

Applied Data Science Capstone Project –

on

Car accident severity

Final Report

By

Shengyu Wu

Table of Contents

1. Introduction

2. Data

3. Methodology

4. Results

5. Discussion

6. Conclusion

1.Introduction

Car accidents have a significant impact on individuals, their families and the nation. It is always one of the top issues in society. According to NSC, in US, an estimated 38,800 people lost their lives to car crashes in 2019 – a 2% decline from 2018 (39,404 deaths) and a 4% decline from 2017 (40,231 deaths). About 4.4 million people were injured seriously enough to require medical attention in crashes last year. Therefore, if there was an algorithm that can predict severity of car accidents, it could be efficient and faster for police to arrive the accident scene and give right help.

This project is attempting to classify varies factors that will cause the accidents and predict the level of severity by leveraging data collected from different kinds of car accidents.

2.Data

For this dataset, we can see there are 38 different attributes, some of them are relatively not important to analyze the car accident severity. As a result, we drop them to emphasize the main factors. For data cleaning, miss values will be replaced by 'other' or 'unknown' based on the information in each column.

The dataset we used can be found at <https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv>

After loading data from csv file to data frame, we do main feature selection:

```
j): df1 = df.drop(["SEVERITYCODE.1", "OBJECTID", "INCKEY", "COLDETKEY", "REPORTNO", "STATUS", "ADDRTYPE", "INTKEY",
"EXCEPTRSCODE", "EXCEPTRSDISC", "PEDCYLCOUNT", "PEDCOUNT", "SDOT_COLCODE", "SDOT_COLDESC", "ST_COLCODE", "SEGLANEKEY", "CROSSWALKKEY", "SDOTCOLN",
"INCDATE", "INCDTMM", "PEDROWNOTGRNT", "UNDERINFL", "HITPARKEDCAR", "ST_COLDESC", "SEVERITYDESC"], axis=1)
df1.head()
```

Out[6]:

	SEVERITYCODE	X	Y	LOCATION	COLLISIONTYPE	PERSONCOUNT	VEHCOUNT	JUNCTIONTYPE	INATTENTIONIND	WEATHER	ROADCOND	LIGHT
0	2	-122.323148	47.703140	5TH AVE NE AND NE 103RD ST	Angles	2	2	At Intersection (intersection related)	NaN	Overcast	Wet	
1	1	-122.347294	47.647172	AURORA BR BETWEEN RAYE ST AND BRIDGE WAY N	Sideswipe	2	2	Mid-Block (not related to intersection)	NaN	Raining	Wet	Dar
2	1	-122.334540	47.607871	4TH AVE BETWEEN SENECA ST AND UNIVERSITY ST	Parked Car	4	3	Mid-Block (not related to intersection)	NaN	Overcast	Dry	
3	1	-122.334803	47.604803	2ND AVE BETWEEN MARION ST AND MADISON ST	Other	3	3	Mid-Block (not related to intersection)	NaN	Clear	Dry	
4	2	-122.306426	47.545739	SWIFT AVE S AND SWIFT AV OFF RP	Angles	2	2	At Intersection (intersection related)	NaN	Raining	Wet	

Then we observed that there are too many missing value in each columns, so we replace them for data cleaning:

```
]: df1['ROADCOND'].replace(np.NaN, "Unknown", inplace=True)

]: df1['LIGHTCOND'].replace(np.NaN, "Unknown", inplace=True)

]: df1['SPEEDING'].replace(np.NaN, "N", inplace=True)

]: avg_X = df1["X"].astype("float").mean(axis=0)
   df1['X'].replace(np.NaN, avg_X, inplace=True)

]: avg_Y = df1["Y"].astype("float").mean(axis=0)
   df1['Y'].replace(np.NaN, avg_Y, inplace=True)

]: df1['LOCATION'].replace(np.NaN, "Unknown", inplace=True)

]: df1.isna().sum()

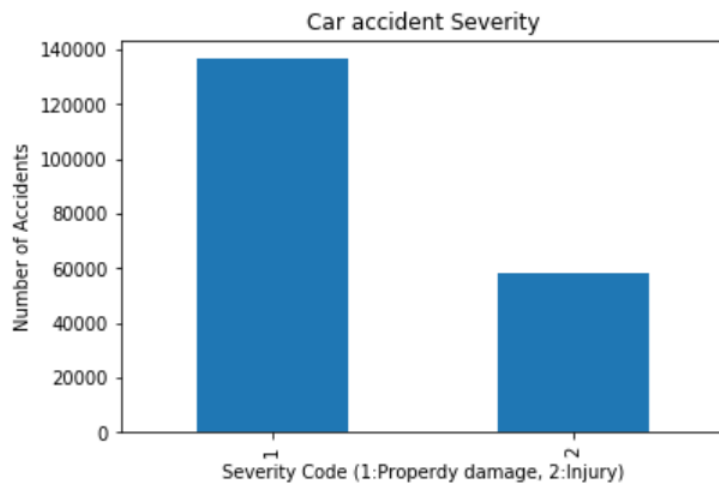
Out[25]: SEVERITYCODE    0
         X              0
         Y              0
         LOCATION      0
         COLLISIONTYPE  0
         PERSONCOUNT  0
         VEHCOUNT     0
         JUNCTIONTYPE  0
         INATTENTIONIND 0
         WEATHER        0
         ROADCOND       0
         LIGHTCOND      0
         SPEEDING       0
         dtype: int64
```

