SEATTLE CAR ACCIDENT SEVERITY PREDICTION

Business Problem:

It is estimated that road traffic accidents cost the United States' economy ~ $810 billion per year, including costs due to property damage, legal costs and associated medical bills. It is therefore important that we understand the factors influence the likelihood of a road traffic accident occurring at a given location, as well as those which influence the severity of the accidents.

The Seattle Department of Transport (SDOT) recorded all road traffic incidents in the Seattle municipal area between Jan 2004–Aug 2020. The Data has a predefined level of Severity caused by an accident. The main objective is to identify the key factors that determine the severity of accidents like Weather, Road Conditions, Light Conditions etc.

The target audience for this work will be city planners and emergency service responders:

By understanding the key factors that influence the severity of accidents, it will be possible to prevent or reduce the Severe or Fatal accidents in future by taking appropriate preventive measures.

Data:

Data Collection:

Data is obtained from all road traffic accidents recorded in the Seattle municipal area between Jan 2004–Aug 2020 by the Seattle Department of Transport (SDOT).

Data is available in Seattle Open Data portal and saved as CSV.

http://data-seattlecitygis.opendata.arcgis.com/datasets/5b5c745e0f1f48e7a53acec63a0022ab_0

The data can be read into a Pandas Data frame using the Pandas read_csv function, and the contents and data types displayed using the head and dtypes functions.

In [2]:
```
# Read the Data
df = pd.read_csv("C://Users/ManojKumar Chalamala/Downloads/Collisions.csv")
df.head()
```

Out[2]:

	X	Y	OBJECTID	INCKEY	COLDETKEY	REPORTNO	STATUS	ADDRTYPE	INTKEY	LOCATION	...	ROADCOND	LIGHTCOND	PEDROV
0	-122.356511	47.517361	1	327920	329420	3856094	Matched	Intersection	34911.0	17TH AVE SW AND SW ROXBURY ST	...	Dry	Daylight	
1	-122.361405	47.702064	2	46200	46200	1791736	Matched	Block	NaN	HOLMAN RD NW BETWEEN 4TH AVE NW AND 3RD AVE NW	...	Wet	Dusk	
2	-122.317414	47.664028	3	1212	1212	3507861	Matched	Block	NaN	ROOSEVELT WAY NE BETWEEN NE 47TH ST AND NE 50T...	...	Dry	Dark - Street Lights On	
3	-122.318234	47.619927	4	327909	329409	EA03026	Matched	Intersection	29054.0	11TH AVE E AND E JOHN ST	...	Wet	Dark - Street Lights On	
4	-122.351724	47.560306	5	104900	104900	2671936	Matched	Block	NaN	WEST MARGINAL WAY SW BETWEEN	...	Ice	Dark - Street Lights On	

Dimensions of Data:

The Dataset contains 221738 rows (accidents) and 40 columns (attributes)

```
[3]: # Dimensions of the Dataframe

df_shape = df.shape
print("Dimensions of the data frame: "+str(df_shape))

Dimensions of the data frame: (221738, 40)
```

Statistical Features of Dataset:

```
In [6]: # Explore the Statistical features of data

df.describe().T.style.background_gradient(cmap='Set2',axis=0)

Out[6]:
```

