Capstone Project: Car Accident Severity

1. Introduction/ Business Problem.

1.1. Background:

The global epidemic of road crash fatalities and disabilities is gradually being recognized as a major public health concern. The first step to being informed about global road safety and to developing effective road safety interventions is to have access to facts.

1.1.1. Annual Global Road Crash Statistics

- Approximately *1.35 million* people die in road crashes each year, 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. More than *90%* of all road fatalities occur in low- and middle-income countries, even though these countries have approximately 60% of the world's vehicles.
- On average, road crashes cost countries *3%* of their gross domestic product.
- Road crashes are the single greatest annual cause of death of healthy U.S. citizens traveling abroad.

1.1.2. Annual United States Road Crash Statistics

- More than *38,000* people die every year 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.
- Pedestrian and bicyclist fatalities continue to rise in the United States. According to the National Highway Traffic Safety Administration (NHTSA), more pedestrians and cyclists were killed in 2018 than in any year since 1990.

1.2. Target Audience:

1.2.1. *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.

1.2.2. Car Insurance Companies:

- Areas where parked cars are prone to being damaged. Owners in those localities may be asked to pay more premium on their car insurance.

1.2.3. *Health-care workers and emergency services in Seattle:*

- Having enough data on the crash can predict the severity and therefore take action more quickly potentially saving lives.

1.3. 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.

1.4. 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 autopilot.

1.5. Data Section.

- The description of the data is discussed and how it will be used to solve the problem raised.

1.5.1. Description of data

The Accident data (provided by seattle.gov: Link) is 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**
7	**UNDERINFL**	**Whether the person was driving under influence**	**DUI can cause accidents**
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**

1.5.2. Exploratory Data Analysis:

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

- **The following classifiers are used 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**

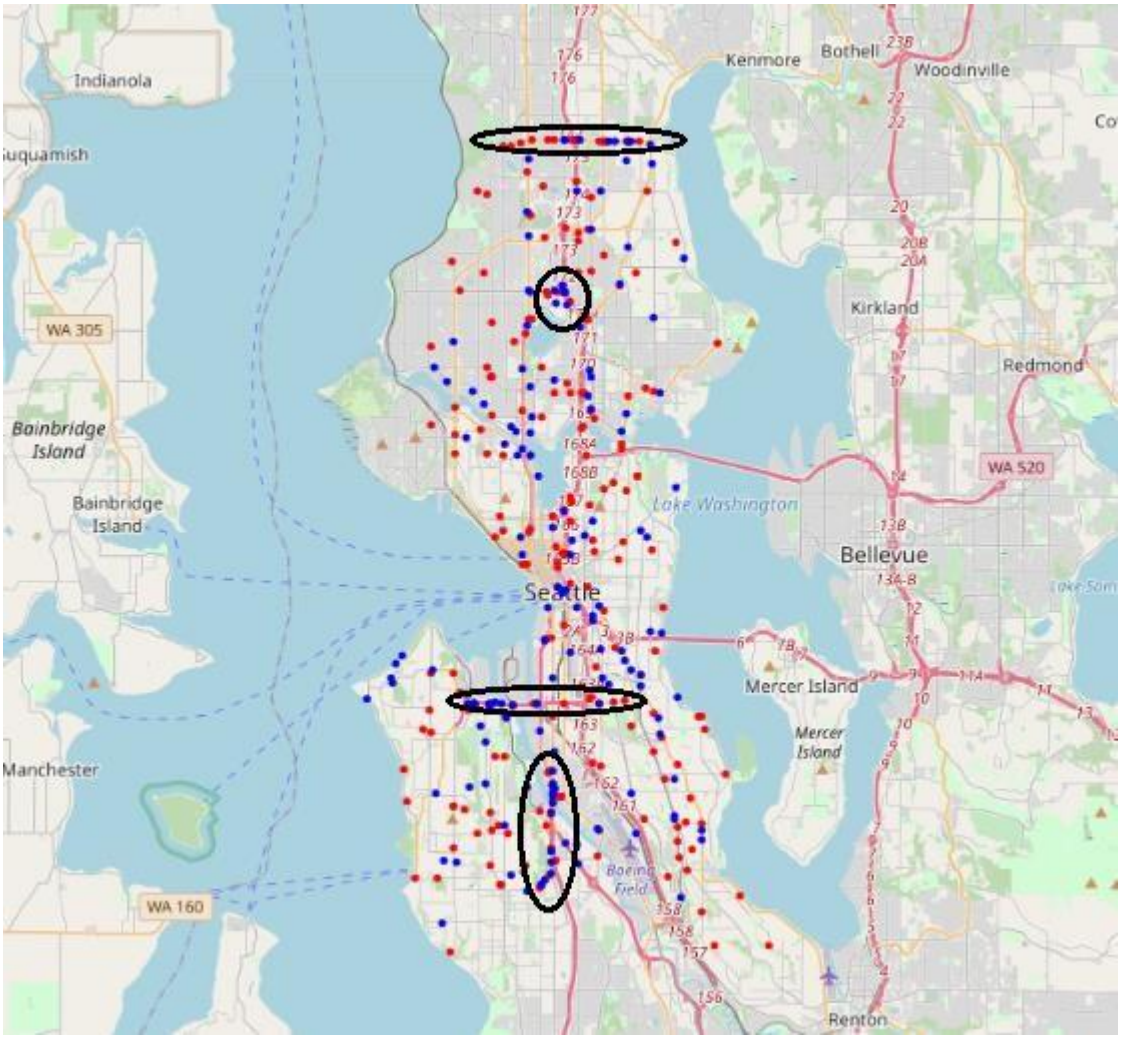
2. Methodology:

