By Yusser Al-Qazwini

IBM Data Science Capstone: Car Accident Severity Report

1. Introduction

Road traffic accidents are a leading cause of death in young people in the Unites States [1][2]. The average number of car accidents in the U.S. is 6 million car accidents every year, and about 6% of those accidents result in at least one death. 3 million people are injured as a result of car accidents and around 2 million drivers experience permanent injuries every year [3].

Analyzing historical vehicle crash data can help us understand the most common factors, including environmental conditions (weather, road surface conditions, and lighting conditions) and their correlation with accident severity. This information can be used to create a prediction model that can be used in conjunction with other Apps like Google Maps to predict the severity of an accident to help drivers be more alert to what can commonly lead to a severe accident. For this project, data from the City of Seattle's' Police Department for the years 2004 until present are utilized.

2. Data

In this project, shared data for Seattle city from Applied Data Science Capstone Project Week1 are used [4]. The dataset consists of 38 columns, 35 columns are the attributes or independent variables. One column* (column A and N) is the dependent or the predicted variable, SEVERITYCODE, and another column (column O) is the description of the code, SEVERITYDESC. The predicted variable has two values: either 1 for property damage only collision or 2 for injury collision. The dataset has more than 194,000 records representing all types of collisions provided by Seattle Police Department and recorded by Traffic record in the timeframe 2004 to 2020. This study aims to predict the impact of environmental conditions of the accidents, namely: WEATHER, ROADCAND, and LIGHTCOND. Brief explanation of each attribute can be found in the file uploaded to Github in the link below.
https://github.com/Yusser89/Coursera_Capstone/blob/master/IBMCapstoneProjectWee1_Part2.pdf

- There is a duplicate, column A and Column N both represent SEVERITYCODE

2.1. Feature Selection

Since the study focuses on environmental conditions of the accidents, we can narrow down the dataset to ‘WEATHER’, ‘ROADCOND’, and ‘LIGHTCOND’.

We begin by importing main libraries followed by loading data file and printing the size of the dataset.

```
In [1]: #import main libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from matplotlib.pyplot import show
        %matplotlib inline
        import seaborn as sns
        !pip -q install folium
        import folium
```

```
In [3]: #load data file and print size of the dataset
        coll_df = pd.read_csv('https://s3.us.cloud-object-storage.appdomain.cloud/cf-
        print('Dimensions of dataset:', coll_df.shape)
```

```
Dimensions of dataset: (194673, 38)
```

The dataset is comprised of 194673 records and 38 features

We can view the columns and first five rows of the dataset to get an idea of the data we are dealing with.

```
In [4]: #View column information
        coll_df.columns
```

```
Out[4]: Index(['SEVERITYCODE', 'X', 'Y', 'OBJECTID', 'INCKEY', 'COLDETKEY', 'REPO
        RTNO',
               'STATUS', 'ADDRTYPE', 'INTKEY', 'LOCATION', 'EXCEPTRSNCODE',
               'EXCEPTRSNDESC', 'SEVERITYCODE.1', 'SEVERITYDESC', 'COLLISIONTYP
        E',
               'PERSONCOUNT', 'PEDCOUNT', 'PEDCYLCOUNT', 'VEHCOUNT', 'INCDATE',
               'INCDTTM', 'JUNCTIONTYPE', 'SDOT_COLCODE', 'SDOT_COLDESC',
               'INATTENTIONIND', 'UNDERINFL', 'WEATHER', 'ROADCOND', 'LIGHTCOND',
               'PEDROWNOTGRNT', 'SDOTCOLNUM', 'SPEEDING', 'ST_COLCODE', 'ST_COLDE
        SC',
               'SEGLANEKEY', 'CROSSWALKKEY', 'HITPARKEDCAR'],
              dtype='object')
```

In [5]:
```
#view the first 5 rows of the dataset
coll_df.head()
```

Out[5]:

	SEVERITYCODE	X	Y	OBJECTID	INCKEY	COLDETKEY	REPORTNO
0	2	-122.323148	47.703140	1	1307	1307	3502005
1	1	-122.347294	47.647172	2	52200	52200	2607959
2	1	-122.334540	47.607871	3	26700	26700	1482393
3	1	-122.334803	47.604803	4	1144	1144	3503937
4	2	-122.306426	47.545739	5	17700	17700	1807429

5 rows × 38 columns

The target variable, 'SEVERITYCODE', is described by 'SEVERITYDESC'. Let's see how many different codes we have.

