IBM Applied Data Science Capstone - Debajyoti Mandal

Introduction:

Road accidents are an unfortunate and unstoppable problem in our life and societies. The Global status report on road safety 2018, launched by WHO in December 2018, highlights that the number of annual road traffic deaths has reached 1.35 million.Every 25 seconds, one person died in road accidents. Road traffic injuries are now the leading killer of people aged 5-29 years. The burden is disproportionately borne by pedestrians, cyclists and motorcyclists, in particular those living in developing countries. The report suggests that the price paid for mobility is too high, especially because proven measures exist. Drastic action is needed to put these measures in place to meet any future global target that might be set and save lives. In this work, I will try to build a model to predict the severity of an accident given the weather and the road conditions. When the road visibility and weather conditions are unfavourable this model will alert the car user.

Business Understanding:

The local government of Seattle is trying to implement some method to alert the car user, police ,traffic system and health system about critical situations to reduce the death and injuries on the road. 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. Besides the aforementioned reasons, 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. In an effort to avoid and reduce the frequency of these type of accidents, I will try to build a model to predict the severity of an accident given the weather and the road conditions. This way we would be able to bring awareness to the drivers and warn people about the possibility of getting into a car accident. We would also be able to know the severity of the accident if it happens.

Data Understanding:

The dataset we select has 194,673 rows and 37 different independent variables.We will use SEVERITY CODE as our dependent variable Y, with different independent variables X to identify the cause of road accidents and level of severity.The dataset are quite large, we need to filter out the missing value and delete the unrelated columns. Then we select the independent variables such as address type, weather, road condition, and light condition to compare with Y which may have more impact on the accidents.The dependent variable, “SEVERITYCODE”, contains numbers that correspond to different levels of severity caused by an accident . The code that corresponds to the severity of the collision:

● 3—fatality

● 2b—serious injury

● 2—injury

● 1—prop damage

● 0—unknown

Other important variables include:

❏ ADDRTYPE: Collision address type: Alley, Block, Intersection ❏ LOCATION: Description of the general location of the collision ❏ PERSONCOUNT: The total number of people involved in the collision helps identify severity involved ❏ PEDCOUNT: The number of pedestrians involved in the collision helps identify severity involved ❏ PEDCYLCOUNT: The number of bicycles involved in the collision helps identify severity involved ❏ VEHCOUNT: The number of vehicles involved in the collision identify severity involved ❏ INCDTTM : The date and time of the incident. ❏ JUNCTIONTYPE: Category of junction at which collision took place helps identify where most collisions occur ❏ WEATHER: A description of the weather conditions during the time of the collision ❏ ROADCOND: The condition of the road during the collision ❏ LIGHTCOND: The light conditions during the collision ❏ SPEEDING: Whether or not speeding was a factor in the collision (Y/N) ❏ SEGLANEKEY: A key for the lane segment in which the collision occurred ❏ CROSSWALKKEY: A key for the crosswalk at which the collision occurred ❏ HITPARKEDCAR: Whether or not the collision involved hitting a parked car

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

Let's understand the data in a bit more depth. We will also try to understand the impact of main attributes that cause road accidents.

Importing the libraries

In [4]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt

%matplotlib inline
```

Downloading the data

In [2]:
```
! wget https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv
```

```
--2020-09-24 06:30:47--  https://s3.us.cloud-object-storage.appdomain.cloud/cf-courses-data/CognitiveClass/DP0701EN/version-2/Data-Collisions.csv
Resolving s3.us.cloud-object-storage.appdomain.cloud (s3.us.cloud-object-storage.appdomain.cloud)... 67.228.254.196
Connecting to s3.us.cloud-object-storage.appdomain.cloud (s3.us.cloud-object-storage.appdomain.cloud)|67.228.254.196|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 73917638 (70M) [text/csv]
Saving to: ‘Data-Collisions.csv’

100%[======================================>] 73,917,638  35.8MB/s   in 2.0s

2020-09-24 06:30:50 (35.8 MB/s) - ‘Data-Collisions.csv’ saved [73917638/73917638]
```

Loading the data into dataframe and creating a copy as df_copy

In [9]:
```
df = pd.read_csv('Data-Collisions.csv')
df_copy = df.copy()
df.head()
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/IPython/core/interactiveshell.py:3020: DtypeWarning: Col
umns (33) have mixed types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Out[9]:

	SEVERITYCODE	X	Y	OBJECTID	INCKEY	COLDETKEY	REPORTNO	STATUS	ADDRTYPE	INTKEY	...	ROADC
0	2	-122.323148	47.703140	1	1307	1307	3502005	Matched	Intersection	37475.0	...	
1	1	-122.347294	47.647172	2	52200	52200	2607959	Matched	Block	NaN	...	
2	1	-122.334540	47.607871	3	26700	26700	1482393	Matched	Block	NaN	...	
3	1	-122.334803	47.604803	4	1144	1144	3503937	Matched	Block	NaN	...	
4	2	-122.306426	47.545739	5	17700	17700	1807429	Matched	Intersection	34387.0	...	

5 rows × 38 columns

Checking the dtypes

In [6]:
```
df.dtypes
```

Out[6]:
```
SEVERITYCODE        int64
X                 float64
Y                 float64
OBJECTID            int64
INCKEY              int64
COLDETKEY           int64
REPORTNO           object
STATUS             object
ADDRTYPE           object
INTKEY            float64
LOCATION           object
EXCEPTRSNCODE      object
EXCEPTRSNDESC      object
SEVERITYCODE.1      int64
SEVERITYDESC       object
COLLISIONTYPE      object
PERSONCOUNT         int64
PEDCOUNT            int64
PEDCYLCOUNT         int64
VEHCOUNT            int64
INCDATE            object
INCDTTM            object
JUNCTIONTYPE       object
SDOT_COLCODE        int64
SDOT_COLDESC       object
INATTENTIONIND     object
UNDERINFL          object
WEATHER            object
ROADCOND           object
LIGHTCOND          object
PEDROWNOTGRNT      object
SDOTCOLNUM        float64
SPEEDING           object
ST_COLCODE         object
ST_COLDESC         object
SEGLANEKEY          int64
CROSSWALKKEY        int64
HITPARKEDCAR       object
dtype: object
```