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.

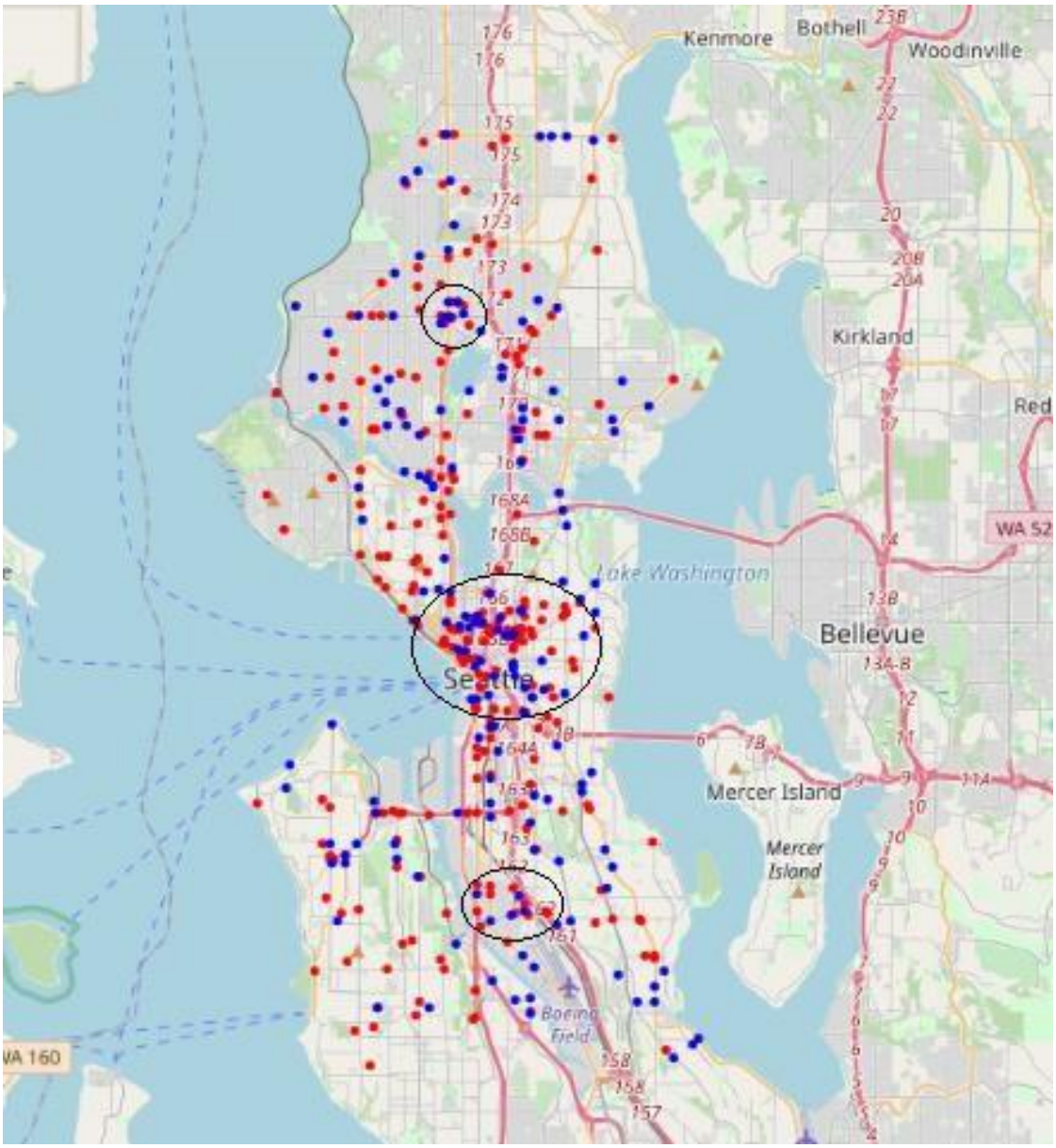
i. Speeding



® Certain roads have a lot of accidents which occur on them due to speeding (*As shown by the circles figure above)*