In [6]:
```
#SEVERITYDESC provides a description of the severity code
print("Road severity description types : ",coll_df['SEVERITYDESC'].value_counts())
```

```
Road severity description types :  Property Damage Only Collision    136485
Injury Collision                                                     58188
Name: SEVERITYDESC, dtype: int64
```

So we have two severity codes: 1 for property damage only collision and 2 for injury collision.

We then narrow down our dataset to the features of interest, namely: 'WEATHER', 'ROADCOND', 'LIGHTCOND'.

In [7]:
```
#Since the study focuses on environmental conditions of the accidents, we can narrow down t
df = coll_df[['SEVERITYCODE', 'SEVERITYDESC', 'WEATHER', 'ROADCOND', 'LIGHTCOND']]
df.head()
```

Out[7]:

	SEVERITYCODE	SEVERITYDESC	WEATHER	ROADCOND	LIGHTCOND
0	2	Injury Collision	Overcast	Wet	Daylight
1	1	Property Damage Only Collision	Raining	Wet	Dark - Street Lights On
2	1	Property Damage Only Collision	Overcast	Dry	Daylight
3	1	Property Damage Only Collision	Clear	Dry	Daylight
4	2	Injury Collision	Raining	Wet	Daylight

In [8]:
```
#print dimension of the new dataset
print('Dimensions of dataset:', df.shape)
```

```
Dimensions of dataset: (194673, 5)
```

2.2. Handling Missing Data

The dataset consists of raw data so there is missing information. First, we will search for question marks and replace them with NANs. Then we will replace all NAN values with the most frequent data from each attribute. In addition to that, we are going to group some types of the features together if they are related to each other.

```
In [9]: #replace all questions marks "?" with NaN
        df.replace("?", np.nan, inplace = True)
        #evaluate missing data or "NAN"
        missing_data = df.isnull()
        for column in missing_data.columns.values.tolist():
            print(column)
            print (missing_data[column].value_counts())
            print("-----------------------------------")
```

```
SEVERITYCODE
False    194673
Name: SEVERITYCODE, dtype: int64
-----------------------------------
SEVERITYDESC
False    194673
Name: SEVERITYDESC, dtype: int64
-----------------------------------
WEATHER
False    189592
True       5081
Name: WEATHER, dtype: int64
-----------------------------------
ROADCOND
False    189661
True       5012
Name: ROADCOND, dtype: int64
-----------------------------------
LIGHTCOND
False    189503
True       5170
Name: LIGHTCOND, dtype: int64
-----------------------------------
```

From the results above, it can be seen that we are missing 5081 weather data, 5012 road condition data, and 5170 light condition data. This missing information needs to be addressed.

Let’s also explore the different types of each feature to see if we can group them together

```
In [10]: #view weather conditions
         print("Weather conditions reported are: ")
         print(df['WEATHER'].value_counts())
         print("-----------------------------------")
         #view road conditions
         print("Road conditions reported are: ")
         print(df['ROADCOND'].value_counts())
         print("-----------------------------------")
         #view light conditions
         print("Road conditions reported are: ")
         print(df['LIGHTCOND'].value_counts())
         print("-----------------------------------")
```

```
Weather conditions reported are:
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
-----------------------------------
Road conditions reported are:
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
-----------------------------------
Light conditions reported are:
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
-----------------------------------
```

Weather conditions can be grouped as follows:

- SevereWeather: Raining, Snowing, Sleet/Hail/Freezing Rain, Fog/Smog/Smoke,
- Blowing Sand/Dirt, Severe Crosswind
- Overcast: PartlyCloudy and Overcast
- Unknown: Other

```
In [11]: #replacing missing values with the most frequent ones and grouping the similar types togeth
df["WEATHER"].replace(np.nan, df['WEATHER'].value_counts().idxmax(), inplace=True)
df["WEATHER"].replace("Other","Unknown",inplace=True)
df["WEATHER"].replace("Partly Cloudy","Overcast",inplace=True)
df["WEATHER"].replace("Raining","SevereWeather",inplace=True)
df["WEATHER"].replace("Snowing","SevereWeather",inplace=True)
df["WEATHER"].replace("Sleet/Hail/Freezing Rain","SevereWeather",inplace=True)
df["WEATHER"].replace("Fog/Smog/Smoke","SevereWeather",inplace=True)
df["WEATHER"].replace("Blowing Sand/Dirt","SevereWeather",inplace=True)
df["WEATHER"].replace("Severe Crosswind","SevereWeather",inplace=True)
df['WEATHER'].value_counts()
```

```
Out[11]: Clear            116216
         SevereWeather     34815
         Overcast          27719
         Unknown           15923
         Name: WEATHER, dtype: int64
```

Road conditions can be grouped as follows:

- IceOilWaterSnow: Ice, Standing Water, Oil, Snow/Slush, Sand/Mud/Dirt
- Unknown: Other

```
In [12]: #replacing missing values with the most frequent ones and grouping the similar types togeth
df["ROADCOND"].replace(np.nan, df['ROADCOND'].value_counts().idxmax(), inplace=True)
df["ROADCOND"].replace("Ice", "IceOilWaterSnow", inplace=True)
df["ROADCOND"].replace("Standing Water", "IceOilWaterSnow", inplace=True)
df["ROADCOND"].replace("Oil", "IceOilWaterSnow", inplace=True)
df["ROADCOND"].replace("Snow/Slush", "IceOilWaterSnow", inplace=True)
df["ROADCOND"].replace("Other", "Unknown", inplace=True)
df["ROADCOND"].replace("Sand/Mud/Dirt", "IceOilWaterSnow", inplace=True)
df['ROADCOND'].value_counts()
```

```
Out[12]: Dry                  129522
         Wet                   47474
         Unknown               15210
         IceOilWaterSnow        2467
         Name: ROADCOND, dtype: int64
```

Light conditions can be grouped as follows:

- Dark-No-Light: Dark — No Street Lights, Dark — Street Lights Off, Dark — Unknown Lighting
- Dark-With-Light: Dark — Street Lights On

  DuskDawn: Dusk, Dawn
- Unknown: Other

```
In [13]: #replacing missing values with the most frequent ones and grouping the similar types togeth
df["LIGHTCOND"].replace(np.nan, df['LIGHTCOND'].value_counts().idxmax(), inplace=True)
df["LIGHTCOND"].replace("Dark - No Street Lights", "Dark-No-Light", inplace=True)
df["LIGHTCOND"].replace("Dark - Street Lights Off", "Dark-No-Light", inplace=True)
df["LIGHTCOND"].replace("Dark - Unknown Lighting", "Dark-No-Light", inplace=True)
df["LIGHTCOND"].replace("Dark - Street Lights On", "Dark-With-Light", inplace=True)
df["LIGHTCOND"].replace("Other", "Unknown", inplace=True)
df["LIGHTCOND"].replace("Dusk", "DuskDawn", inplace=True)
df["LIGHTCOND"].replace("Dawn", "DuskDawn", inplace=True)
df['LIGHTCOND'].value_counts()
```

```
Out[13]: Daylight           121307
Dark-With-Light     48507
Unknown             13708
DuskDawn             8404
Dark-No-Light        2747
Name: LIGHTCOND, dtype: int64
```

Let’s check if we have any null values

```
In [14]: #display dataset information: attribute name, count, how many are null, and data type
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194673 entries, 0 to 194672
Data columns (total 5 columns):
SEVERITYCODE    194673 non-null int64
SEVERITYDESC    194673 non-null object
WEATHER         194673 non-null object
ROADCOND        194673 non-null object
LIGHTCOND       194673 non-null object
dtypes: int64(1), object(4)
memory usage: 7.4+ MB
```

3. Methodology

In this section of the report, exploratory data analysis, inferential statistical testing, and machine learnings used are described.