3.Methodology

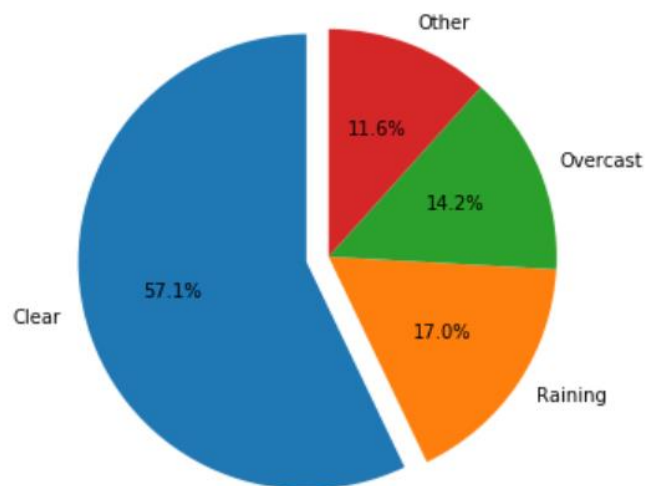
In this approach, supervised learning will be used to map inputs to outputs as the dataset is labelled. The question we defined is "Are there any factors having bigger effect on causing the car accident and increasing the severity?" Since this is a Yes/No question, we will use 3 classification algorithms to create machine learning models:

- Logistic Regression
- K-Nearest Neighbors (KNN)
- Decision Tree

For data visualization, we plot bar chart for different types of accident and pie charts for relationships between relative features and the car severity.



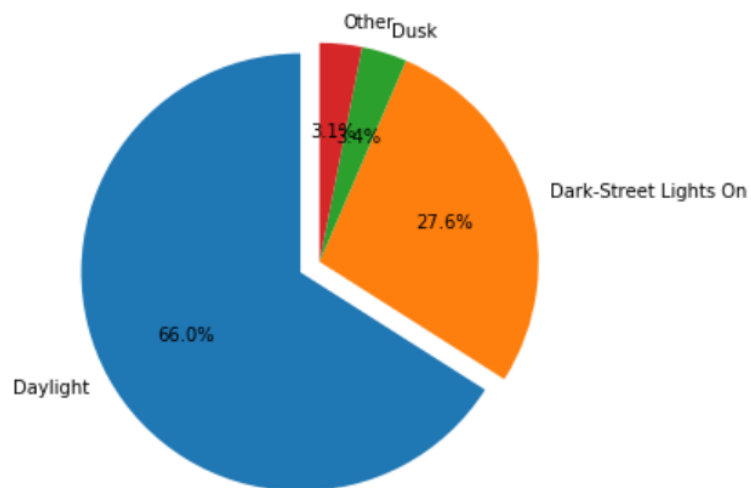
Effect of Weather Conditions on the Car Severity



```
6]: df_w = df1['WEATHER'].value_counts()
df_w
```

```
Out[26]: Clear      111135
         Raining    33145
         Overcast   27714
         Unknown    20172
         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
```

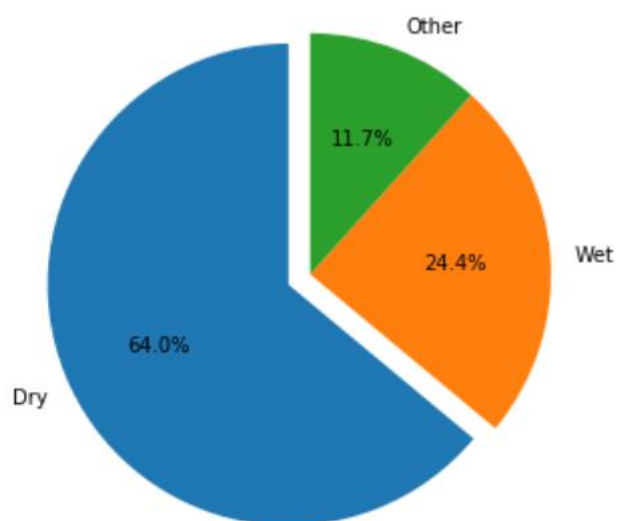
Effect of Light Conditions on the Car Severity



```
|: df_1 = df1['LIGHTCOND'].value_counts()
df_1
```

```
Out[28]: Daylight      116137
         Dark - Street Lights On  48507
         Unknown      18643
         Dusk         5902
         Dawn         2502
         Dark - No Street Lights  1537
         Dark - Street Lights Off  1199
         Other         235
         Dark - Unknown Lighting  11
         Name: LIGHTCOND, dtype: int64
```

