IBM Data Science Professional Certificate

Capstone Project: To Predict the Severity of a Traffic Accident

Monica

[monica110394@gmail.com (mailto:monica110394@gmail.com)](mailto:monica110394@gmail.com)

[https://www.linkedin.com/in/monica110394/ (https://www.linkedin.com/in/monica110394/)](https://www.linkedin.com/in/monica110394/)

[https://github.com/monica110394/Coursera_Capstone (https://github.com/monica110394/Coursera_Capstone)](https://github.com/monica110394/Coursera_Capstone)

Date: 9-10-2020

Data Introduction

In [1]:

```
# imporing libraries
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from scipy import stats

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
print('Hello Capstone Project Course!')
```

```
Hello Capstone Project Course!
```

In [3]:

```
# Loading the dataset
data = pd.read_csv('Data-Collisions.csv')

# knowing the dimensions of the dataset
print('Number of rows:', data.shape[0],'\nNumber of Columns', data.shape[1])
data.head()
```

```
Number of rows: 194673
Number of Columns 38
```

Out[3]:

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

5 rows × 38 columns

Variable Selection

In [4]:

```
# knowing the attributes present in the dataset
print('Column Names:\n\n', data.columns)
```

```
Column Names:

 Index(['SEVERITYCODE', 'X', 'Y', 'OBJECTID', 'INCKEY', 'COLDETKEY', 'REPORT
NO',
       'STATUS', 'ADDRTYPE', 'INTKEY', 'LOCATION', 'EXCEPTRSNCODE',
       'EXCEPTRSNDESC', 'SEVERITYCODE.1', 'SEVERITYDESC', 'COLLISIONTYPE',
       'PERSONCOUNT', 'PEDCOUNT', 'PEDCYLCOUNT', 'VEHCOUNT', 'INCDATE',
       'INCDTTM', 'JUNCTIONTYPE', 'SDOT_COLCODE', 'SDOT_COLDESC',
       'INATTENTIONIND', 'UNDERINFL', 'WEATHER', 'ROADCOND', 'LIGHTCOND',
       'PEDROWNOTGRNT', 'SDOTCOLNUM', 'SPEEDING', 'ST_COLCODE', 'ST_COLDES
C',
       'SEGLANEKEY', 'CROSSWALKKEY', 'HITPARKEDCAR'],
      dtype='object')
```

In [5]:

```
# keeping only the necessary columns
data = data[['SEVERITYCODE', 'ADDRTYPE', 'COLLISIONTYPE', 'PERSONCOUNT', 'PEDCOUNT',
             'PEDCYLCOUNT', 'VEHCOUNT', 'JUNCTIONTYPE', 'SDOT_COLCODE', 'INATTENTIONIND',
 'UNDERINFL', 'WEATHER', 'ROADCOND', 'LIGHTCOND', 'SPEEDING', 'ST_COLCODE', 'HITPARKEDCAR'

print('Updated Features:\n', data.columns)
print('\nNumber of rows:', data.shape[0],'\nNumber of Columns', data.shape[1])
```

```
Updated Features:
 Index(['SEVERITYCODE', 'ADDRTYPE', 'COLLISIONTYPE', 'PERSONCOUNT', 'PEDCOUN
T',
       'PEDCYLCOUNT', 'VEHCOUNT', 'JUNCTIONTYPE', 'SDOT_COLCODE',
       'INATTENTIONIND', 'UNDERINFL', 'WEATHER', 'ROADCOND', 'LIGHTCOND',
       'SPEEDING', 'ST_COLCODE', 'HITPARKEDCAR'],
      dtype='object')

Number of rows: 194673
Number of Columns 17
```

Feature Engineering

In [6]:

```
# checking for null values
data.isnull().sum()
```

Out[6]:

```
SEVERITYCODE           0
ADDRTYPE            1926
COLLISIONTYPE       4904
PERSONCOUNT            0
PEDCOUNT               0
PEDCYLCOUNT            0
VEHCOUNT               0
JUNCTIONTYPE        6329
SDOT_COLCODE           0
INATTENTIONIND    164868
UNDERINFL           4884
WEATHER             5081
ROADCOND            5012
LIGHTCOND           5170
SPEEDING          185340
ST_COLCODE            18
HITPARKEDCAR           0
dtype: int64
```

In [7]:

```
# removing rows with high number of null values
data.drop(columns=['SPEEDING', 'INATTENTIONIND'], inplace = True)
print('Updated Features:\n', data.columns)
print('\nNumber of rows:', data.shape[0],'\nNumber of Columns', data.shape[1])
```

```
Updated Features:
 Index(['SEVERITYCODE', 'ADDRTYPE', 'COLLISIONTYPE', 'PERSONCOUNT', 'PEDCOUN
T',
       'PEDCYLCOUNT', 'VEHCOUNT', 'JUNCTIONTYPE', 'SDOT_COLCODE', 'UNDERINF
L',
       'WEATHER', 'ROADCOND', 'LIGHTCOND', 'ST_COLCODE', 'HITPARKEDCAR'],
      dtype='object')

Number of rows: 194673
Number of Columns 15
```