3.1. Data Visualization

Number of accidents are plotted against each environmental factor (feature) with percentage of each type of each feature to understand the impact of each factor.

First let’s see the impact of **weather conditions.**

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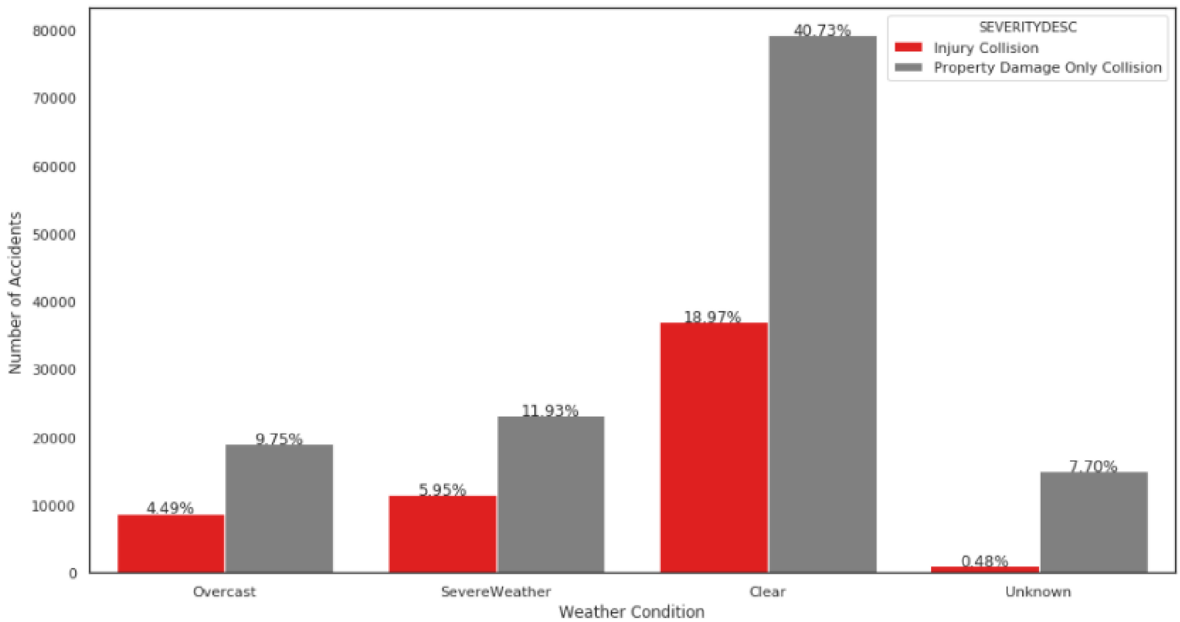
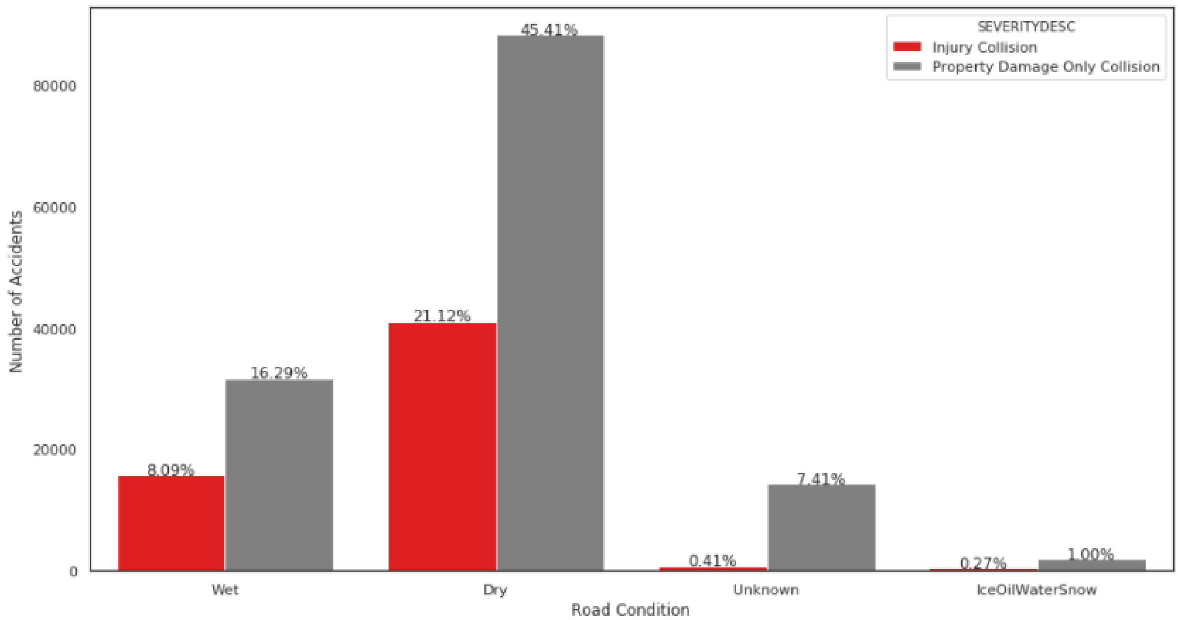
```
In [15]: #Weather conditions
plt.figure(figsize=(15,8))
sns.set(style="white")
custom_palette = ["red","grey"]
sns.set_palette(custom_palette)
total = float(len(df)) # one person per row
ax = sns.countplot(x="WEATHER", hue="SEVERITYDESC", data=df) # for Seaborn version 0.7 and
ax.set(xlabel="Weather Condition", ylabel = "Number of Accidents")

for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2%}'.format(height/total),
            ha="center")
show()
```