Checking for null values

In [7]:
```
df.isna().sum().to_frame().rename(columns={0: 'NaN Count'})
```

Out[7]:

	NaN Count
SEVERITYCODE	0
X	5334
Y	5334
OBJECTID	0
INCKEY	0
COLDETKEY	0
REPORTNO	0
STATUS	0
ADDRTYPE	1926
INTKEY	129603
LOCATION	2677
EXCEPTRSNCODE	109862
EXCEPTRSNDESC	189035
SEVERITYCODE.1	0
SEVERITYDESC	0
COLLISIONTYPE	4904
PERSONCOUNT	0
PEDCOUNT	0
PEDCYLCOUNT	0
VEHCOUNT	0
INCDATE	0
INCDTTM	0
JUNCTIONTYPE	6329
SDOT_COLCODE	0
SDOT_COLDESC	0
INATTENTIONIND	164868

	NaN Count
UNDERINFL	4884
WEATHER	5081
ROADCOND	5012
LIGHTCOND	5170
PEDROWNOTGRNT	190006
SDOTCOLNUM	79737
SPEEDING	185340
ST_COLCODE	18
ST_COLDESC	4904
SEGLANEKEY	0
CROSSWALKKEY	0
HITPARKEDCAR	0

There are missing values in multiple columns as can be seen above. Based on business understanding and the volume of null values in columns some are irrelevant. Removing the irrelevant data attributes, the primary attributes for developing the model are:

COLLISIONTYPE: Collision type WEATHER: Weather conditions during the time of the collision. ROADCOND: The condition of the road during the collision. LIGHTCOND: The light conditions during the collision. UNDERINFL: Whether or not a driver involved was under the influence of drugs or alcohol.

These features contain missing values below 3% of the total amount of samples which is acceptable.

Our target variable SEVERITYCODE that corresponds to the severity of the collision:

1: Property Damage only collision which is the same as Not injured collision

2: Injury collision By looking to the target variable I know it's a binary classification problem.

In [16]:
```
df['SEVERITYCODE'].value_counts().to_frame()
```

Out[16]:

	SEVERITYCODE
1	136485
2	58188

In [17]:
```
df['SEVERITYDESC'].value_counts().to_frame()
```

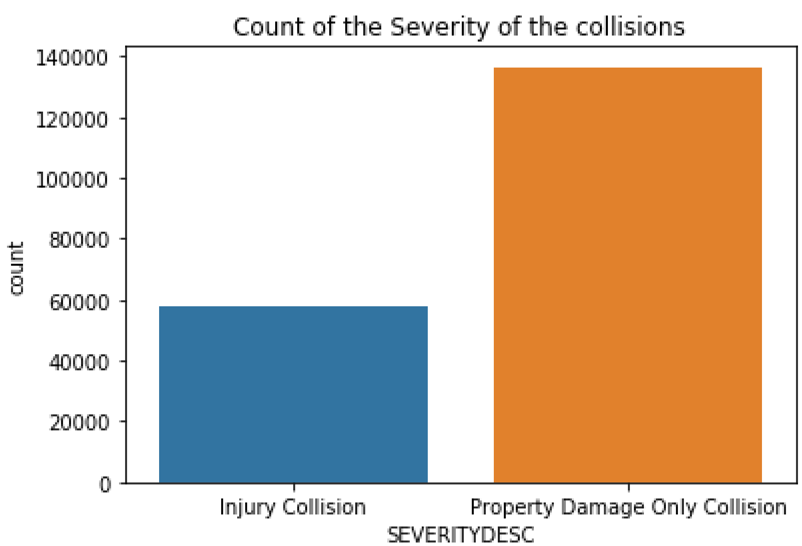
Out[17]:

	SEVERITYDESC
Property Damage Only Collision	136485
Injury Collision	58188

let's visualise the data

In [31]:
```
sns.countplot(x="SEVERITYDESC", data=df)
plt.title('Count of the Severity of the collisions')
```

Out[31]: Text(0.5, 1.0, 'Count of the Severity of the collisions')



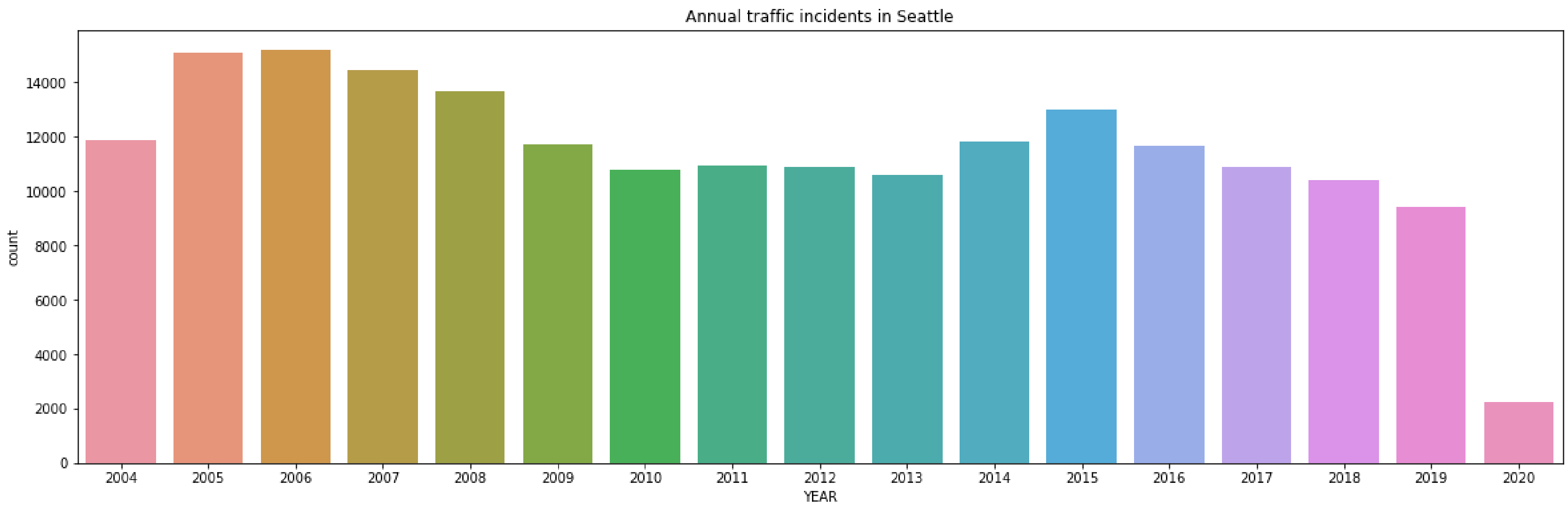
Convert incident date to Year Month Day of Week

