Car Accident Severity Prediction

Predicting car accident is valuable for public health and insurance company

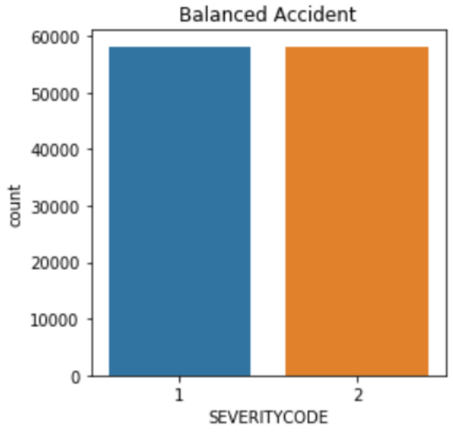
- In order to reduce the number of car accident, a model must be developed in order to anticipate by making prediction of car accident severity.
- This prediction will be used to alert the driver to be more careful when conditions are gathered for an accident.
- An insurance company could use this model as a service to alert their customer, thus we can reduce the car accident and the company can make more benefit by saving compensation due to car accident.

DATA UNDERSTANDING

- Dataset of 194673 records occurring between 2004 and 2020 and having 37 columns describing the details of each accident.
- Our target is to predict the severity of an accident using dependent variable 'SEVERITYCODE' with two values (1 or 2) which correspond to the severity of the collision. For the independent variable we will use the weather conditions, road conditions, light conditions, locations and speeding which will be categorized and converted to code for each category during the data preparation.

SEVERITYCODE	WEATHER	ROADCOND	LIGHTCOND	LOCATION	SPEEDING	WEATHER_CODE	ROADCOND_CODE	LIGHTCOND_CODE	LOCATION_CODE	SPEEDING_CODE
2	Overcast	Wet	Daylight	5TH AVE NE AND NE 103RD ST	NaN	4	8	5	8793	-1
1	Raining	Wet	Dark - Street Lights On	AURORA BR BETWEEN RAYE ST AND BRIDGE WAY N	NaN	6	8	2	10707	-1
1	Overcast	Dry	Daylight	4TH AVE BETWEEN SENECA ST AND UNIVERSITY ST	NaN	4	0	5	8049	-1

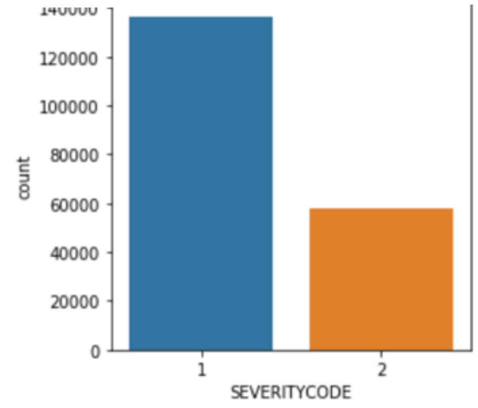
```
Out[23]: SEVERITYCODE         int64
         WEATHER           category
         ROADCOND          category
         LIGHTCOND         category
         LOCATION          category
         SPEEDING          category
         WEATHER_CODE          int8
         ROADCOND_CODE         int8
         LIGHTCOND_CODE        int8
         LOCATION_CODE        int16
         SPEEDING_CODE         int8
         dtype: object
```

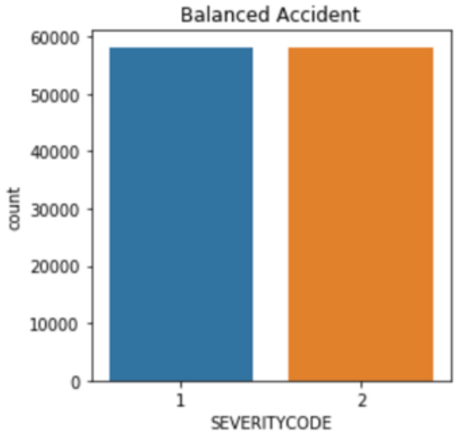


HE DATA

ased model, we will randomly balance CODE where records with severity 1 is d with severity 2.

