Introduction/Business Problem:

The Seattle government is going to prevent avoidable car accidents by employing methods that alert drivers, health system, and police to remind them to be more careful in critical situations. In most cases, not paying enough attention during driving, abusing drugs and alcohol or driving at very high speed are the main causes of occurring accidents that can be prevented by enacting harsher regulations. Apart from these , weather, visibility, or road conditions are the major uncontrollable factors that can be prevented by revealing hidden patterns in the data and announcing warning to the local government, police and drivers on the targeted roads.

The target audience of the project is local Seattle government, police, rescue groups, and last but not least, car insurance institutes. The model and its results are going to provide some advice for the target audience to make insightful decisions for reducing the number of accidents and injuries for the city.

Using the collisions data provided by Coursera for the final capstone course, I wanted to look into the severity of car accidents that are due to bad weather conditions. How many car accidents are caused due to bad weather conditions? This data will bring awareness to people to drive extra cautiously during bad weather!

Data

The data was collected by the Seattle Police Department and Accident Traffic Records Department from 2004 to present.

The data consists of 37 independent variables and 194,673 rows. The dependent variable, “SEVERITYCODE”, contains numbers that correspond to different levels of severity caused by an accident from 0 to 4.

Severity codes are as follows:

0: Little to no Probability (Clear Conditions)

1: Very Low Probability — Chance or Property Damage

2: Low Probability — Chance of Injury

3: Mild Probability — Chance of Serious Injury

4: High Probability — Chance of Fatality

Furthermore, because of the existence of null values in some records, the data needs to be preprocessed before any further processing.

Data Preprocessing

We can see that dataset in the original form is not ready for data analysis. In order to prepare the data, first, we need to drop the non-relevant columns. In addition, most of the features are of object data types that need to be converted into numerical data types. After analyzing the data set, I have decided to focus on only four features, severity, weather conditions, road conditions, and light conditions, among others.

To get a good understanding of the dataset, I have checked different values in the features. The results show, the target feature is imbalance, so we use a simple statistical technique to balance it.

```
[19]: df["SEVERITYCODE"].value_counts()

[19]: 1    136485
      2     58188
      Name: SEVERITYCODE, dtype: int64
```

As you can see, the number of rows in class 1 is almost three times bigger than the number of rows in class 2. It is possible to solve the issue by down sampling the class 1.

```
21]: from sklearn.utils import resample
```

```
25]: df_maj= df[df.SEVERITYCODE==1]
     df_min= df[df.SEVERITYCODE==2]

     df_maj_dsample= resample(df_maj,
                              replace=False,
                              n_samples=58188,
                              random_state=123)

     balanced_df= pd.concat([df_maj_dsample,df_min])

     balanced_df.SEVERITYCODE.value_counts()

25]: 2    58188
     1    58188
     Name: SEVERITYCODE, dtype: int64
```

Methodology

For implementing the solution, I have used Github as a repository and running Jupyter Notebook to preprocess data and build Machine Learning models. For coding, I have used Python and its popular packages such as Pandas, NumPy and Sklearn.

Once I have loaded the data into Pandas Dataframe, I used '*dtypes*' attribute to check the feature names and their data types. Then I have selected the most important features to predict the severity of accidents in Seattle. Among all the features, the following features have the most influence in the accuracy of the predictions:

- "WEATHER",
- "ROADCOND",
- "LIGHTCOND"

Also, as I mentioned earlier, “SEVERITYCODE” is the target variable.