In [11]:
```
df['INCDATE']=df['INCDATE'].str[:10]

df[['YEAR', 'MONTH','DAY']]=df["INCDATE"].str.split("/", expand=True)

df['INCDATE'] = pd.to_datetime(df['INCDATE'])

df['DAYOFWEEK'] = df['INCDATE'].dt.dayofweek
```

let's find the number of person effected per year by car accident

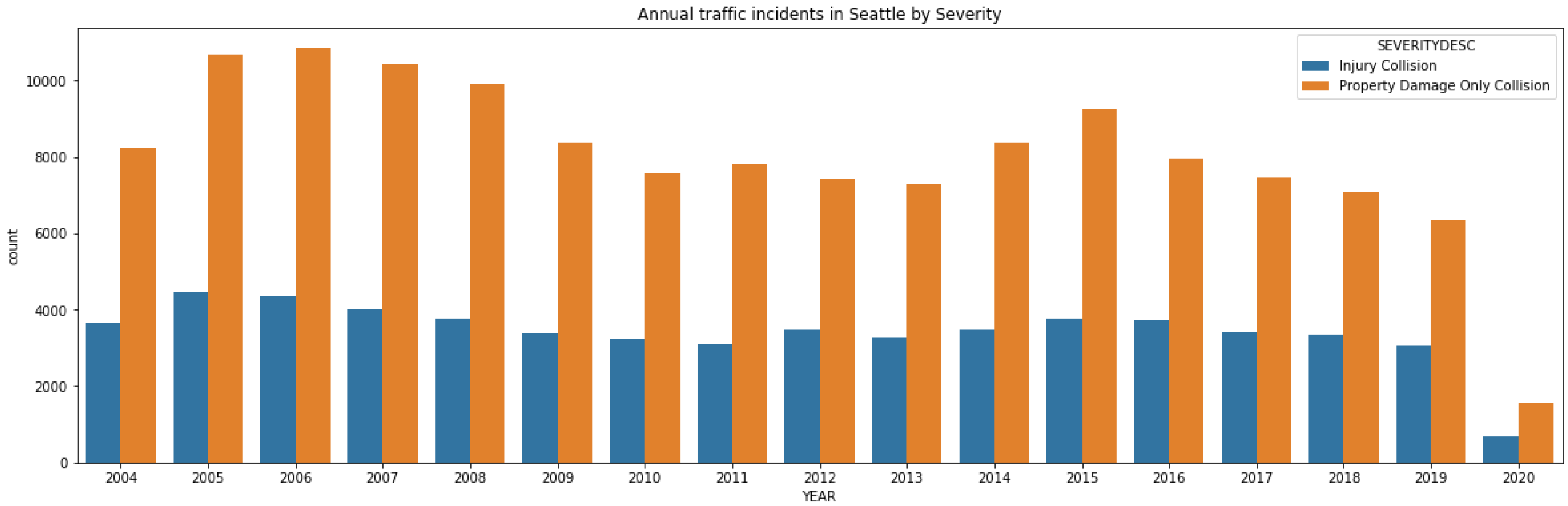
In [30]:
```
plt.figure(figsize=(20,6))
sns.countplot(x="YEAR", data=df)
plt.title('Annual traffic incidents in Seattle')
```

Out[30]:
```
Text(0.5, 1.0, 'Annual traffic incidents in Seattle')
```



In [27]:
```
plt.figure(figsize=(20,6))
sns.countplot(x="YEAR", hue="SEVERITYDESC", data=df)
plt.title('Annual traffic incidents in Seattle by Severity')
```

Out[27]:
```
Text(0.5, 1.0, 'Annual traffic incidents in Seattle by Severity')
```



We notice there is a considerably high amount of incidents in all the years except 2020 because the recorded incidents are only till May 2020 and not a whole year. We can also infer from the plots that no injury collisions are always more likely to happen.