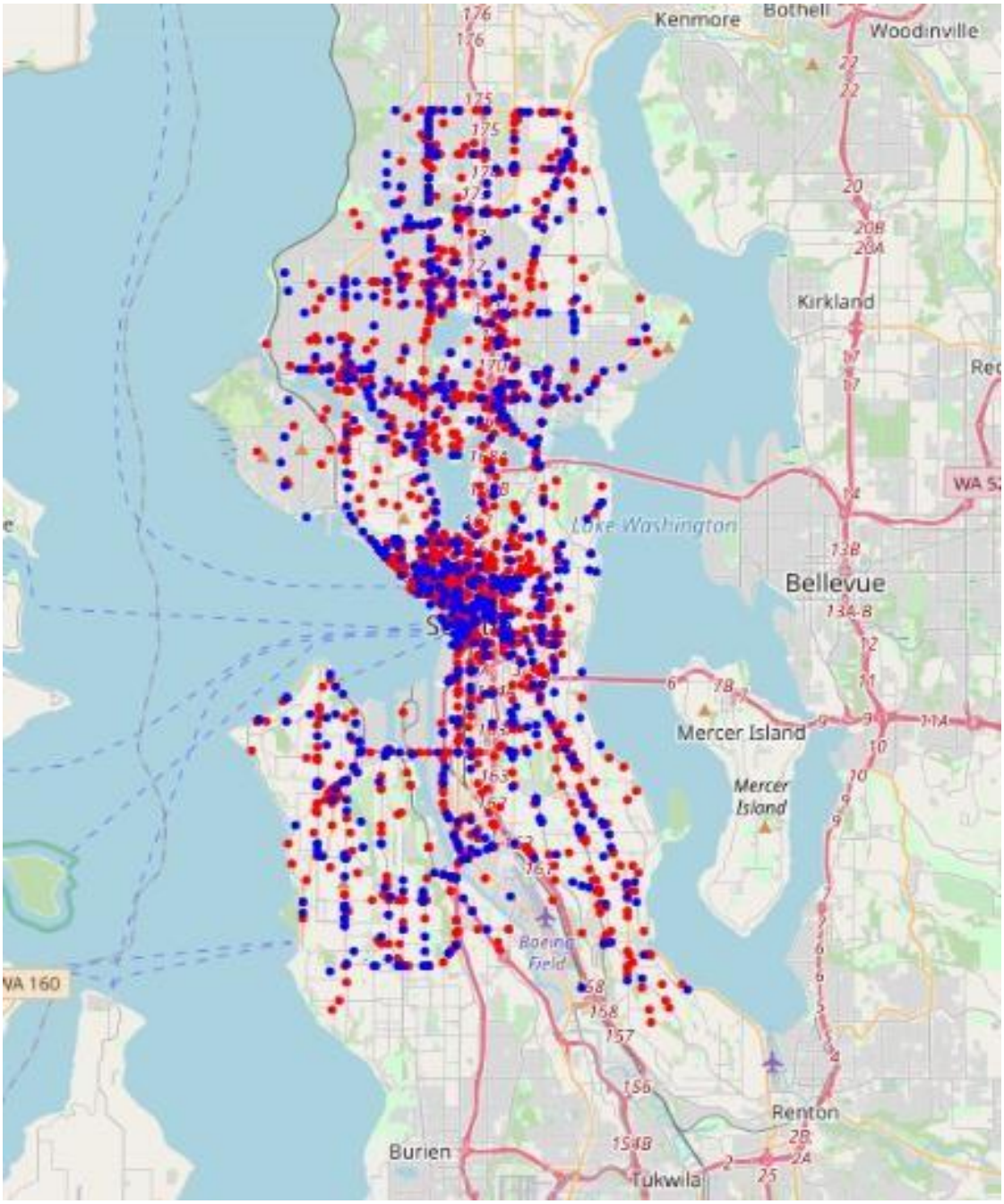
® The government of Seattle can introduce proper traffic management in the form of speed restricting interventions (e.g. speed bumps). This can cause reduction in accidents due to speeding.