I have run a value count on road (‘ROADCOND’) and weather condition (‘WEATHER’) to get ideas of the different road and weather conditions. I also have run a value count on light condition (’LIGHTCOND’), to see the breakdowns of accidents occurring during the different light conditions. The results can be seen below:

```
[26]: df["WEATHER"].value_counts()

[26]: Clear                       111135
      Raining                      33145
      Overcast                     27714
      Unknown                      15091
      Snowing                        907
      Other                          832
      Fog/Smog/Smoke                 569
      Sleet/Hail/Freezing Rain       113
      Blowing Sand/Dirt               56
      Severe Crosswind                25
      Partly Cloudy                    5
      Name: WEATHER, dtype: int64

[27]: df["ROADCOND"].value_counts()

[27]: Dry               124510
      Wet                47474
      Unknown            15078
      Ice                 1209
      Snow/Slush          1004
      Other                132
      Standing Water       115
      Sand/Mud/Dirt         75
      Oil                   64
      Name: ROADCOND, dtype: int64
```

```
[28]: df["LIGHTCOND"].value_counts()
```

```
[28]: Daylight                    116137
      Dark - Street Lights On      48507
      Unknown                      13473
      Dusk                          5902
      Dawn                          2502
      Dark - No Street Lights       1537
      Dark - Street Lights Off      1199
      Other                          235
      Dark - Unknown Lighting         11
      Name: LIGHTCOND, dtype: int64
```

Analyzing data types of each column:

```
73]: df.info() #Analysing data types of each column

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194673 entries, 0 to 194672
Data columns (total 68 columns):
 #   Column                                                    Non-Null Count   Dtype
---  ------                                                    --------------   -----
 0   SEVERITYCODE                                              194673 non-null  int64
 1   X                                                         194673 non-null  float64
 2   Y                                                         194673 non-null  float64
 3   INCKEY                                                    194673 non-null  int64
 4   PERSONCOUNT                                               194673 non-null  int64
 5   PEDCOUNT                                                  194673 non-null  int64
 6   PEDCYLCOUNT                                               194673 non-null  int64
 7   VEHCOUNT                                                  194673 non-null  int64
 8   SDOT_COLCODE                                              194673 non-null  int64
 9   SEGLANEKEY                                                194673 non-null  int64
 10  CROSSWALKKEY                                              194673 non-null  int64
 11  JUNCTIONTYPE_At Intersection (but not related to intersection)  194673 non-null  uint8
 12  JUNCTIONTYPE_At Intersection (intersection related)      194673 non-null  uint8
 13  JUNCTIONTYPE_Driveway Junction                            194673 non-null  uint8
 14  JUNCTIONTYPE_Mid-Block (but intersection related)        194673 non-null  uint8
 15  JUNCTIONTYPE_Mid-Block (not related to intersection)     194673 non-null  uint8
 16  JUNCTIONTYPE_Ramp Junction                                194673 non-null  uint8
 17  JUNCTIONTYPE_Unknown                                      194673 non-null  uint8
 18  LIGHTCOND_Dark - No Street Lights                         194673 non-null  uint8
 19  LIGHTCOND_Dark - Street Lights Off                        194673 non-null  uint8
 20  LIGHTCOND_Dark - Street Lights On                         194673 non-null  uint8
 21  LIGHTCOND_Dark - Unknown Lighting                         194673 non-null  uint8
```

```
 41  COLLISIONTYPE_Left Turn                                     194673 non-null  uint8
 42  COLLISIONTYPE_Other                                         194673 non-null  uint8
 43  COLLISIONTYPE_Parked Car                                    194673 non-null  uint8
 44  COLLISIONTYPE_Pedestrian                                    194673 non-null  uint8
 45  COLLISIONTYPE_Rear Ended                                    194673 non-null  uint8
 46  COLLISIONTYPE_Right Turn                                    194673 non-null  uint8
 47  COLLISIONTYPE_Sideswipe                                     194673 non-null  uint8
 48  WEATHER_Blowing Sand/Dirt                                   194673 non-null  uint8
 49  WEATHER_Clear                                               194673 non-null  uint8
 50  WEATHER_Fog/Smog/Smoke                                      194673 non-null  uint8
 51  WEATHER_Other                                               194673 non-null  uint8
 52  WEATHER_Overcast                                            194673 non-null  uint8
 53  WEATHER_Partly Cloudy                                       194673 non-null  uint8
 54  WEATHER_Raining                                             194673 non-null  uint8
 55  WEATHER_Severe Crosswind                                    194673 non-null  uint8
 56  WEATHER_Sleet/Hail/Freezing Rain                            194673 non-null  uint8
 57  WEATHER_Snowing                                             194673 non-null  uint8
 58  WEATHER_Unknown                                             194673 non-null  uint8
 59  HITPARKEDCAR_N                                              194673 non-null  uint8
 60  HITPARKEDCAR_Y                                              194673 non-null  uint8
 61  ADDRTYPE_Alley                                              194673 non-null  uint8
 62  ADDRTYPE_Block                                              194673 non-null  uint8
 63  ADDRTYPE_Intersection                                       194673 non-null  uint8
 64  UNDERINFL_0                                                 194673 non-null  uint8
 65  UNDERINFL_1                                                 194673 non-null  uint8
 66  UNDERINFL_N                                                 194673 non-null  uint8
 67  UNDERINFL_Y                                                 194673 non-null  uint8
dtypes: float64(2), int64(9), uint8(57)
```