Now lets find the collision types

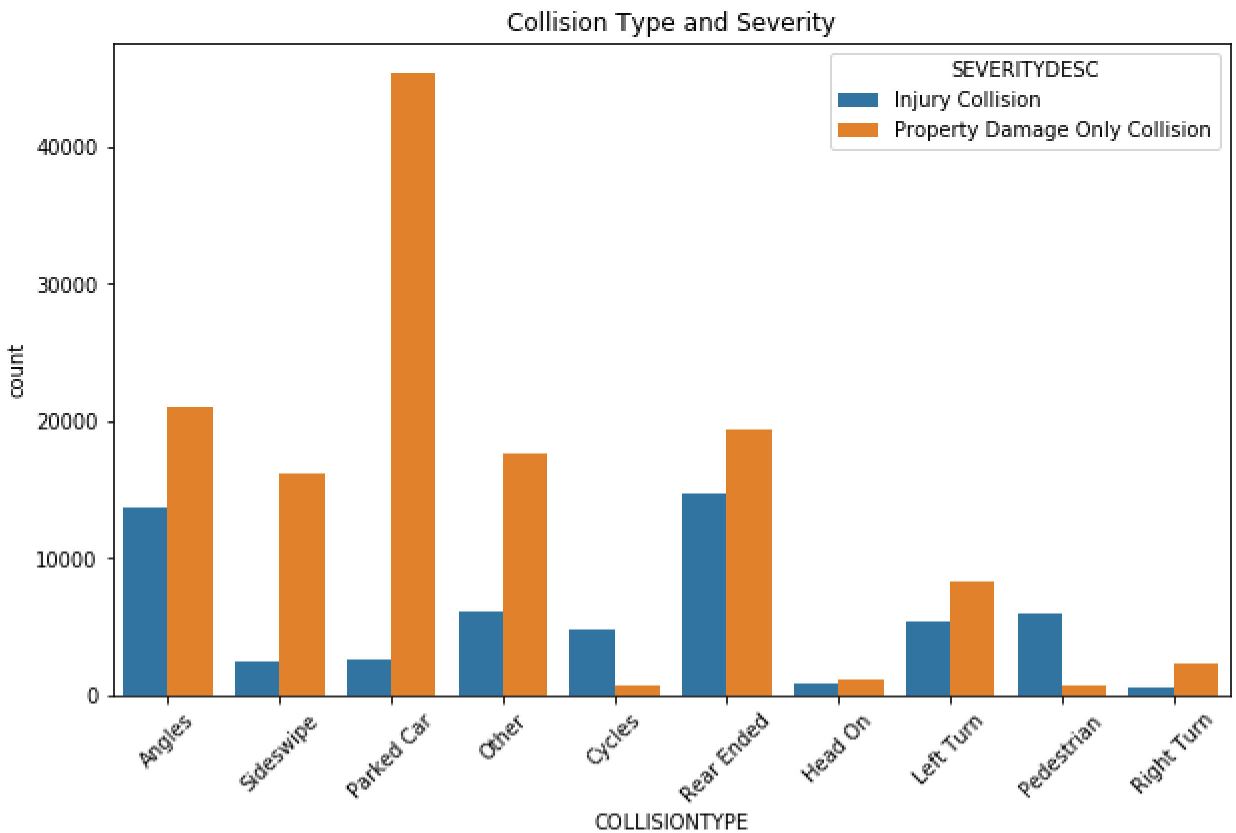
In [45]:
```
df['COLLISIONTYPE'].value_counts().sort_values(ascending=False).to_frame()
```

Out[45]:

	COLLISIONTYPE
Parked Car	47987
Angles	34674
Rear Ended	34090
Other	23703
Sideswipe	18609
Left Turn	13703
Pedestrian	6608
Cycles	5415
Right Turn	2956
Head On	2024

In [48]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="COLLISIONTYPE", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
plt.title('Collision Type and Severity')
```

Out[48]: Text(0.5, 1.0, 'Collision Type and Severity')



There is a considerable difference on the collision occurences according to collision types. Most commonly the accidents happen with parked cars, angles, sideswipe and rear ended.

Now lets find the impact of weather condition

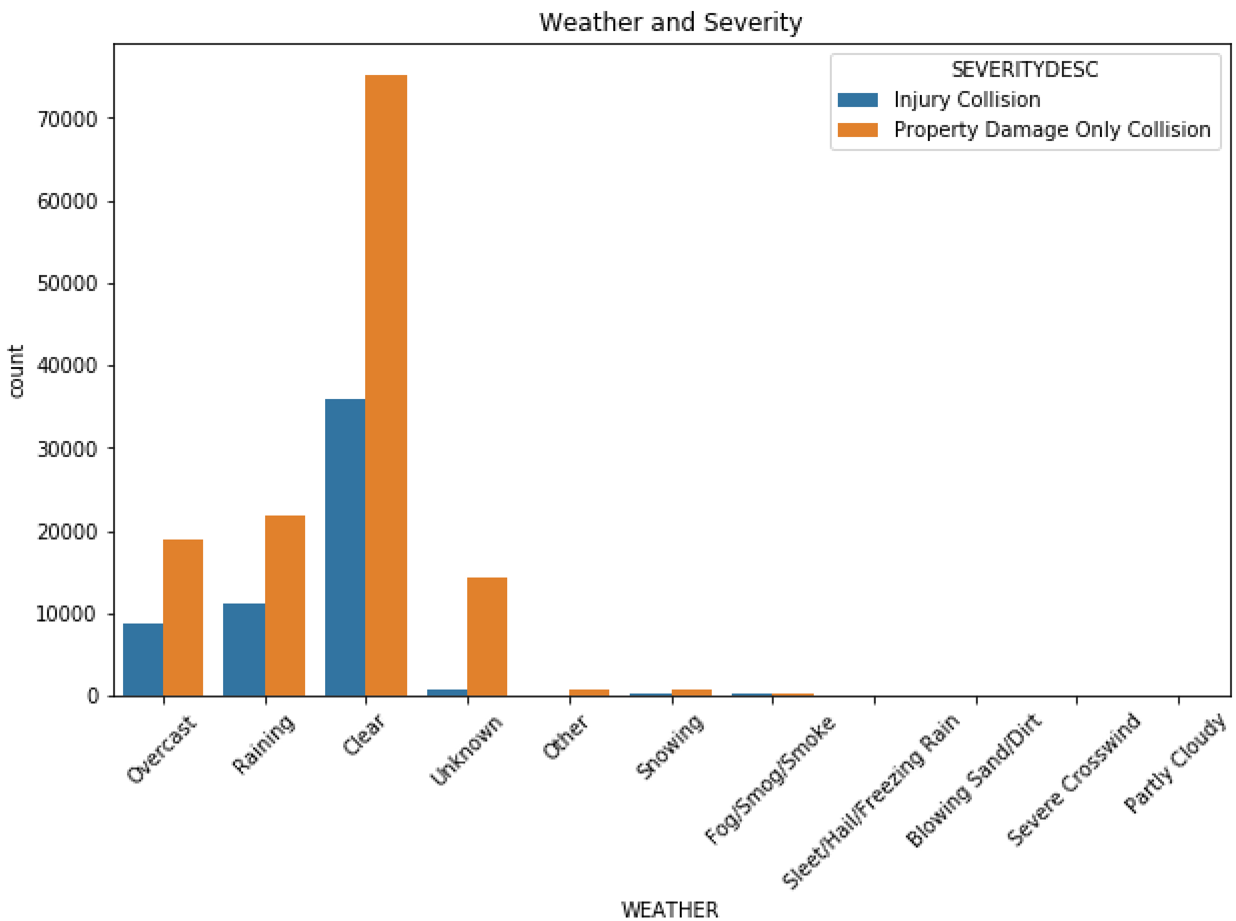
In [49]:
```
df['WEATHER'].value_counts().sort_values(ascending=False).to_frame()
```

Out[49]:

	WEATHER
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

In [50]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="WEATHER", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
plt.title('Weather and Severity')
```