ii. Driving Under Influence:



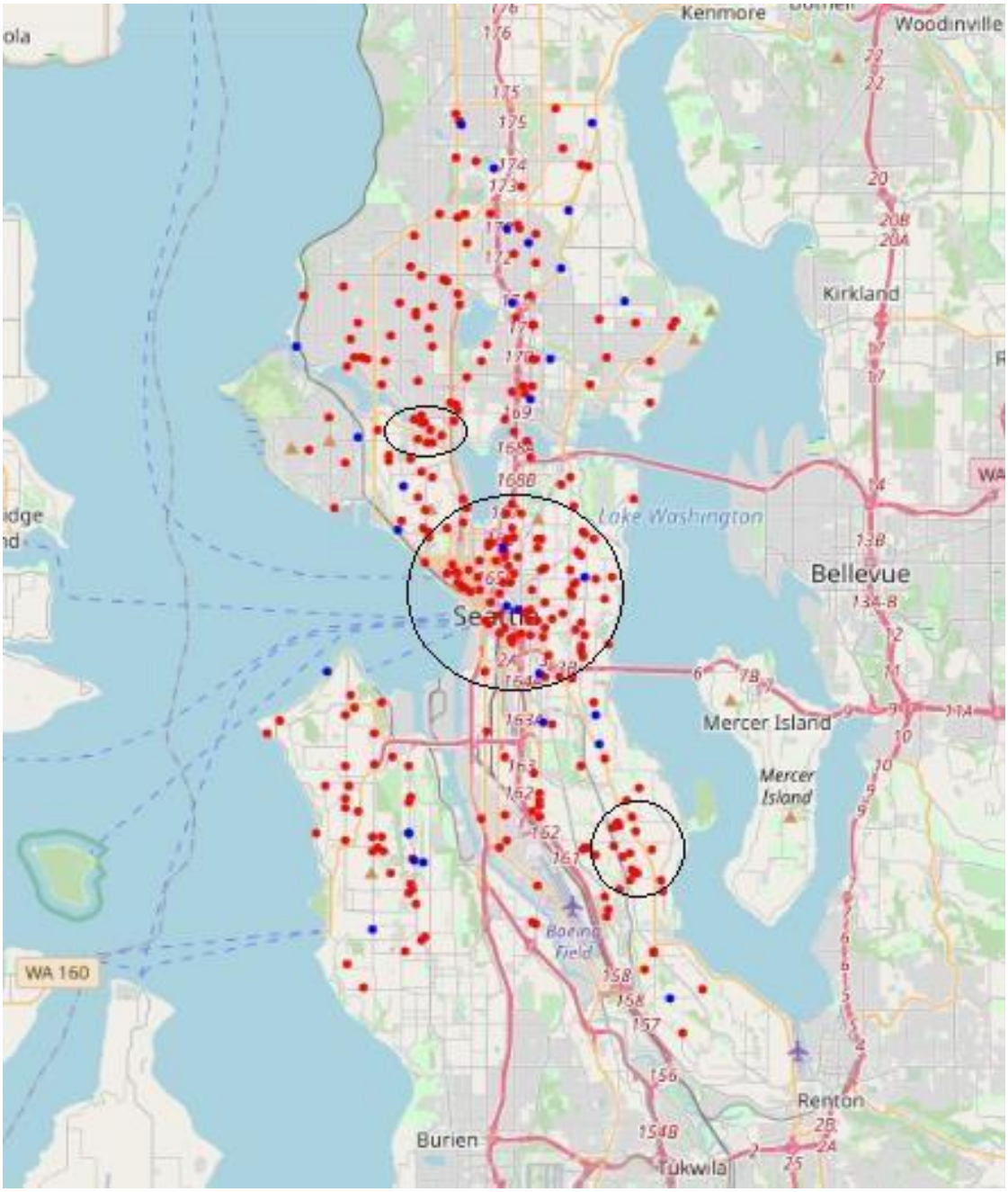
® The above map shows, the points where accidents are caused due to DUI. The Seattle government can introduce Police check-ups on vehicles that are entering nodes where one has high density of accidents caused by DUI (*shown in black circles*). This can reduce potential accidents before they happen.