	count	mean	std	min	25%	50%	75%	max
X	214260	-122.331	0.0300583	-122.419	-122.349	-122.33	-122.312	-122.239
Y	214260	47.6202	0.056059	47.4956	47.5771	47.616	47.6643	47.7341
OBJECTID	221738	110870	64010.4	1	55435.2	110870	166304	221738
INCKEY	221738	145007	89372.4	1001	71721.2	127358	210119	334276
COLDETKEY	221738	145237	89749.6	1001	71721.2	127358	210339	335776
INTKEY	72027	37637	52000.8	23807	28653	29973	33984	764413
PERSONCOUNT	221738	2.22674	1.4697	0	2	2	3	93
PEDCOUNT	221738	0.0380945	0.201704	0	0	0	0	6
PEDCYLCOUNT	221738	0.0273521	0.164512	0	0	0	0	2
VEHCOUNT	221738	1.72944	0.830529	0	2	2	2	15
INJURIES	221738	0.373964	0.73205	0	0	0	1	78
SERIOUSINJURIES	221738	0.0152026	0.158004	0	0	0	0	41
FATALITIES	221738	0.0017002	0.044967	0	0	0	0	5
SDOT_COLCODE	221737	13.3833	7.29829	0	11	11	14	87
SDOTCOLNUM	127205	7.97106e+06	2.61152e+06	1.00702e+06	6.00703e+06	8.03301e+06	1.0181e+07	1.3072e+07
SEGLANEKEY	221738	262.625	3252.88	0	0	0	0	525241
CROSSWALKKEY	221738	9568.04	71427.8	0	0	0	0	[illegible]

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Data Preprocessing:

Remove the data with unknown information in the Target variable

The predefined target variable in the data determines the Car Accident Severity. However, there are few rows in the data frame with 'SEVERITYCODE = 0' which means an accident with "Unknown" Severity. We cannot use these accident data with unknown information to predict the Car Accident severity. So, these rows should be dropped.

```
In [8]: # Identify the rows with SeverityDESC = Unknown
        df['SEVERITYDESC'].value_counts()
```

```
Out[8]: Property Damage Only Collision    137776
        Injury Collision                   58842
        Unknown                            21657
        Serious Injury Collision            3111
        Fatality Collision                   352
        Name: SEVERITYDESC, dtype: int64
```

```
In [9]: # Remove the Unknown Accident Severity rows
        Unknown = df['SEVERITYDESC'] == 'Unknown'
        df.drop(df.index[Unknown], inplace=True)

        # Reset index of the data frame
        df.reset_index(inplace=True)
```

:

Relabel the Target Variable

The Target Variable "SEVERITYCODE" is having values (0, 1, 2, 2b, 3). It contains categorical values. So, this must be converted into numerical format. We have already dropped the rows with code value "0". So, we are left with (1, 2, 2b, 3)

Relabel the codes from (1, 2, 2b, 3) to (1, 2, 3, 4).

```
In [10]: # Values before Conversion
         print(df["SEVERITYCODE"].value_counts())

         # Convert the target variable value from (1. 2, 2b, 3) to (1, 2, 3, 4) by changing 2b to 3 and 3 to 4

         for i in range(0,len(df["SEVERITYCODE"])):
             if df["SEVERITYDESC"][i] == 'Serious Injury Collision':
                 df["SEVERITYCODE"][i] = 3
             if df["SEVERITYDESC"][i] == 'Fatality Collision':
                 df["SEVERITYCODE"][i] = 4

         # Converted values
         df["SEVERITYCODE"].value_counts()

         1     137776
         2      58842
         2b      3111
         3        352
         Name: SEVERITYCODE, dtype: int64
```

```
Out[10]: 1    137776
         2     58842
         3      3111
         4       352
         Name: SEVERITYCODE, dtype: int64
```

Remove Columns with unnecessary information:

Columns containing descriptions and identification numbers that would not help in the classification are dropped from the dataset to reduce the complexity and dimensionality of the dataset.

```
In [11]: df = df.drop(['OBJECTID','INCKEY','LOCATION','COLDETKEY','REPORTNO','STATUS','INTKEY','EXCEPTRSNCODE',
                       'EXCEPTRSNDESC','SEVERITYDESC','INCDATE','SDOT_COLCODE','SDOT_COLDESC','SDOTCOLNUM','ST_COLCODE',
                       'ST_COLDESC','SEGLANEKEY','CROSSWALKKEY','INCDTTM'],axis=1)
         df.columns
```

```
Out[11]: Index(['index', 'X', 'Y', 'ADDRTYPE', 'SEVERITYCODE', 'COLLISIONTYPE',
                'PERSONCOUNT', 'PEDCOUNT', 'PEDCYLCOUNT', 'VEHCOUNT', 'INJURIES',
                'SERIOUSINJURIES', 'FATALITIES', 'JUNCTIONTYPE', 'INATTENTIONIND',
                'UNDERINFL', 'WEATHER', 'ROADCOND', 'LIGHTCOND', 'PEDROWNOTGRNT',
                'SPEEDING', 'HITPARKEDCAR'],
               dtype='object')
```

Finding missing values and handling them:

Empty boxes, ‘Unknown’ and ‘Other’ were values considered as missing values. These were replaced with NA to make the dataset uniform.