Out[50]: `Text(0.5, 1.0, 'Weather and Severity')`



Visualizing weather conditions, we notice most incidents happened in a Clear weather. That could be because drivers inattention in clear condition. We can check the correlation between WEATHER and INATTENTIONIND(whether or not collision was due to inattention), but 85% of the data is missing which may lead to wrong inferences.

Now lets find the impact of road condition

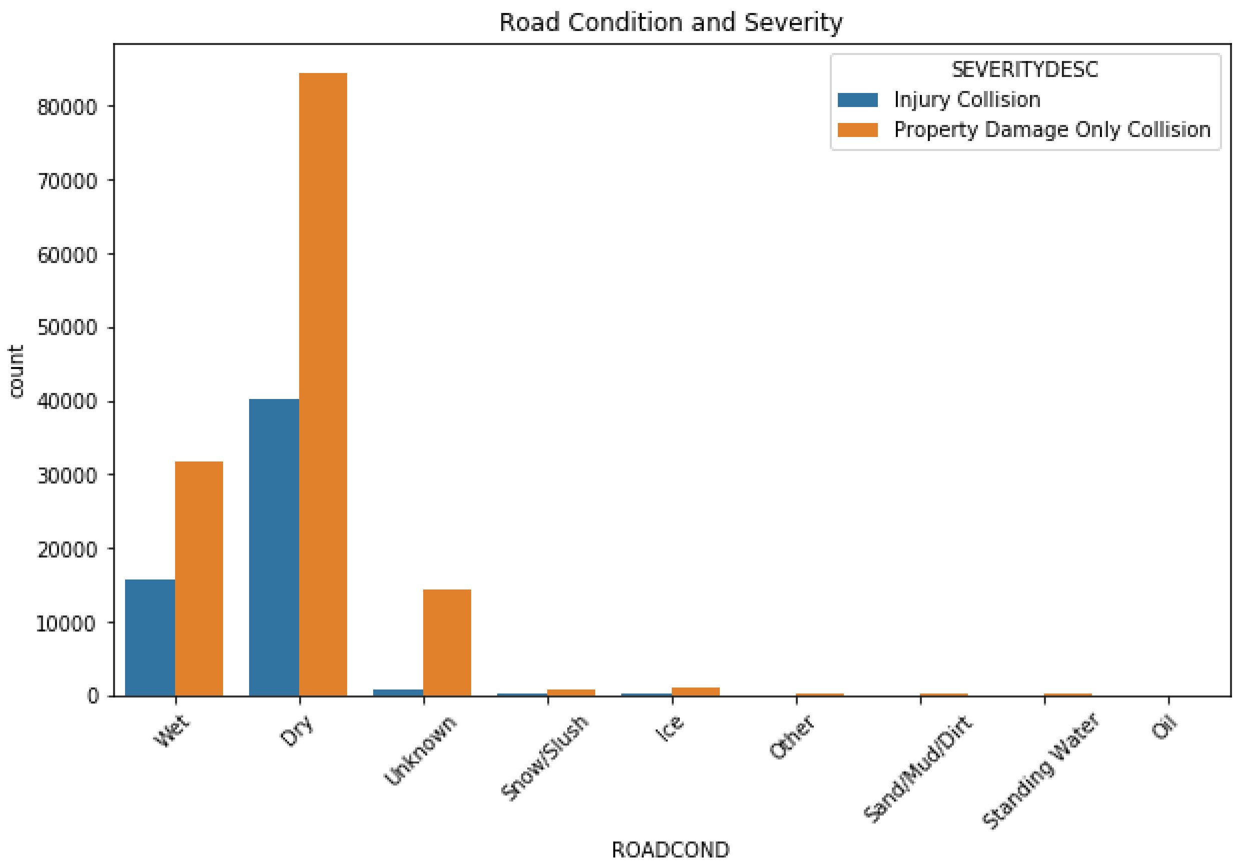
In [51]:
```
df['ROADCOND'].value_counts().sort_values(ascending=False).to_frame()
```

Out[51]:

	ROADCOND
Dry	124510
Wet	47474
Unknown	15078
Ice	1209
Snow/Slush	1004
Other	132
Standing Water	115
Sand/Mud/Dirt	75
Oil	64

In [52]:
```python
plt.figure(figsize=(10,6))
sns.countplot(x="ROADCOND", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
plt.title('Road Condition and Severity')
```

Out[52]: `Text(0.5, 1.0, 'Road Condition and Severity')`



The most common road condition is Dry road condition followed by Wet road condition.