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.

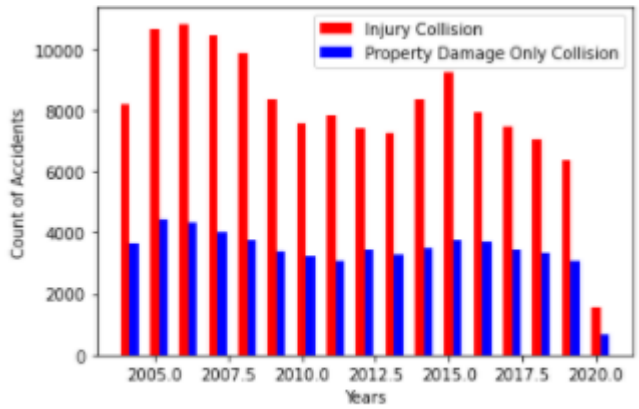
iv. Hitting Parked Cars



® 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.

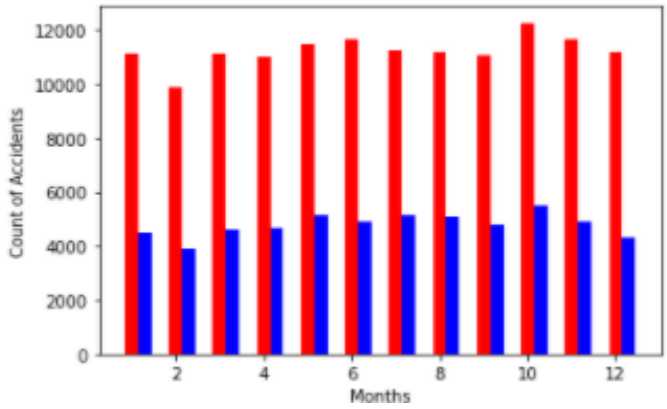
b) Plotting count of accidents based on the following factors:

1. Year:



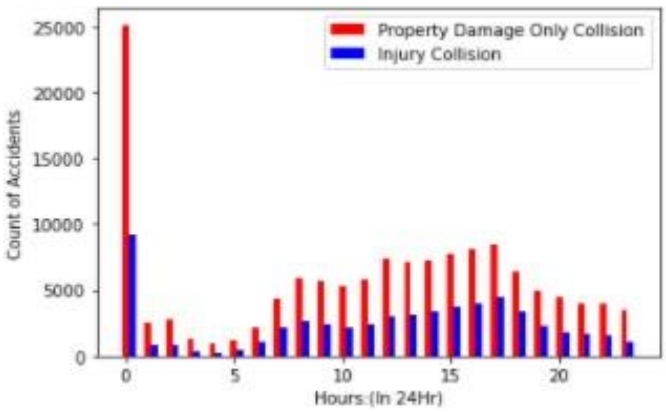
1. The Number of accidents in both the Severity classes have been decreasing over the years.
2. The drastic drop in 2020 is due to there being data for part of the year.

2. Months



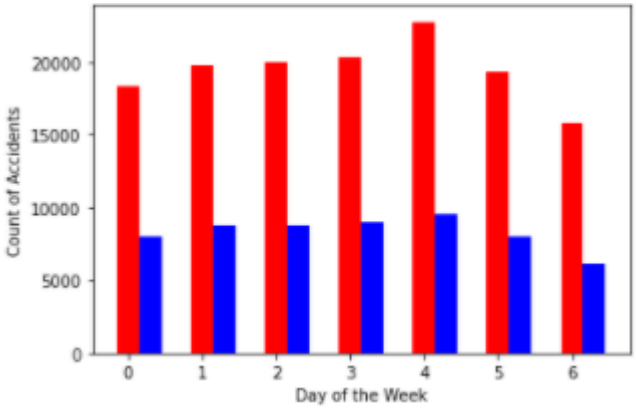
1. October 2020 has the most number of crashes in the year.
2. Number of crashed further decreases in the months of November and then December 2020

3. Hours in 24-hour format



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

4. Day of Week



1. 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%.

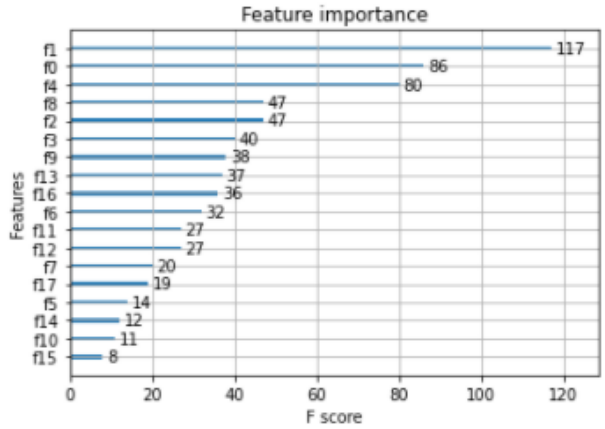
® The Gradient Boost classifier predicts the Severity of the accident (Injury Collision, Property Damage Only Collision) up to ~76.3% accuracy.

® 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]
```



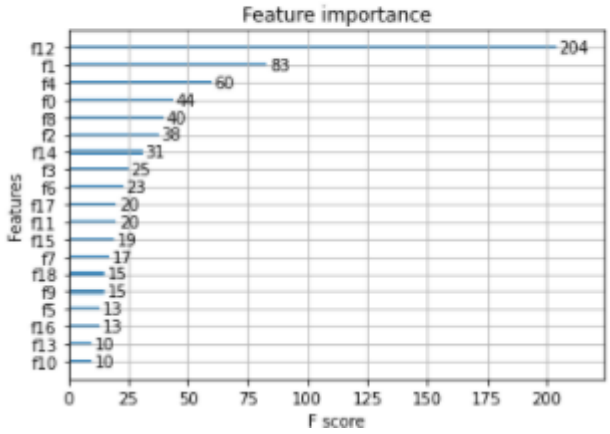
The most important feature was:

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:

- Collision Type
- Person Count
- Vehicle Count

3. 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-week 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.