In [8]:

```
# checking for null values
data.isnull().sum()
```

Out[8]:

```
SEVERITYCODE       0
ADDRTYPE        1926
COLLISIONTYPE   4904
PERSONCOUNT        0
PEDCOUNT           0
PEDCYLCOUNT        0
VEHCOUNT           0
JUNCTIONTYPE    6329
SDOT_COLCODE       0
UNDERINFL       4884
WEATHER         5081
ROADCOND        5012
LIGHTCOND       5170
ST_COLCODE        18
HITPARKEDCAR       0
dtype: int64
```

In [9]:

```
# removing rows with null values
data.dropna(axis=0, inplace = True)
# data.reset_index(inplace = True)
print('Updated Features:\n', data.columns)
print('\nNumber of rows:', data.shape[0],'\nNumber of Columns', data.shape[1])
print('\nNumber of Null Values', data.isnull().sum())
```

```
Updated Features:
 Index(['SEVERITYCODE', 'ADDRTYPE', 'COLLISIONTYPE', 'PERSONCOUNT', 'PEDCOUN
T',
       'PEDCYLCOUNT', 'VEHCOUNT', 'JUNCTIONTYPE', 'SDOT_COLCODE', 'UNDERINF
L',
       'WEATHER', 'ROADCOND', 'LIGHTCOND', 'ST_COLCODE', 'HITPARKEDCAR'],
      dtype='object')

Number of rows: 182895
Number of Columns 15

Number of Null Values SEVERITYCODE     0
ADDRTYPE         0
COLLISIONTYPE    0
PERSONCOUNT      0
PEDCOUNT         0
PEDCYLCOUNT      0
VEHCOUNT         0
JUNCTIONTYPE     0
SDOT_COLCODE     0
UNDERINFL        0
WEATHER          0
ROADCOND         0
LIGHTCOND        0
ST_COLCODE       0
HITPARKEDCAR     0
dtype: int64
```

In [10]:

```
# checking the datatypes of the features
print('Data types of all attributes:\n\n', data.dtypes)
```

```
Data types of all attributes:

 SEVERITYCODE      int64
ADDRTYPE          object
COLLISIONTYPE     object
PERSONCOUNT        int64
PEDCOUNT           int64
PEDCYLCOUNT        int64
VEHCOUNT           int64
JUNCTIONTYPE      object
SDOT_COLCODE       int64
UNDERINFL         object
WEATHER           object
ROADCOND          object
LIGHTCOND         object
ST_COLCODE        object
HITPARKEDCAR      object
dtype: object
```

In [11]:

```
# converting string labels into numbers
from sklearn import preprocessing

le = preprocessing.LabelEncoder()

data['ADDRTYPE'] = le.fit_transform(data['ADDRTYPE'])
data['COLLISIONTYPE'] = le.fit_transform(data['COLLISIONTYPE'])
data['JUNCTIONTYPE'] = le.fit_transform(data['JUNCTIONTYPE'])
data['UNDERINFL'] = le.fit_transform(data['UNDERINFL'])
data['WEATHER'] = le.fit_transform(data['WEATHER'])
data['ROADCOND'] = le.fit_transform(data['ROADCOND'])
data['LIGHTCOND'] = le.fit_transform(data['LIGHTCOND'])
data['HITPARKEDCAR'] = le.fit_transform(data['HITPARKEDCAR'])
```

In [12]:

```
# changing to categorical data types
data['SEVERITYCODE'] = data['SEVERITYCODE'].astype('category')
data['ADDRTYPE'] = data['ADDRTYPE'].astype('category')
data['COLLISIONTYPE'] = data['COLLISIONTYPE'].astype('category')
data['JUNCTIONTYPE'] = data['JUNCTIONTYPE'].astype('category')
data['SDOT_COLCODE'] = data['SDOT_COLCODE'].astype('category')
data['UNDERINFL'] = data['UNDERINFL'].astype('category')
data['WEATHER'] = data['WEATHER'].astype('category')
data['ROADCOND'] = data['ROADCOND'].astype('category')
data['LIGHTCOND'] = data['LIGHTCOND'].astype('category')
data['ST_COLCODE'] = data['ST_COLCODE'].astype('category')
data['HITPARKEDCAR'] = data['HITPARKEDCAR'].astype('category')
```