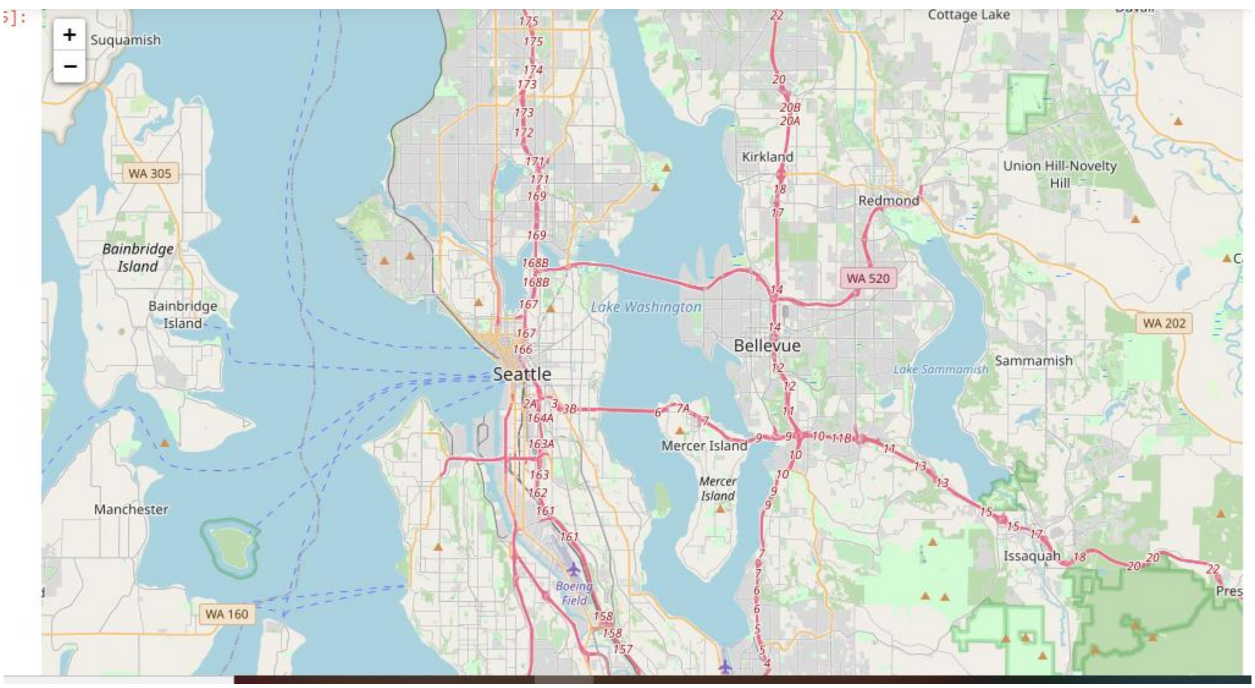
```
df.replace(r'^\s*$', np.nan, regex=True)
df.replace("Unknown", np.nan, inplace = True)
df.replace("Other", np.nan, inplace = True)
```