We can see from the graph above that majority of the accidents happened in clear weather. I was expecting to see more accidents in severe weather. We need more information on ‘Unknown’ weather conditions as the percentage should not be neglected particularly for accidents that caused property damage only.

Let’s now see the impact of **road conditions.**

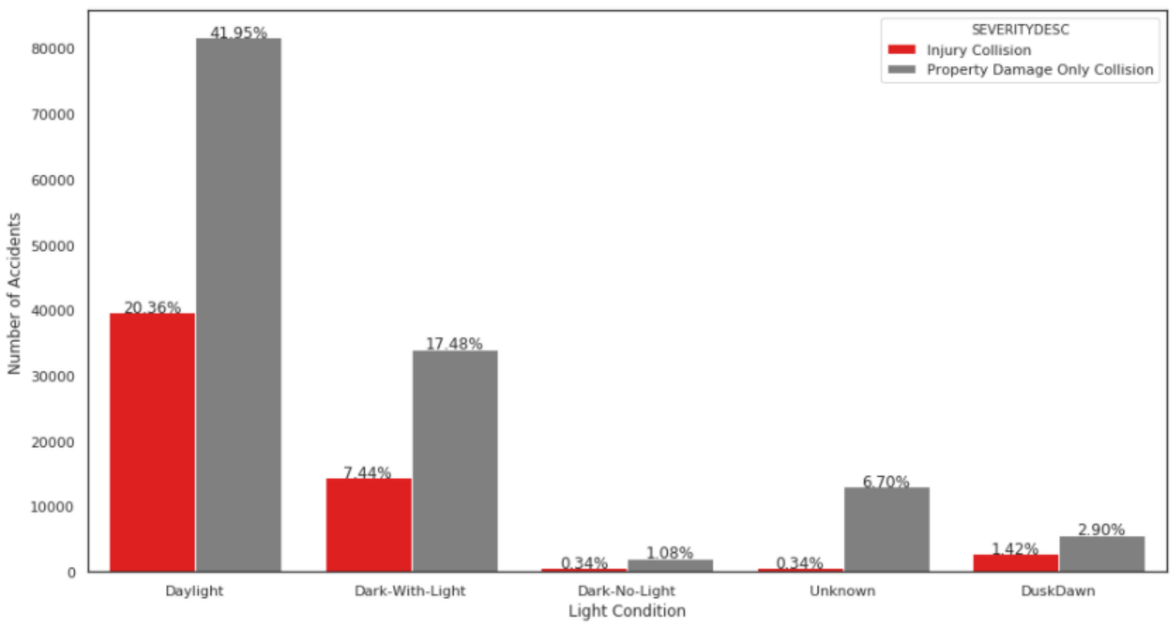
```
In [16]: #road conditions
plt.figure(figsize=(15,8))
sns.set(style="white")
custom_palette = ["red","grey"]
sns.set_palette(custom_palette)
total = float(len(df)) # one person per row
#ax = sns.barplot(x="class", hue="who", data=titanic)
ax = sns.countplot(x="ROADCOND", hue="SEVERITYDESC", data=df) # for Seaborn version 0.7 anc
ax.set(xlabel="Road Condition", ylabel = "Number of Accidents")
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2%}'.format(height/total),
            ha="center")
show()
```



We can see from the graph above that majority of the accidents happened on dry roads. I was expecting to see more accidents on wet or icy, snowy, oily roads! We also need more information on ‘Unknown’ road conditions as the percentage should not be neglected particularly for accidents that caused property damage only.

And finally let’s examine the impact of **light conditions.**

```
In [17]: #light conditions
         plt.figure(figsize=(15,8))
         sns.set(style="white")
         custom_palette = ["red","grey"]
         sns.set_palette(custom_palette)
         total = float(len(df)) # one person per row
         #ax = sns.barplot(x="class", hue="who", data=titanic)
         ax = sns.countplot(x="LIGHTCOND", hue="SEVERITYDESC", data=df) # for Seaborn version 0.7 ar
         ax.set(xlabel="Light Condition", ylabel = "Number of Accidents")
