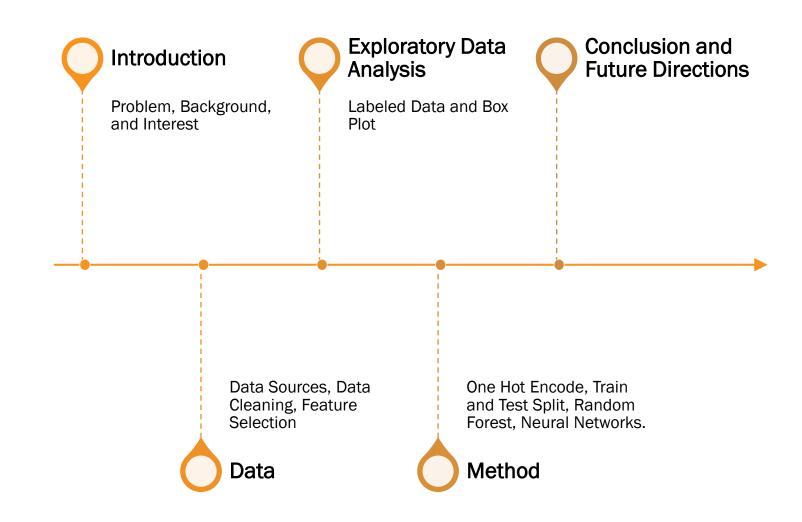


# Table of Contents



## Introduction

### Background

There are many uncertainties on the road that could happened at any time to anyone. Those uncertainties could lead to a traffic accident. For example, bad weather, speed, location, and human error determine how the accident is. But is there any correlation between all those uncertainties factors with the severity of an accident? Imagine, if we could predict the severity of an accident by the location, weather, road, time, etc., then the driver could be more aware or more careful or take another road or cancel the plan.

### 2. Problem

The projects aim to predict the severity of an accident based on the road condition, weather, time, etc.

### 3. Interest

Government, traffic police, and driver could use the data to predict the severity of traffic accident and decide what to do faster.

### Data

### 1. Data Sources

The data that is used in this project is collision data from Seattle Government from 2004 till present. The data contains 38 features, 194673 rows, with a categorical label that consists of 1 and 2 where 1 represents property damage and 2 represents injury. For more information about the data, visit <a href="here">here</a>.

### 2. Feature Selection

In this part, I delete some features and most of them because have a lot of NaN values, a description that has already been represent in other features, and irrelevant based on the correlation value.

### Data

### 3. Data Cleaning

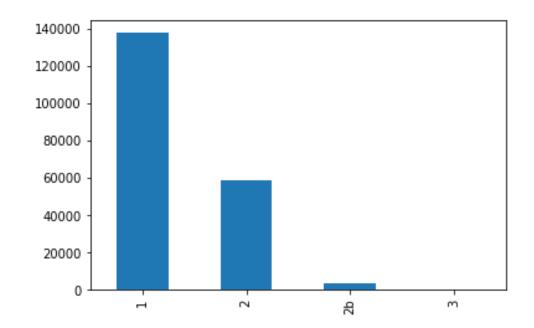
There are several problems with the dataset and the most important one is the NaN values because we cannot analysis the data with NaN values in it. In this section, the data in certain columns will be deleted, filled, or replace based on its value.

First the filled data. The columns that consist of NaN data in categories will be filled with 'unknown' because I will transform the categories text data to one hot encoding. Second is the deleted data. For latitude and longitude data, there are about 5,000 NaN values. Since I can't replace the data with anything, I decided to delete the row. Third is the replaced data. Some features contain some strange values. Like 'Underinfl' consists of 'Y', 'N', nan, '0', and '1', so I changed '0' and '1' consecutively to 'N' and 'Y'.

## Exploratory Data Analysis

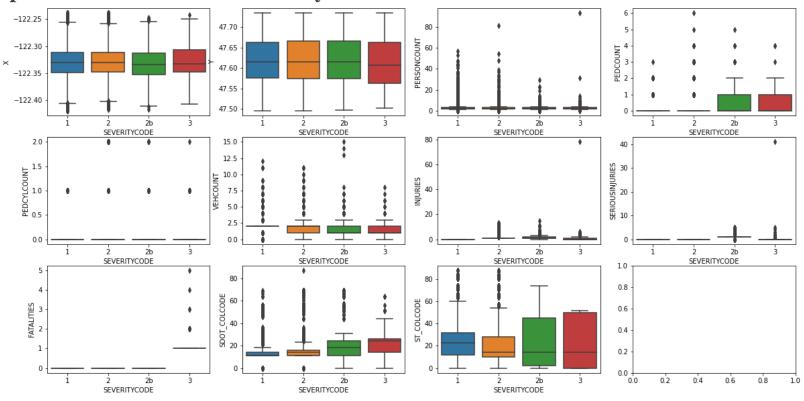
### 1. Labeled Data

Categories	Description	Count	
1	Property Damage	137776	
2	Injury	58842	
2b	Serious Injury	3111	
3	Fatality	352	



## Exploratory Data Analysis

### 2. Relationship Between Features and Severity Code



## Method

### 1. One Hot Encode

This method is to transform a categorical data to several columns of data with 0 and 1 values. Since the data has a lot of categorical features, this method is useful. After the data is transformed, the features of data became 58 features in total.

### 2. Split Train Test

Split train and test data are a method to avoid overfitting. I am using a scikit learn package with test size equals to 0.65 and shuffle rows is true.

## Random Forest Classifier

Categories	Precision	Recall	F1 Score
1	1	1	1
2	1	1	1
2b	0.99	0.99	0.99
3	1	0.85	0.92
Accuracy			1
Macro avg	1	0.96	0.98
Weighted avg	1	1	1

## Neural Networks

Categories	Precision	Recall	F1 Score
1	1	1	1
2	1	1	1
2b	1	0.99	0.99
3	1	0.99	1
Accuracy			1
Macro avg	1	0.99	1
Weighted avg	1	1	1

## Conclusion & Future Directions

#### 1. Conclusion

In this project I analyzed a data of severity of traffic accidents at Seattle from 2004 till present using Random Forest and Neural Networks. Based on the classification report table, shown that neural networks gave a better result than random forest classifier especially for category '3'. But in conclusions, both methods are given a good result to predict future traffic accidents.

### 2. Future Directions

In this project, I am only using two classification models, however there are still many models that I haven't tried that might fit best for this problem.