# **Data Understanding**

This project is based on the data set provided by Seattle Police Department and recorded by Traffic Records of the City of Seattle City. The purpose of analyzing this data set is to find the conditions that will lead to car collisions (84 types of collisions).

The data set consist 38 columns and 194,673 rows,

The dependent variable is "SEVERITYCODE" and for simplicity we use "WEATHER"," ROADCOND" and "LIGHTCOND" as independent variables.

Before starting data analysis, we need to pre-process the data set due to the existence of null values in some records and imbalance of "SEVERITYCODE".

### 1.1. Dependent variable "SEVERITYCODE"

The "SEVERITYCODE" stated the severity of the collision into the following 5 baskets using corresponded codes in the data set:

- I. Fatality-3
- II. Serious injury-2b
- III. Injury-2
- IV. Prop damage-1
- V. Unknown-0

After using value\_counts(), I find there is only level 1 prop damage and level 2 injury in our data set.

#### 1.2. Possible independent variables Within the 38 columns:

- 1. 2 of them are dependent variable "SEVERITYCODE"
- 2. 2 of them are coordinates
- 3. 2 of them are time
- 4. 29 of them are either code or unrelated information
- 5. The rest 3 of them are useful in this study

After examining all variables, I find that the useful independent variables are:

WEATHER, ROADCOND and LIGHTCOND.

## 1.3. Data Pre-processing (using python)

#### 1.3.1. Missing Data

By using isnull().sum(), I find that my independent variables have null values. By using value\_counts(), I find there is an 'Unknown' value which should be treated as missing value.

So, I changed 'Unknown' to null and calculated the percentage of null values to decide what should I do with null values.

## null count null percentage

SEVERITYCODE	0	0.000000
WEATHER	20172	0.103620
ROADCOND	20090	0.103199
LIGHTCOND	18643	0.095766

Since WEATHER, ROADCOND and LIGHTCOND are all categorical data

and the null percentages are lower than 20%, I decide to use the mode to replace the null values.

Also, I deleted columns with value 'Others' due to it is ambiguous and its low percentage.

### 1.3.2.Balancing Data

After dealing with the missing data, I find that label is imbalanced.

```
#Imbalanced Data dfn['SEVERITYCODE'].value_counts()
```

1 135525 2 57981

Name: SEVERITYCODE, dtype: int64

So, I used resample() function for down-sampling to fix this.

```
#create new dataset, Balanced df
bdf=[dfn_majority_down, dfn_minority]
bdf=pd. concat(bdf)
bdf['SEVERITYCODE'].value_counts()
```

5798157981

Name: SEVERITYCODE, dtype: int64

## 1.3.3. Turning categorical variables into quantitative variables

By using pd.get\_dummies() we get our new numerical variables. There are 24 columns in our new dataframe.

#### 1.3.4. Data Normalization

I split the data into training set (70%) and test set (30%) and normalized training set.

```
# normalization
s = StandardScaler()
X_train_scale = s.fit_transform(X_train)
X_test_scale = s. transform(X_test)
X_train_scale
array([[-0.01530107, 0.70421448, -0.05535852, ..., -0.11796075,
         0.66479142, -0.18107437],
       [-0.01530107, 0.70421448, -0.05535852, ..., -0.11796075,
         0.66479142, -0.18107437],
       [-0.01530107, 0.70421448, -0.05535852, ..., -0.11796075,
         0.66479142, -0.18107437],
       [-0.01530107, -1.42002193, -0.05535852, ..., -0.11796075,
        -1.50423121, -0.18107437],
       [-0.01530107, 0.70421448, -0.05535852, ..., -0.11796075,
         0.66479142, -0.18107437],
       [-0.01530107, -1.42002193, -0.05535852, ..., -0.11796075,
         0.66479142, -0.18107437]])
```