         for p in ax.patches:
             height = p.get_height()
             ax.text(p.get_x()+p.get_width()/2.,
                     height + 3,
                     '{:1.2%}'.format(height/total),
                     ha="center")
         show()
```



It can be seen from the graph above that majority of accidents happened during the day with daylight. This also was not as I expected! Again, we need more information on ‘Unknown’ light conditions as the percentage should not be neglected particularly for accidents that caused property damage only.

3.2 Machine Learning Model Selection

The preprocessed dataset can be split into training and test sub datasets (70% for training and 30% for testing) using the scikit learn “train_test_split” method. Since the target column (SEVERITYCODE) is categorical, a classification model is used to predict the severity of an accident. Three classification models were trained and evaluated, namely: K-Nearest Neighbor, Decision Tree, and Logistic Regression.

We will start by defining the X (independent variables) and y (dependent variable) as follows.

```
In [18]: #SEVERITYCODE is the dependent variable to be predicted and it is already numerical
         y = np.asarray(df["SEVERITYCODE"])
         y[0:5]

Out[18]: array([2, 1, 1, 1, 2])
```

```
In [19]: #defining X as the enviromental features
         Feature = df[['WEATHER', 'ROADCOND','LIGHTCOND']]
         X = Feature.values
         X[0:5]

Out[19]: array([['Overcast', 'Wet', 'Daylight'],
                ['SevereWeather', 'Wet', 'Dark-With-Light'],
                ['Overcast', 'Dry', 'Daylight'],
                ['Clear', 'Dry', 'Daylight'],
                ['SevereWeather', 'Wet', 'Daylight']], dtype=object)
```