Effect of Road Conditions on the Car Severity



```
] : df_r = df1['ROADCOND'].value_counts()  
df_r
```

```
Out[31]: Dry          124510  
Wet          47474  
Other        20222  
Ice          1209  
Snow/Slush   1004  
Standing Water  115  
Sand/Mud/Dirt  75  
Oil          64  
Name: ROADCOND, dtype: int64
```

3.Results

Import scikit-learn library, then we can use an evaluation approach called Train/Test Split.

```
] : from sklearn.model_selection import train_test_split  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4)  
print('Train set:', X_train.shape, y_train.shape)  
print('Test set:', X_test.shape, y_test.shape)
```

```
Train set: (155738, 11) (155738,)  
Test set: (38935, 11) (38935,)
```

Logistic Regression


```
] : LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)  
LR
```

```
Out[45]: 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.predict(X_test)  
print("Logistic Regresion's Accuracy: ", metrics.accuracy_score(y_test, yhat))
```

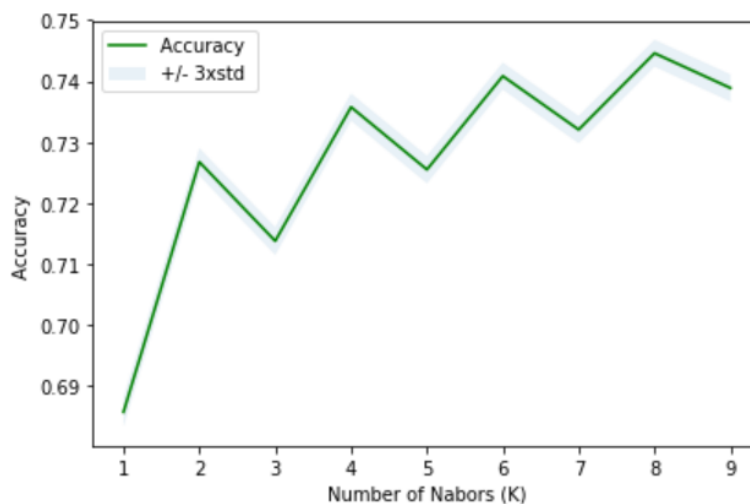
```
Logistic Regression's Accuracy: 0.7358674714267369
```

K nearest neighbor (KNN)

```
8]:  #Finding the best k  
Ks = 10  
mean_acc = np.zeros((Ks-1))  
std_acc = np.zeros((Ks-1))  
ConfusionMx = [];  
for n in range(1, Ks):  
  
    #Train Model and Predict  
    knNeigh = KNeighborsClassifier(n_neighbors = n).fit(X_train, y_train)  
    yhat1 = knNeigh.predict(X_test)  
  
    mean_acc[n-1] = metrics.accuracy_score(y_test, yhat1);  
  
    std_acc[n-1] = np.std(yhat1==y_test)/np.sqrt(yhat1.shape[0])  
  
mean_acc
```

Out[48]: array([0.68573263, 0.72674971, 0.71377938, 0.73573905, 0.7254912 ,
0.74082445, 0.73204058, 0.74457429, 0.73887248])

```
|:  plt.plot(range(1, Ks), mean_acc, 'g')  
plt.fill_between(range(1, Ks), mean_acc - 1 * std_acc, mean_acc + 1 * std_acc, alpha=0.10)  
plt.legend(('Accuracy ', '+/- 3xstd'))  
plt.ylabel('Accuracy')  
plt.xlabel('Number of Nabors (K)')  
plt.tight_layout()  
plt.show()
```



Decision Tree

```
0]: DTree = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
DTree.fit(X_train, y_train)
```

```
Out[50]: 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')
```

```
0]: yhat2 = DTree.predict(X_test)
print("DecisionTrees' s Accuracy: ", metrics.accuracy_score(y_test, yhat2))

DecisionTrees' s Accuracy: 0.7520226017721844
```

4.Discussion

Based on the result, it can be considered that if we incorporate with more factors, the accuracy might be higher. In addition, we observed that there are two types of severity, one of them was property damage and another was injury. Since the data was unbalance between these two types, the result would be different after we balance the dataset or predicting severity based only on accidents that cause injury. During modelling, the processing time of KNN was much longer than the other two algorithms and ended with lowest accuracy, Jaccard and F1 score. So Decision Tree and Logistic Regression should be more suitable for this prediction.

5.Conclusion

In this study, we found that more than half of car accidents happen on dry road during clear weather days under daylight, which was the most common condition in daily life. Other than that, more than 15 percent of accidents happen in rainy days on wet and dark street with lights on. Explanatory data analysis has done to give insight into the relationship between the features and the severity of the accidents. For improving the accuracy of this machine learning process, we could collect more data on speeding and add more features that should be relevant to the accidents such as age of driver, years of driving license and so on.