Balanced record





2. Defining the independent variable and the target variable:

```
X = np.asarray(study[['WEATHER_CODE','ROADCOND_CODE','LIGHTCOND_CODE', 'LOCATION_CODE', 'SPEEDING_CODE']])
X[0:5]
```

```
array([[ 4.0000e+00,  8.0000e+00,  5.0000e+00,  8.7930e+03, -1.0000e+00],
       [ 6.0000e+00,  8.0000e+00,  2.0000e+00,  1.0707e+04, -1.0000e+00],
       [ 4.0000e+00,  0.0000e+00,  5.0000e+00,  8.0490e+03, -1.0000e+00],
       [ 1.0000e+00,  0.0000e+00,  5.0000e+00,  4.6470e+03, -1.0000e+00],
       [ 6.0000e+00,  8.0000e+00,  5.0000e+00,  2.2787e+04, -1.0000e+00]])
```

```
y = np.asarray(study['SEVERITYCODE'])
y[0:5]
```

```
array([2, 1, 1, 1, 2])
```

3. Normalizing the data and splitting training/test set:

```
X = preprocessing.StandardScaler().fit(X).transform(X)
X[0:5]
```

```
array([[ 0.35364615,  1.50545441,  0.3912104 , -0.45743913, -0.22440165],
       [ 1.04520829,  1.50545441, -1.18714134, -0.17720325, -0.22440165],
       [ 0.35364615, -0.68713674,  0.3912104 , -0.56637095, -0.22440165],
       [-0.68369706, -0.68713674,  0.3912104 , -1.06447047, -0.22440165],
       [ 1.04520829,  1.50545441,  0.3912104 ,  1.59147464, -0.22440165]])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=4)
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (136271, 5) (136271,)
Test set: (58402, 5) (58402,)
```

BUILDING THE MODEL

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
LR
```

```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='liblinear',
          tol=0.0001, verbose=0, warm_start=False)
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion="entropy", max_depth=4)
dt.fit(X_train, y_train)
dt
```

```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=4,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

EVALUATING THE MODEL

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
LR
```

```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='liblinear',
          tol=0.0001, verbose=0, warm_start=False)
```

```
yhat_lr = LR.predict(X_test)
yhat_lr[0:5]
```

```
array([1, 1, 1, 1, 1])
```

```
yhat_prob = LR.predict_proba(X_test)
yhat_prob
```

```
array([[0.73023109, 0.26976891],
       [0.68054332, 0.31945668],
       [0.65708122, 0.34291878],
       ...,
       [0.58469252, 0.41530748],
       [0.8187009 , 0.1812991 ],
       [0.68958664, 0.31041336]])
```

```
from sklearn.metrics import jaccard_similarity_score
from sklearn.metrics import f1_score
from sklearn.metrics import log_loss
```

```
print("Jaccard: ",jaccard_similarity_score(y_test, yhat_lr))
print("F1 Score: ",f1_score(y_test,yhat_lr,average='weighted'))
print("LogLoss :",log_loss(y_test, yhat_prob))
```

```
Jaccard:  0.7030581144481354
F1 Score:  0.5812429210363583
LogLoss : 0.6003036801500582
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion="entropy", max_depth=4)
dt.fit(X_train, y_train)
dt
```

```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=4,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

```
yhat_dt = dt.predict(X_test)
yhat_dt[0:5]
```

```
array([1, 1, 1, 1, 1])
```

```
print("F1 Score: ",f1_score(y_test,yhat_dt,average='weighted'))
print("Jaccard: ",jaccard_similarity_score(y_test, yhat_dt))
```

```
F1 Score:  0.5809904188654375
Jaccard:  0.7034519365775145
```

	LOGISTIC REGRESSION	DECISION TREE
LOG LOSS	0.60	
F1 SCORE	0.58	0.58
JACCARD	0.70	0.70

CONCLUSION

In conclusion we build model based on the location, speeding, weather, road and light conditions which can help the decision making of alerting motorists and emergency services call handlers.

This model can be used by and insurance company to alert customer about risk of accident which can save life, improve public health and make benefit for the company by saving compensations.


THANKS