X data needs to be converted to numerical data to be used in the classification models. This can be achieved by using Label Encoding.

```
In [20]: #categorical boolean mask
         categorical_feature_mask = Feature.dtypes==object
         categorical_feature_mask

Out[20]: WEATHER      True
         ROADCOND     True
         LIGHTCOND    True
         dtype: bool
```

```
In [21]: #filter categorical columns using mask and turn it into a list
         categorical_cols = Feature.columns[categorical_feature_mask].tolist()
         categorical_cols

Out[21]: ['WEATHER', 'ROADCOND', 'LIGHTCOND']
```

```
In [22]: #import labelencoder to convert each class under specified feature to a numerical value.
         from sklearn.preprocessing import LabelEncoder
         # instantiate labelencoder object
         le = LabelEncoder()
```

```
In [23]: #apply le on categorical feature columns
         Feature[categorical_cols] = Feature[categorical_cols].apply(lambda col: le.fit_transform(col))
         Feature[categorical_cols].head(10)
```

Out[23]:

	WEATHER	ROADCOND	LIGHTCOND
0	1	3	2
1	2	3	1
2	1	0	2
3	0	0	2
4	2	3	2
5	0	0	2
6	2	3	2
7	0	0	2
8	0	0	2
9	0	0	2

In [24]:
```
#display the feature list as numerical values
X = Feature.values
X[0:5]
```

Out[24]:
```
array([[1, 3, 2],
       [2, 3, 1],
       [1, 0, 2],
       [0, 0, 2],
       [2, 3, 2]])
```

It is always better to normalize the features data.

In [25]:
```
#normalize the feature data
from sklearn import preprocessing
X = preprocessing.StandardScaler().fit(X).transform(X)
X[0:5]
```

Out[25]:
```
array([[ 0.24982869,  1.6059602 ,  0.11844397],
       [ 1.23126144,  1.6059602 , -1.14979445],
       [ 0.24982869, -0.68884852,  0.11844397],
       [-0.73160406, -0.68884852,  0.11844397],
       [ 1.23126144,  1.6059602 ,  0.11844397]])
```

3.2.1. Model

It's time to build our models by first splitting our data into training and testing sets of 70% and 30% respectively.

In [60]:
```
#Test/Train split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=4)
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (136271, 3) (136271,)
Test set: (58402, 3) (58402,)
```

3.2.1.1. K Nearest Neighbor (KNN)

KNN is used to predict the severity of an accident of an unknown dataset based on its proximity in the multi-dimensional hyperspace of the feature set to its “k” nearest neighbors, which have known outcomes. Since finding the best k is memory-consuming and time-consuming, we will use k=25 based on [5].

```
In [61]: from sklearn.neighbors import KNeighborsClassifier
         k = 25
         #Train Model and Predict
         neigh = KNeighborsClassifier(n_neighbors = k).fit(X_train,y_train)
         neigh

Out[61]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                              metric_params=None, n_jobs=None, n_neighbors=25, p=2,
                              weights='uniform')
```

```
In [63]: #train dataset
         Kyhat_train = neigh.predict(X_train)
         Kyhat_train[0:5]

Out[63]: array([1, 1, 1, 1, 1])
```

```
In [86]: #test dataset
         Kyhat_test = neigh.predict(X_test)
         Kyhat_test[0:5]

Out[86]: array([1, 1, 1, 1, 1])
```

3.2.1.2. Decision Tree

A decision tree model is built from historical data of accident severity in relationship to environmental conditions. Then the trained decision tree can be used to predict the severity of an accident. Since finding the maximum depth is also memory and time consuming, will use max_depth=30 based on [5].

```
In [66]: from sklearn.tree import DecisionTreeClassifier
         SevTree = DecisionTreeClassifier(criterion="entropy", max_depth = 30)
         SevTree.fit(X_train,y_train)
         SevTree # it shows the default parameters

Out[66]: DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=30,
                                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')
```

```
In [69]: #train dataset
         dyhat_train = SevTree.predict(X_train)
         dyhat_train[0:5]

Out[69]: array([1, 1, 1, 1, 1])
```

```
In [84]: #test dataset
         dyhat_test = SevTree.predict(X_test)
         dyhat_test[0:5]

Out[84]: array([1, 1, 1, 1, 1])
```