74]:
```
df.nunique() #Analysing number of unique values per column
```

74]:
```
SEVERITYCODE                 2
X                        23563
Y                        23839
INCKEY                  194673
PERSONCOUNT                 47
                         ...
ADDRTYPE_Intersection        2
UNDERINFL_0                  2
UNDERINFL_1                  2
UNDERINFL_N                  2
UNDERINFL_Y                  2
Length: 68, dtype: int64
```

5]:
```
df.isna().sum() #Finding total number of missing values in the data.
```

5]:
```
SEVERITYCODE             0
X                        0
Y                        0
INCKEY                   0
PERSONCOUNT              0
                        ..
ADDRTYPE_Intersection    0
UNDERINFL_0              0
UNDERINFL_1              0
UNDERINFL_N              0
UNDERINFL_Y              0
Length: 68, dtype: int64
```

After balancing SEVERITYCODE feature, and standardizing the input feature, the data has been ready for building machine learning models.

I have employed three machine learning models: Logistic regression

Decision Tree random forest After importing necessary packages and splitting preprocessed data into test and train sets, for each machine learning model, I have built and evaluated the model and shown the results as follow:

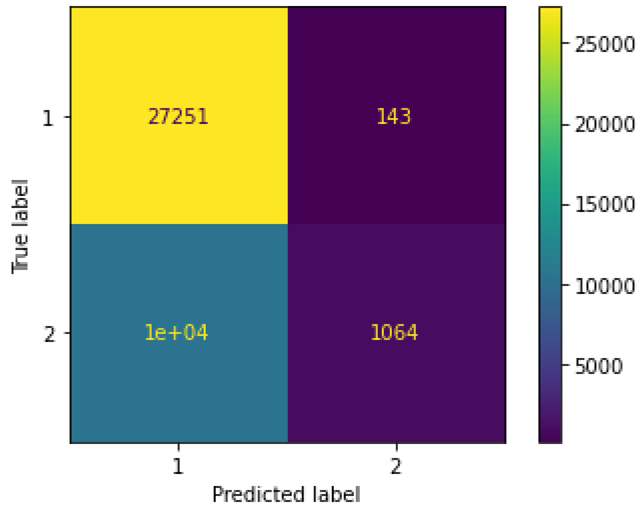
```
### Using Logistic Regression Model
```

[67]:

```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import plot_confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report


LR = LogisticRegression(max_iter=100000)

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.20)

LR.fit(X_train,y_train)
score = LR.score(X_test, y_test)
print(score)

#y_pred = LR.predict(X_test)


plot_confusion_matrix(LR,X_test,y_test)

y_pred = LR.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
0.7272377038654168
              precision    recall  f1-score   support
```

```
0.7272377038654168
              precision    recall  f1-score   support

           1       0.72      0.99      0.84     27394
           2       0.88      0.09      0.17     11541

    accuracy                           0.73     38935
   macro avg       0.80      0.54      0.50     38935
weighted avg       0.77      0.73      0.64     38935
```