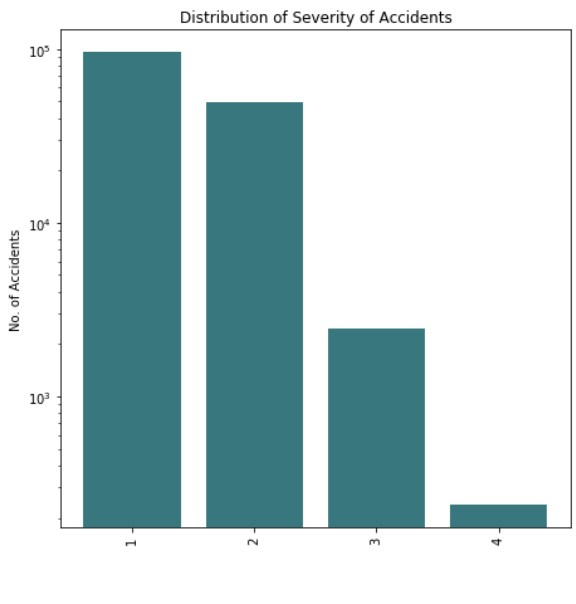
remove columns with more than 20% values missing

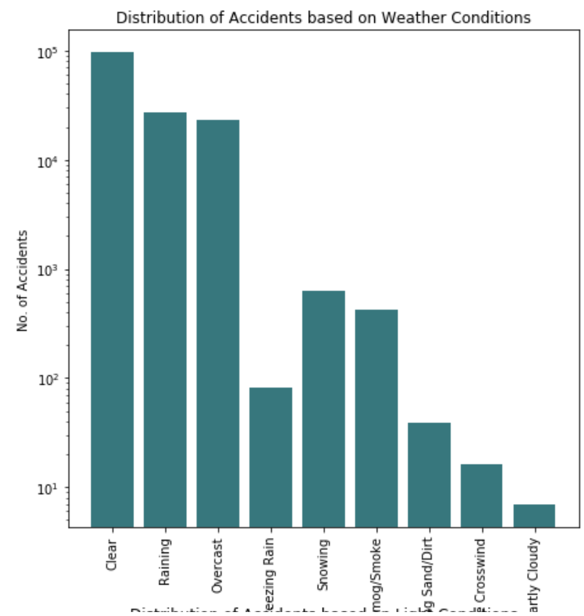
```
#removing columns with more than 20% values missing (INATTENTIONIND,PEDROWNOTGRNT,SPEEDING)
df = df.drop(["INATTENTIONIND","PEDROWNOTGRNT","SPEEDING"],axis=1)

#removing rows for columns with less than 20% values missing (X, Y,COLLISIONTYPE,JUNCTIONTYPE,
                                                              #UNDERINFL,WEATHER,ROADCOND,LIGHTCOND)
df.dropna(subset=["X","Y","COLLISIONTYPE","JUNCTIONTYPE","UNDERINFL","WEATHER","ROADCOND","LIGHTCOND"],
          axis=0, inplace=True)
```

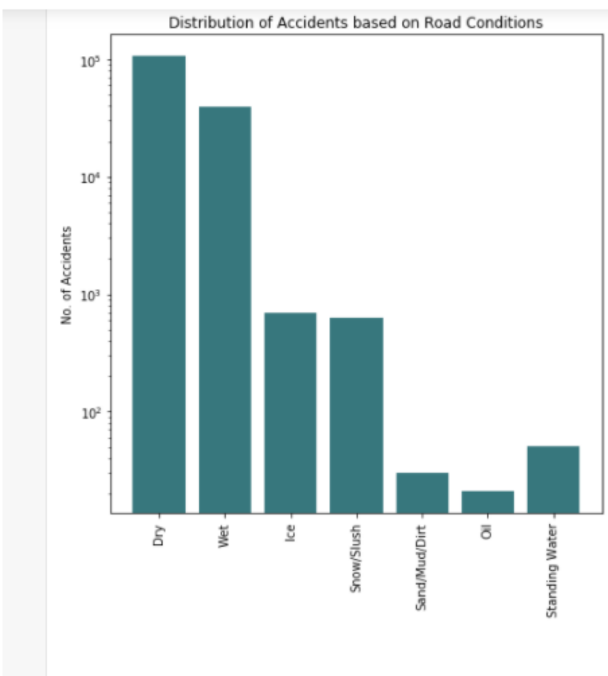
Visualizing the Data:

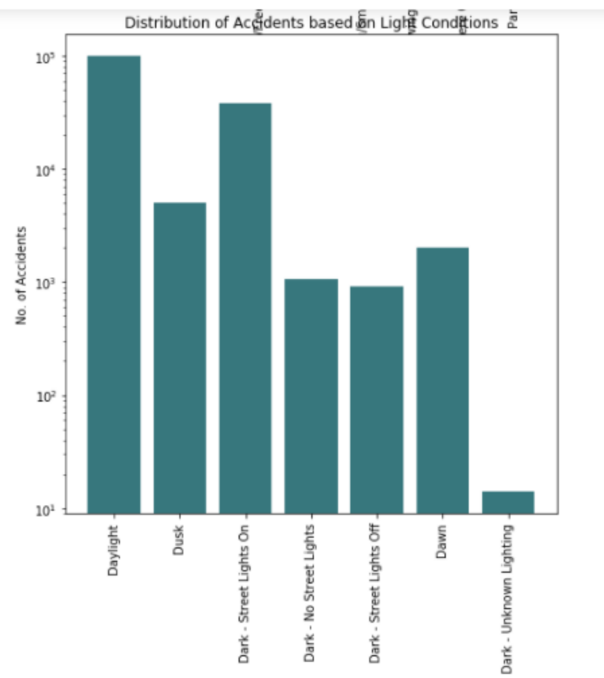
Seattle City Map of Accidents:

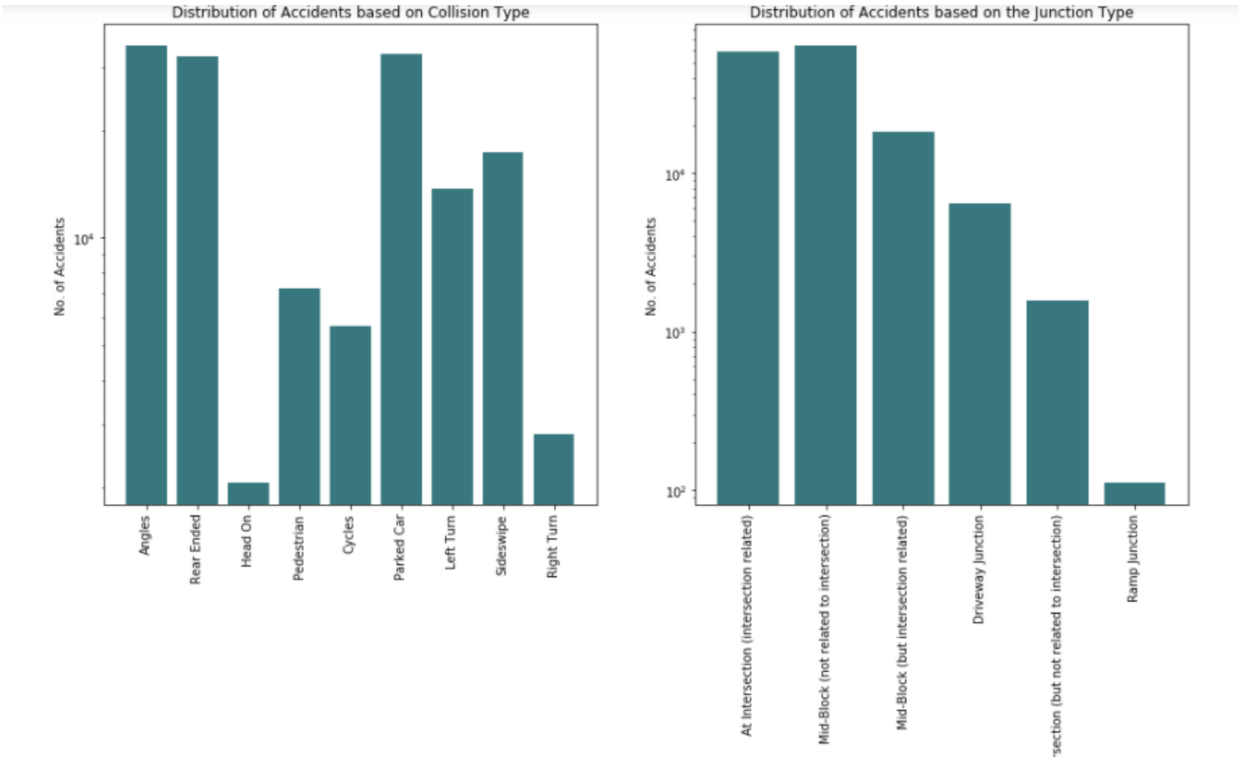



Distribution of Severity of Accidents
No. of Accidents
10^5
10^4
10^3
1
2
3
4


Distribution of Accidents based on Weather Conditions
No. of Accidents
10^5
10^4
10^3
10^2
10^1
Clear
Raining
Overcast
eezing Rain
Snowing
mog/Smoke
g Sand/Dirt
Crosswind
artly Cloudy


Distribution of Accidents based on Road Conditions
No. of Accidents
10^5
10^4
10^3
10^2
Dry
Wet
Ice
Snow/Slush
Sand/Mud/Dirt
Oil
Standing Water


Distribution of Accidents based on Light Conditions
No. of Accidents
10^5
10^4
10^3
10^2
10^1
Daylight
Dusk
Dark - Street Lights On
Dark - No Street Lights
Dark - Street Lights Off
Dawn
Dark - Unknown Lighting



Most accidents (75.6%) occurred in clear or overcast (i.e. dry) weather conditions. The remaining 24.4% took place either in severe conditions (such as severe winds) or during periods of precipitation (rain, snow, fog, etc).

Road conditions at the time of each accident. Clearly the road conditions are related to the prevailing weather at the time (e.g. if there is rain, the roads are likely to be wet), however conditions are not wholly determined by the weather. For instance, 61 accidents occurred on roads where oil was present.

The light conditions at the time of each accident. 62.6% accidents occurred during daylight hours, while 26.2% of accidents occurred at nighttime in areas with streetlights (i.e. urban areas). The remaining 11.2% of accidents include those which happened at dawn/dusk, or on roads with no/faulty streetlights.

Balancing the Dataset:

As is clear from the histogram of severity code shown above most accidents involve either no injuries, or minor injuries only. Only a small number of accidents involve serious injuries or fatalities. If we train a classification model on these data, the model will be biased. To fix this issue we need to resample the data.

The Dataset contains 4 target variables i.e., Severity code: 1, 2, 3, and 4

Property Damage Only Collision Severity Code 1
Injury Collision Severity Code 2
Serious Injury Collision Severity Code 3
Fatality Collision Severity Code 4

Combined the Severity codes 2, 3 and 4 to one Severity. i.e., making it "0" which is completely related to Fatal or Injury. Code 1 represents Property damage.

```
In [23]: MyData['SEVERITYCODE'] = [1 if b=="1" else 0 for b in MyData.SEVERITYCODE]

         MyData['SEVERITYCODE'].value_counts()

Out[23]: 1    95913
         0    52258
         Name: SEVERITYCODE, dtype: int64
```

Down sample the Severity code 1 to match the number of Samples in Severity code 0

```
In [24]: # shuffling and creating a balanced dataset
         MyData= MyData.sample(frac=1,random_state=0,replace=False)

         # 1 - Put all severity code 2 class in a separate dataset.
         df_scode2 = MyData.loc[MyData['SEVERITYCODE'] == 0]

         # 2 - Randomly select 58188 observations from the severity code 1(majority class)
         df_scode1 = MyData.loc[MyData['SEVERITYCODE'] == 1].sample(n=52258,random_state=42)

         # 3 - concatenating datasets to get balanced dataset
         MyData_balanced = pd.concat([df_scode1,df_scode2])
         MyData_balanced = MyData_balanced.sample(frac=1,random_state=0,replace=False)

         #checking if dataset balanced
         print(MyData_balanced['SEVERITYCODE'].value_counts())
         MyData_balanced.info()

         1    52258
         0    52258
         Name: SEVERITYCODE, dtype: int64
```

Encoding Categorical columns and creating dummy Variables

Machine Learning model should be trained only on numerical data. So, convert all Categorical Columns to numerical format by creating Dummy Variables.

