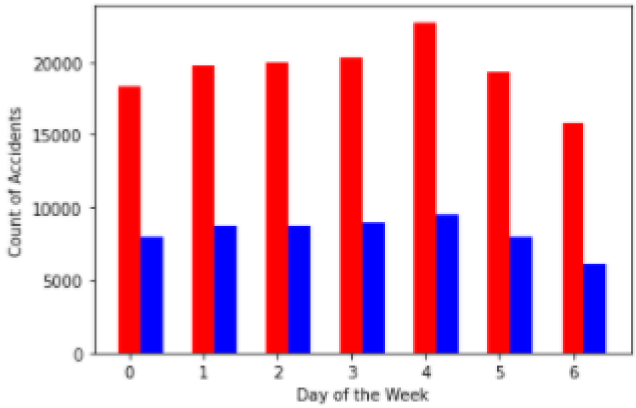
Number of crashed further decreases in the months of November and then December

3. Hours in 24-hour format



The highest number of accidents by far happen at midnight from 12AM to 1 AM.

4. Day of Week



The day with the highest number of cases in the day is Friday

C. Using Classification Algorithms to classify label (SEVERITY) with the selected features.

1. K Nearest Neighbours
2. Logistic Regression
3. Decision Tree Classifier
4. XGBoost Classifier
5. Random Forest Classifier
6. Support Vector Machine

The data was first split into the train, test sets and then pre-processed. This was all achieved using the sklearn library.

RESULTS

The Results of the classification are as follows:

Sl No.	Classifier	F1 Score	Jaccard Score
1	K Nearest Neighbours	0.692301	0.72841916
2	Logistic Regression	0.708354	0.75225376
3	Decision Tree Classifier	0.685308	0.68396045
4	**XGBoost Classifier**	**0.727591**	**0.76296391**
5	Random Forest Classifier	0.715156	0.76013869
6	Support Vector Machine	0.714600	0.75934249

The Classifier that performed the best was the XGBoost Gradient Classifier with an accuracy of 76.29%

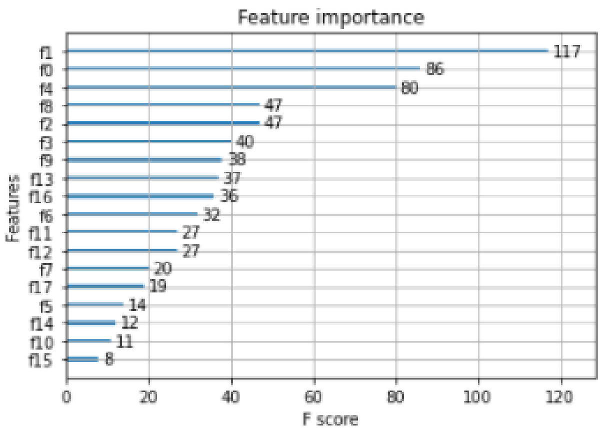
The Gradient Boost classifier predicts the Severity of the accident (Injury Collision, Property Damage Only Collision) up to ~76.3% accuracy

Feature Importance Analysis:

The result of Feature importance with Collision Type dropped:

The Accuracy of XGBoost is 0.7583, and F1 Score: 0.7094

```
[0.07443821 0.07192027 0.25724676 0.23176846 0.02890782 0.03441104
 0.01322539 0.09828424 0.06546744 0.02278161 0.01066418 0.01878568
 0.05245251 0.00642101 0.00306294 0.00153579 0.0039697  0.00465685]
```



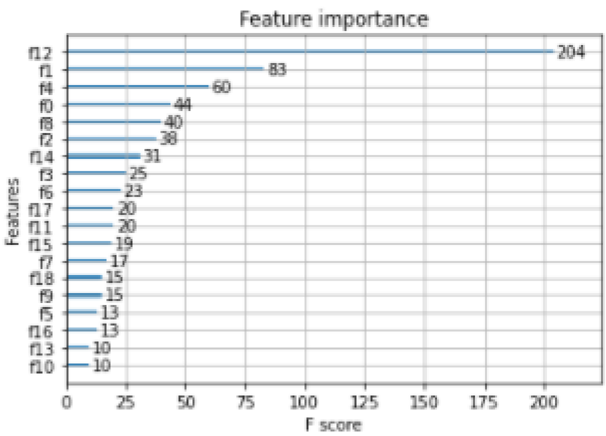
The most important feature was:

I. Person Count
II. Address Type
III. Vehicle Count

The result of Feature Importance with Collision Type included:

The Accuracy of XGBoost is 0.7629, and F1 Score: 0.7275

```
[0.02028692 0.06733859 0.207039   0.24447267 0.04043719 0.00791223
 0.02458902 0.06431133 0.06126108 0.01831033 0.00958071 0.01768854
 0.19400577 0.00911685 0.0035155  0.00395693 0.00174351 0.0021102
 0.00232353]
```



The most important features were:

I. Collision Type
II. Person Count
III. Vehicle Count

Conclusion:

The data-set has been used to classify the severity of the accidents based on certain select features.

The exploratory data analysis shows density of accidents based on geography based on Speeding, Driving Under Influence, In-attention and Hitting Parked Cars.

The frequency of accidents was plotted yearly, monthly, hourly and day-wise to generate insights.

From a machine learning standpoint. The most important features were: Collision Type, Person Count, Vehicle Count and Address Type. The Gradient Boost algorithm performed the best.