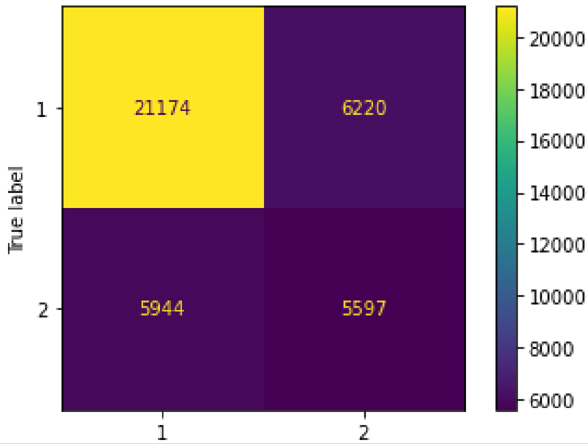


Using Decision Tree Classifier

```
9]: from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import  cross_val_score

DT = DecisionTreeClassifier()

DT.fit(X_train,y_train)
score_1 = DT.score(X_test, y_test)
print(score_1)
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(DT,X_test,y_test)

y_pred_1 = DT.predict(X_test)

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_1))
```

```
0.6875818672145885
              precision    recall  f1-score   support

           1       0.78      0.77      0.78     27394
           2       0.47      0.48      0.48     11541
```

```
0.6875818672145885
              precision    recall  f1-score   support

           1       0.78      0.77      0.78     27394
           2       0.47      0.48      0.48     11541

    accuracy                           0.69     38935
   macro avg       0.63      0.63      0.63     38935
weighted avg       0.69      0.69      0.69     38935
```



Saving completed

Mode

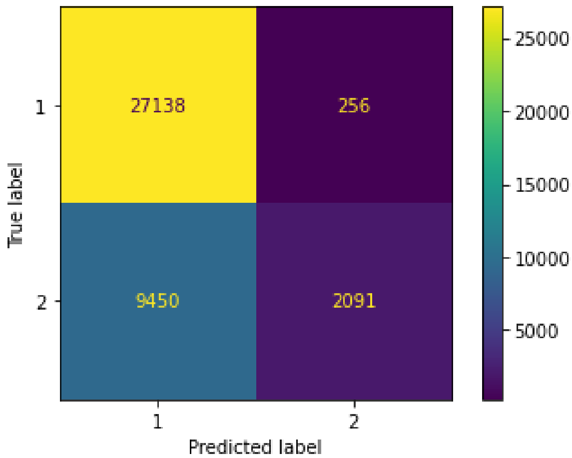
Using Random Forest Classifier

0]:

```python
from sklearn.ensemble import RandomForestClassifier

random_forest = RandomForestClassifier(n_estimators=100, max_depth=2, random_state=0)

random_forest.fit(X_train,y_train)
score_2 = random_forest.score(X_test, y_test)
print(score_2)

plot_confusion_matrix(random_forest,X_test,y_test)


y_pred_2 = random_forest.predict(X_test)

print(classification_report(y_test, y_pred_2))
```

```
0.7507127263387697
              precision    recall  f1-score   support

           1       0.74      0.99      0.85     27394
           2       0.89      0.18      0.30     11541

    accuracy                           0.75     38935
   macro avg       0.82      0.59      0.57     38935
weighted avg       0.79      0.75      0.69     38935
```

1	0.74	0.99	0.85	27394
2	0.89	0.18	0.30	11541
accuracy			0.75	38935
macro avg	0.82	0.59	0.57	38935
weighted avg	0.79	0.75	0.69	38935



Results and Evaluations

Conclusion

Based on the dataset provided for this capstone from weather, road, and light conditions pointing to certain classes, we can conclude that particular conditions have a somewhat impact on whether or not travel could result in property damage (class 1) or injury (class 2)