Encoding Categorical columns and creating dummies

```
In [25]:
         Feature = MyData_balanced.iloc[:,1:]

         #Encoding Categorical Features - Training Dataset
         Feature = pd.get_dummies(data=Feature, columns=['ADDRTYPE','COLLISIONTYPE','JUNCTIONTYPE','WEATHER',
                                                         'ROADCOND','LIGHTCOND','UNDERINFL','HITPARKEDCAR'])
         del Feature["SEVERITYCODE"]
```

```
In [33]: Feature.isnull().sum(axis=0)

Out[33]: X                                                          0
         Y                                                          0
         PERSONCOUNT                                                0
         PEDCOUNT                                                   0
         PEDCYLCOUNT                                                0
         VEHCOUNT                                                   0
         INJURIES                                                   0
         SERIOUSINJURIES                                            0
         FATALITIES                                                 0
         ADDRTYPE_Block                                             0
         ADDRTYPE_Intersection                                      0
         COLLISIONTYPE_Angles                                       0
         COLLISIONTYPE_Cycles                                       0
         COLLISIONTYPE_Head On                                      0
         COLLISIONTYPE_Left Turn                                    0
         COLLISIONTYPE_Parked Car                                   0
         COLLISIONTYPE_Pedestrian                                   0
         COLLISIONTYPE_Rear Ended                                   0
         COLLISIONTYPE_Right Turn                                   0
         COLLISIONTYPE_Sideswipe                                    0
         JUNCTIONTYPE_At Intersection (but not related to intersection)   0
         JUNCTIONTYPE_At Intersection (intersection related)        0
         JUNCTIONTYPE_Driveway Junction                             0
         JUNCTIONTYPE_Mid-Block (but intersection related)          0
         JUNCTIONTYPE_Mid-Block (not related to intersection)       0
         JUNCTIONTYPE_Ramp Junction                                 0
         WEATHER_Blowing Sand/Dirt                                  0
         WEATHER_Clear                                              0
         WEATHER_Fog/Smog/Smoke                                     0
         WEATHER_Overcast                                           0
         WEATHER_Partly Cloudy                                      0
         WEATHER_Raining                                            0
         WEATHER_Severe Crosswind                                   0
         WEATHER_Sleet/Hail/Freezing Rain                           0
         WEATHER_Snowing                                            0
         ROADCOND_Dry                                               0
         ROADCOND_Ice                                               0
         ROADCOND_Oil                                               0
         ROADCOND_Sand/Mud/Dirt                                     0
         ROADCOND_Snow/Slush                                        0
         ROADCOND_Standing Water                                    0
         ROADCOND_Wet                                               0
         LIGHTCOND_Dark - No Street Lights                          0
         LIGHTCOND_Dark - Street Lights Off                         0
         LIGHTCOND_Dark - Street Lights On                          0
         LIGHTCOND_Dark - Unknown Lighting                          0
         LIGHTCOND_Dawn                                             0
         LIGHTCOND_Daylight                                         0
         LIGHTCOND_Dusk                                             0
         UNDERINFL_0                                                0
         UNDERINFL_N                                                0
         UNDERINFL_Y                                                0
         HITPARKEDCAR_N                                             0
         HITPARKEDCAR_Y                                             0
         dtype: int64
```

From the above listed, we can see that the Data is balanced and cleaned. This Data is perfect to build the Model.

Forward Steps:

Split the data in to testing (30%) and training (70%) subsamples and then build the following models for evaluation:

1. Decision Tree
2. Random Forest
3. Logistic Regression
4. Support Vector Machine