Now lets find the impact of light condition

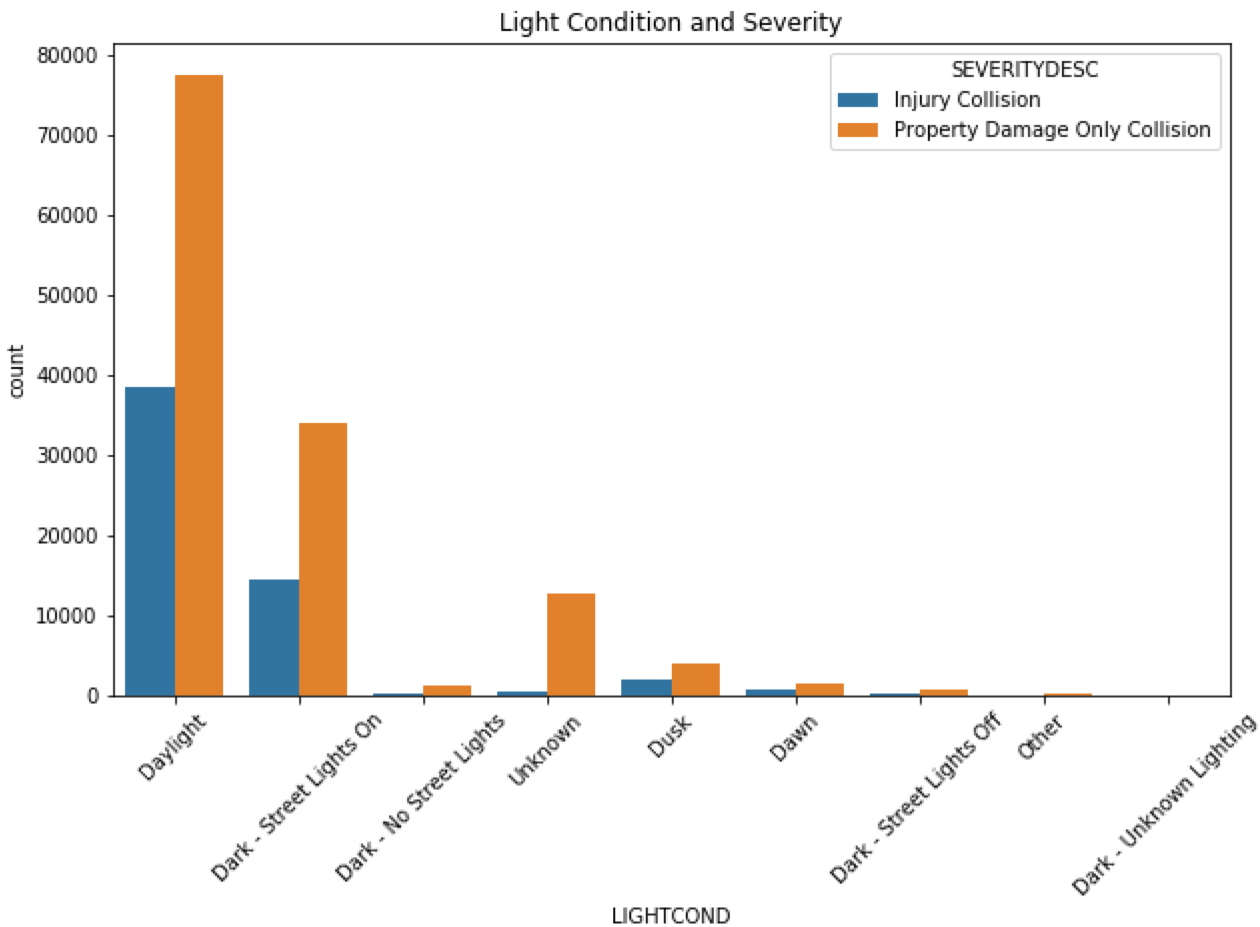
In [53]:
```
df['LIGHTCOND'].value_counts().sort_values(ascending=False).to_frame()
```

Out[53]:

	LIGHTCOND
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

In [54]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="LIGHTCOND", hue="SEVERITYDESC", data=df)
plt.xticks(rotation=45)
plt.title('Light Condition and Severity')
```

Out[54]: `Text(0.5, 1.0, 'Light Condition and Severity')`



Visualizing impact of light conditions, we notice most incidents happened in Daylight. This again leads to the same inference we had hile visualizing impact of weather condition.

Now lets find the impact of Driver under influence of drugs or alcohol

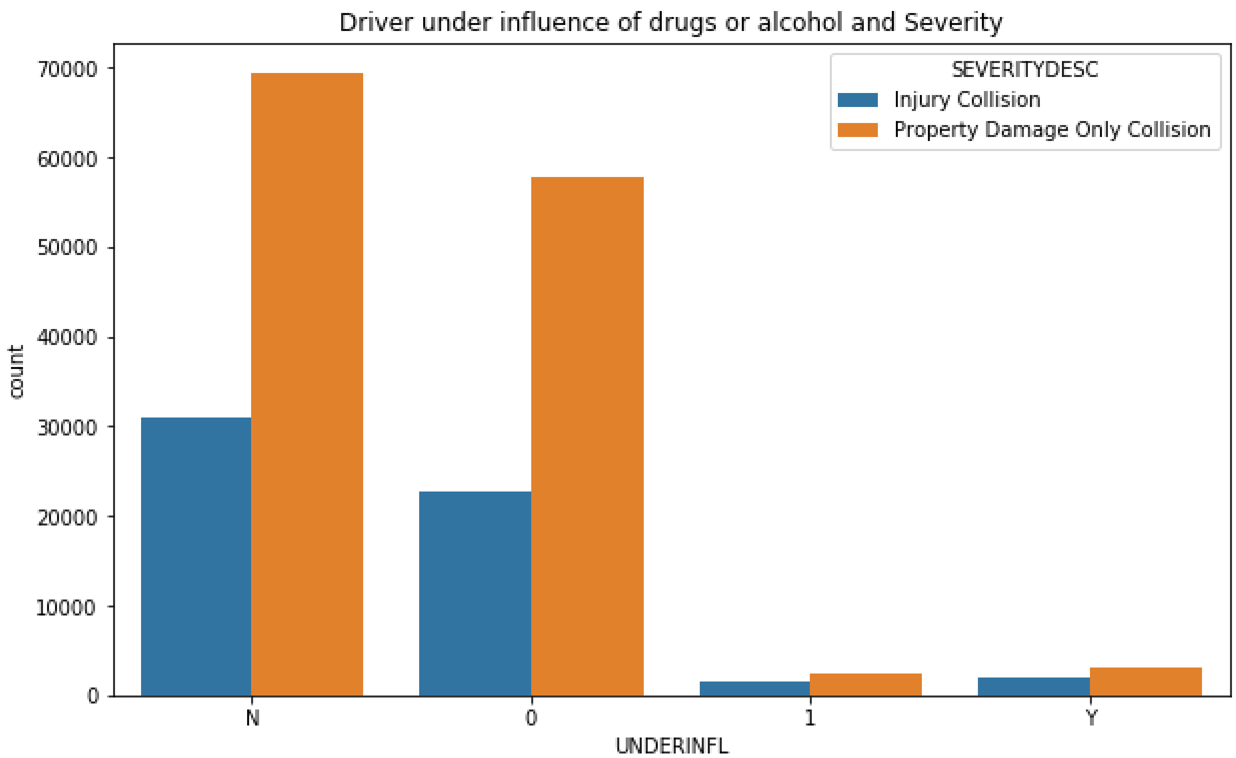
In [55]:
```
df['UNDERINFL'].value_counts().sort_values(ascending=False).to_frame()
```

Out[55]:

	UNDERINFL
N	100274
0	80394
Y	5126
1	3995

In [57]:
```
plt.figure(figsize=(10,6))
sns.countplot(x="UNDERINFL", hue="SEVERITYDESC", data=df)
plt.title('Driver under influence of drugs or alcohol and Severity')
```

Out[57]:
```
Text(0.5, 1.0, 'Driver under influence of drugs or alcohol and Severity')
```



It can be cleary inferred here that in most incidents, drivers were not under any influence.

We have now visualized the impact of different features on severity. Overall, we can infer that no-injury accidents in normal driving conditions are prevalent.

Now that we move to next steps of model building, we will choose COLLISIONTYPE, WEATHER, ROADCOND, LIGHTCOND and UNDERINFL as attributes to classify SEVERITYCODE. We will use some popular machine learning algorithms (SVM, Logistic Regression, Naive Bayes and KNN) build up models to analyze their performance and predict the collision severity. But before we do so, we need to clean the data so that we have balanced predictions.

Methodology, Results, Discussion and conclusion:

As a Part of model building and prediction we eill proceed in the following manner:

1. Data preparation and cleaning

We will start with Data cleaning procedure to make the dataset usable to the machine learning algorithm models. We will perform the following steps:

● Dropping irrelevant variables and attributes - Out of the 37 attributes, we will use COLLISIONTYPE, WEATHER, ROADCOND, LIGHTCOND and UNDERINFL as attributes to classify SEVERITYCODE.

● Dealing with missing values - Since COLLISIONTYPE, WEATHER, ROADCOND, LIGHTCOND and UNDERINFL attributes only have 3% of missing data, we will drop them.

●Treating the categorical variables with Label encoding - COLLISIONTYPE, WEATHER, ROADCOND, LIGHTCOND and UNDERINFL attributes are categorical data and hence we will use label encoding.

●Train/Test split and data normalization Now treating all attributes we will separate the independent variables to dataset A and dependent variable 'SEVERITYCODE' to dataset B. After, we will use this data to randomly pick samples and split in this ratio:

70% to train the model 30% to test the model

Following the split we will normalize the data to make sure there is no bias.

2. Classification: Modeling and Result Evaluation

We will make three models and then proceed to model evaluation. The steps will be as follows:

● KNN: Classifies unseen data through the majority of its 'neighbours'. After obtaining each model's predictions we will evaluate their accuracy, precison, f1-score, log-loss and compare and discuss the results.

● Logistic Regression: Classifies data by estimating the probability of classes.

● Decision Tree: Classifies by breaking down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed.

● Model Evaluation using test set.

● Creating confusion matrices.

3. Discussion and Conclusion

After obtaining the results and evaluating them, we will draw inferences on our observations. Finally, will conclude with the results of our analysis.

Let's start with the Data preparation and cleaning

1. Data preparation and cleaning:

1.1. Choosing only the relevant attributes and dealing with missing values.

In [59]:
```
data = df[['COLLISIONTYPE', 'WEATHER', 'ROADCOND', 'LIGHTCOND', 'UNDERINFL', 'SEVERITYCODE']]
data = data.dropna()
data.head()
```

Out[59]:

	COLLISIONTYPE	WEATHER	ROADCOND	LIGHTCOND	UNDERINFL	SEVERITYCODE
0	Angles	Overcast	Wet	Daylight	N	2
1	Sideswipe	Raining	Wet	Dark - Street Lights On	0	1
2	Parked Car	Overcast	Dry	Daylight	0	1
3	Other	Clear	Dry	Daylight	N	1
4	Angles	Raining	Wet	Daylight	0	2

1.2. Checking the dtypes

In [61]:
```
data.dtypes
```

Out[61]:
```
COLLISIONTYPE    object
WEATHER          object
ROADCOND         object
LIGHTCOND        object
UNDERINFL        object
SEVERITYCODE      int64
dtype: object
```

1.3. Converting Categorical features to numerical values by label encoding

In [62]:
```
data['UNDERINFL'].replace(to_replace=['N','Y','0'], value=[0,1,0],inplace=True)
data['UNDERINFL'].value_counts()
```

Out[62]:
```
0    180219
1      9097
Name: UNDERINFL, dtype: int64
```

In [64]:
```
from sklearn.preprocessing import LabelEncoder

attributes = data[['COLLISIONTYPE', 'WEATHER', 'ROADCOND', 'LIGHTCOND', 'UNDERINFL']]

for attribute in ['COLLISIONTYPE', 'WEATHER', 'ROADCOND', 'LIGHTCOND']:
    attributes[attribute] = attributes[attribute].astype('|S')
    attributes[attribute] = LabelEncoder().fit_transform(attributes[attribute])

attributes.head()
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view
-versus-copy
/opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view
-versus-copy
```

Out[64]:

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

Defining the independent variable X -> Attributes and dependent variable Y -> Severity Code

In [65]:
```
X = attributes
y = data['SEVERITYCODE'].values
```

1.4. Train/Test split and data normalization

In [66]:

```
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=0)
X_train.head()
```

Out[66]:

	COLLISIONTYPE	WEATHER	ROADCOND	LIGHTCOND	UNDERINFL
109717	0	1	0	5	0
9615	7	1	0	5	0
133991	3	1	0	5	0
76012	5	1	0	5	0
97913	9	10	7	8	0

In [67]:
```
from sklearn import preprocessing