3.2.1.3. Logistic Regression

Logistic Regression is useful when the observed dependent variable, y, is categorical. It produces a formula that predicts the probability of the class label as a function of the independent variables. An inverse-regularisation strength of C=0.01 is used as in [5].

```
In [71]: from sklearn.linear_model import LogisticRegression
         LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
         LR

Out[71]: 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)
```

```
In [80]: #train dataset
         lyhat_train = LR.predict(X_train)
         lyhat_train[0:5]

Out[80]: array([1, 1, 1, 1, 1])
```

```
In [87]: #test dataset
         lyhat_test = LR.predict(X_test)
         lyhat_test[0:5]

Out[87]: array([1, 1, 1, 1, 1])
```

4. Results (Model Evaluation)

Accuracy of the 3 models is calculated using these metrics: Jaccard Similarity Score, F1-SCORE, and LOGLOSS (with Linear Regression).

```
In [110]: from sklearn import metrics
          from sklearn.metrics import log_loss
          from sklearn.metrics import classification_report, confusion_matrix
          from sklearn.metrics import jaccard_similarity_score

          print('Jaccard Similarity Score: ')
          print('KNN Model: ', jaccard_similarity_score(y_test,Kyhat_test))
          print('Decision Tree: ', jaccard_similarity_score(y_test,dyhat_test))
          print('Logistic Regression: ', jaccard_similarity_score(y_test,lyhat_test))
          print('--------------------------')
          print('F1-SCORE: ')
          print('KNN Model: ', metrics.f1_score(y_test,Kyhat_test, average='weighted'))
          print('Decision Tree: ', metrics.f1_score(y_test,dyhat_test, average='weighted'))
          print('Logistic Regression: ', metrics.f1_score(y_test,lyhat_test, average='weighted'))
          print('--------------------------')
          print('LOGLOSS for Logistic Regression: ')
          lyhat_test_prob=LR.predict_proba(X_test)
          print(log_loss(y_test,lyhat_test_prob))
```

```
Jaccard Similarity Score:
KNN Model:  0.6941543097839115
Decision Tree:  0.7034348138762371
Logistic Regression:  0.7034519365775145
--------------------------
F1-SCORE:
KNN Model:  0.5912085352895935
Decision Tree:  0.5809821168927154
Logistic Regression:  0.5809904188654375
--------------------------
LOGLOSS for Logistic Regression:
0.5991064490814039
```

5. Discussion

First the dataset had categorical data of type ‘object’. Label encoding was used to convert categorical features to numerical values. The imbalanced data issue was ignored because there was a problem installing imbalanced-learn to use imblearn.

Once data was cleaned and analyzed, it was fed into three ML models: K-Nearest Neighbor, Decision Tree, and Logistic Regression. Values of k, max depth and inverse-regularisation strength C were taken from [5]. Evaluation metrics used to test the accuracy of the models were Jaccard Similarity Index, F-1 SCORE and LOGLOSS for Logistic Regression.

It is highly recommended to solve the data imbalance problem for more accurate results.

6. Conclusion

The goal of this project is to analyze historical vehicle crash data to understand the correlation of environmental conditions (weather, road surface, and lighting conditions) with accident severity. Vehicle accident data from the City of Seattle’s’ Police Department for the years 2004 until present were Used. The data was cleaned, and features related to environmental conditions were selected and analyzed. It was found that majority of accidents happened in clear weather, dry roads, and during daytime which wasn't what I expected. Machine learning models; K-Nearest Neighbor, Decision Tree and Logistic Regression were used to predict the severity of an accident based on certain environmental conditions. The models used were also evaluated using different accuracy metrics.

7. References

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