X= preprocessing.StandardScaler().fit(X).transform(X)
X_train = preprocessing.StandardScaler().fit(X_train).transform(X_train.astype(float))
X_test = preprocessing.StandardScaler().fit(X_test).transform(X_test.astype(float))
X_train[0:5]
X_test[0:5]
```

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: DataConversionWarnin
g: Data with input dtype int64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/opt/conda/envs/Python36/lib/python3.6/site-packages/ipykernel/__main__.py:3: DataConversionWarning: Data wit
h input dtype int64 were all converted to float64 by StandardScaler.
  app.launch_new_instance()
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: DataConversionWarnin
g: Data with input dtype int64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/opt/conda/envs/Python36/lib/python3.6/site-packages/sklearn/preprocessing/data.py:645: DataConversionWarnin
g: Data with input dtype int64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
```

Out[67]:
```
array([[ 0.90028023, -0.72579269, -0.71028447, -1.39919831, -0.22518559],
       [-1.61258466, -0.72579269, -0.71028447,  0.35042853, -0.22518559],
       [ 0.18231884, -0.72579269, -0.71028447, -1.39919831, -0.22518559],
       [ 0.90028023,  0.32670431, -0.71028447,  0.93363748, -0.22518559],
       [-1.61258466, -0.72579269, -0.71028447,  0.35042853, -0.22518559]])
```

2. Classification: Modeling and Result Evaluation

2.1. K - Nearest Neighbors(KNN)

In [70]:
```
from sklearn.neighbors import KNeighborsClassifier
KNN_model = KNeighborsClassifier(n_neighbors = 2).fit(X_train, y_train)
KNN_model
```

Out[70]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=2, p=2,
           weights='uniform')
```

2.2. Logistic Regression (LR)

In [71]:
```
from sklearn.linear_model import LogisticRegression

LR_model = LogisticRegression(C=0.0001, solver='liblinear')
LR_model.fit(X_train, y_train)
LR_model
```

Out[71]:
```
LogisticRegression(C=0.0001, 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)
```

2.3. Decision Tree (DT)

In [72]:
```
from sklearn.tree import DecisionTreeClassifier

DT_model = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
DT_model.fit(X_train, y_train)
DT_model
```

Out[72]:
```
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')
```

2.4. Model Evaluation using Test set

In [76]:
```python
from sklearn import metrics
from sklearn.metrics import jaccard_similarity_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score

# KNN Model
yhat = KNN_model.predict(X_test)
yhat_knn = yhat
jaccard = jaccard_similarity_score(y_test, yhat)
f1_score_knn = f1_score(y_test, yhat, average='weighted')
precision_knn = precision_score(y_test, yhat, average='weighted')
knn_report = ['KNN', round(jaccard,2), round(f1_score_knn,2), round(precision_knn,2)]

# Logistic regression Model
yhat_proba = LR_model.predict_proba(X_test)
yhat = LR_model.predict(X_test)
yhat_lr = yhat
jaccard = jaccard_similarity_score(y_test, yhat)
f1_score_lr = f1_score(y_test, yhat, average='weighted')
precision_lr = precision_score(y_test, yhat, average='weighted')
lr_report = ['Logistic Regression', round(jaccard,2), round(f1_score_lr,2), round(precision_lr,2)]

# Decision tree Model
yhat = DT_model.predict(X_test)
yhat_tree = yhat
jaccard = jaccard_similarity_score(y_test, yhat)
f1_score_tree = f1_score(y_test, yhat, average='weighted')
precision_tree = precision_score(y_test, yhat, average='weighted')
tree_report = ['Decision Tree', round(jaccard,2), round(f1_score_tree,2), round(precision_tree,2)]


Model_eval_report = pd.DataFrame(data=np.array([knn_report,  lr_report, tree_report]),
                      columns=['Algorithm', 'Jaccard', 'F1-score', 'Precision'])
Model_eval_report
```

Out[76]:

	Algorithm	Jaccard	F1-score	Precision
0	KNN	0.74	0.67	0.74
1	Logistic Regression	0.7	0.58	0.68
2	Decision Tree	0.75	0.69	0.78

For all three models Jaccard score is above 70%. The highest accuracy model is the Decision Tree Classifier.

2.5. Creating Confusion Matrices for result evaluation:

KNN Confusion Matrix:

In [77]:
```
from sklearn.metrics import confusion_matrix

print('KNN Confusion Matrix')
tn, fp, fn, tp = confusion_matrix(y_test, yhat_knn).ravel()
(tn, fp, fn, tp)
```

```
KNN Confusion Matrix
```

Out[77]:
```
(38708, 999, 13974, 3114)
```

Logistic Regression Confusion Matrix:

In [79]:
```
print('Logistic Regression Confusion Matrix')
tn, fp, fn, tp = confusion_matrix(y_test, yhat_lr).ravel()
(tn, fp, fn, tp)
```

```
Logistic Regression Confusion Matrix
```

Out[79]:
```
(39655, 52, 16999, 89)
```

Decision Tree Confusion Matrix:

In [78]:
```
print('Decision Tree Confusion Matrix')
tn, fp, fn, tp = confusion_matrix(y_test, yhat_tree).ravel()
(tn, fp, fn, tp)
```

```
Decision Tree Confusion Matrix
```

Out[78]:
```
(39170, 537, 13755, 3333)
```

From the Confusion Matrices e are able to visulaize the number of samples that are classified correctly as well as incorrectly for all the models.

3. Discussion and Conclusion

So, here in this entire model building, evaluation and analysis we evaluated the performance of 3 machine learning algorithms on the Seattle Collision dataset to predict the severity of an accident knowing the weather and road conditions. We had primarily categorical data to deal with and label encoding became very handy while handling the data. The three models performed very similary, but Decision Tree was found to be the best model.

However, we chose only 5 attributes out of 37 based upon our initial analysis of data in the Data understandng part. We can however go on to choose further attributes in order to make more consideration while developing the models. We can also look into hyper parameterization techniques to develop a much better model. All in all this was very enlightening and the models we developed had a fair accuracy.