In [13]:

```
print('Dataframe Summary:\n')
print(data.info())
```

```
Dataframe Summary:

<class 'pandas.core.frame.DataFrame'>
Int64Index: 182895 entries, 0 to 194672
Data columns (total 15 columns):
 #   Column          Non-Null Count   Dtype   
---  ------          --------------   -----   
 0   SEVERITYCODE    182895 non-null  category
 1   ADDRTYPE        182895 non-null  category
 2   COLLISIONTYPE   182895 non-null  category
 3   PERSONCOUNT     182895 non-null  int64   
 4   PEDCOUNT        182895 non-null  int64   
 5   PEDCYLCOUNT     182895 non-null  int64   
 6   VEHCOUNT        182895 non-null  int64   
 7   JUNCTIONTYPE    182895 non-null  category
 8   SDOT_COLCODE    182895 non-null  category
 9   UNDERINFL       182895 non-null  category
 10  WEATHER         182895 non-null  category
 11  ROADCOND        182895 non-null  category
 12  LIGHTCOND       182895 non-null  category
 13  ST_COLCODE      182895 non-null  category
 14  HITPARKEDCAR    182895 non-null  category
dtypes: category(11), int64(4)
memory usage: 8.9 MB
None
```

In [14]:

```
print('Statistical Summary:')
data.describe(include ='all')
```

```
Statistical Summary:
```

Out[14]:

	SEVERITYCODE	ADDRTYPE	COLLISIONTYPE	PERSONCOUNT	PEDCOUNT	PEDCY
count	182895.0	182895.0	182895.0	182895.000000	182895.000000	18289
unique	2.0	3.0	10.0	NaN	NaN	
top	1.0	1.0	5.0	NaN	NaN	
freq	126270.0	119362.0	43119.0	NaN	NaN	
mean	NaN	NaN	NaN	2.476268	0.038995	
std	NaN	NaN	NaN	1.370912	0.202960	
min	NaN	NaN	NaN	0.000000	0.000000	
25%	NaN	NaN	NaN	2.000000	0.000000	
50%	NaN	NaN	NaN	2.000000	0.000000	
75%	NaN	NaN	NaN	3.000000	0.000000	
max	NaN	NaN	NaN	81.000000	6.000000	

In [15]:

```
# renaming columns
data.rename(columns={'SEVERITYCODE':'SEVERITY', 'ADDRTYPE':'ADDRESS TYPE', 'COLLISIONTYPE'
                     'PERSONCOUNT':'#PEOPLE INVOLVED', 'PEDCOUNT':'#PEDESTRIANS INVOLVED',
                     'PEDCYLCOUNT':'#BICYCLES INVOLVED', 'VEHCOUNT':'#VEHICLES INVOLVED',
                     'JUNCTIONTYPE':'JUNCTION TYPE', 'SDOT_COLCODE':'COLLISION DESC', 'UNDI
                     'ROADCOND':'ROAD CONDITION', 'LIGHTCOND':'LIGHT CONDITION',
                     'ST_COLCODE':'STATE COLLISION DESC', 'HITPARKEDCAR':'PARKED CAR HIT'}.
data.head()
```

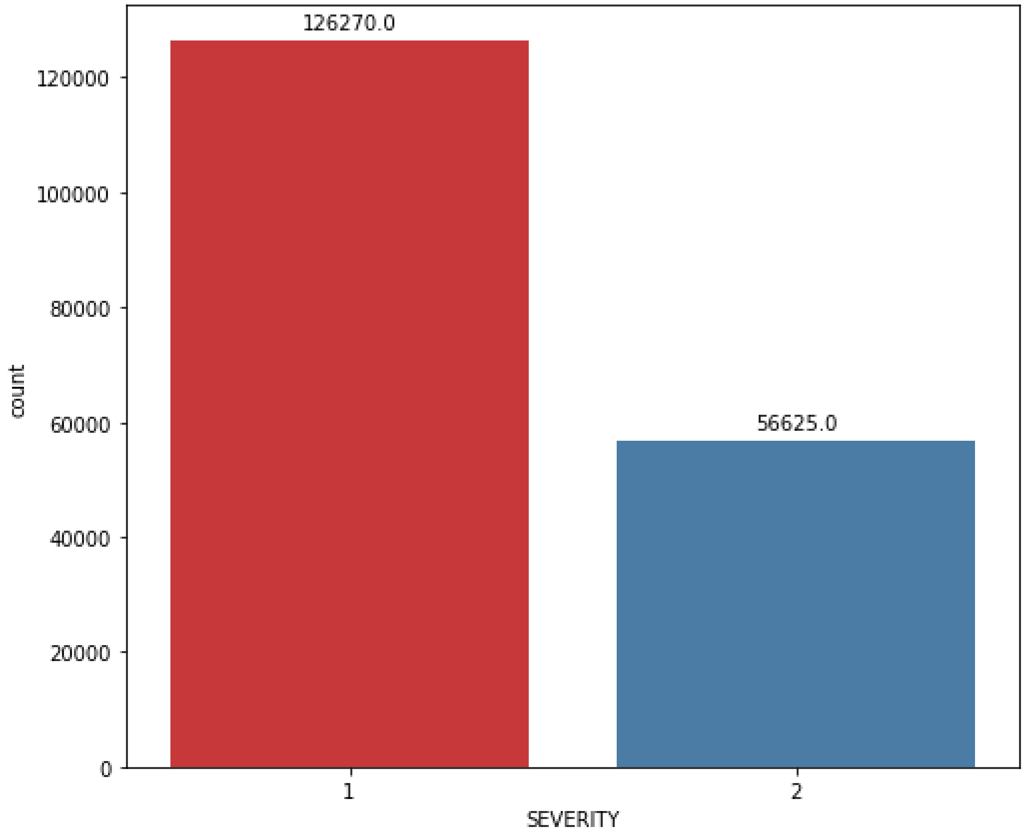
Out[15]:

	SEVERITY	ADDRESS TYPE	COLLISION TYPE	#PEOPLE INVOLVED	#PEDESTRIANS INVOLVED	#BICYCLES INVOLVED	#VEHICLES INVOLVED	JU
0	2	2	0	2	0	0	2	
1	1	1	9	2	0	0	2	
2	1	1	5	4	0	0	3	
3	1	1	4	3	0	0	3	
4	2	2	0	2	0	0	2	

Balancing dataset

In [16]:

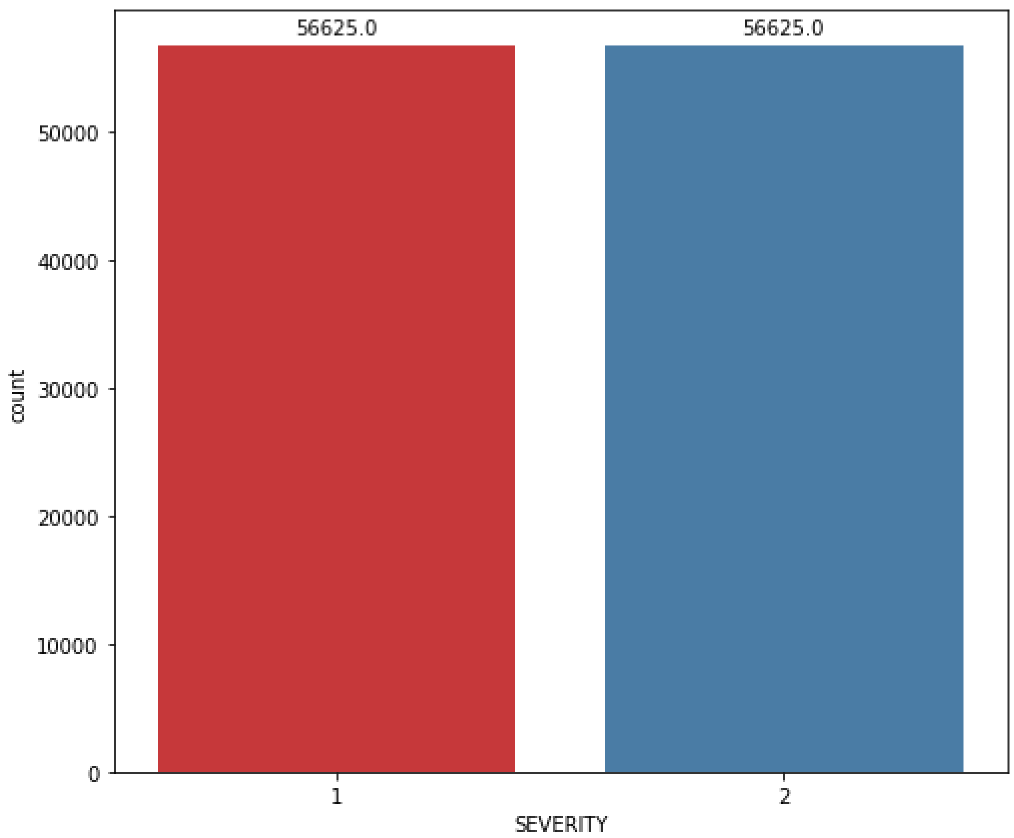
```
plt.figure(figsize=(8,7))
g = sns.countplot(data = data, x = 'SEVERITY', palette="Set1", saturation=0.7)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



In [17]:

```
# balancing the dataset
sev1 = data[data['SEVERITY']==1].sample(n = 56625, random_state=1)
sev2 = data[data['SEVERITY']==2].sample(n = 56625, random_state=1)
data = pd.concat([sev1, sev2])

print('\nNumber of rows:', data.shape[0],'\nNumber of Columns', data.shape[1])

plt.figure(figsize=(8,7))
g = sns.countplot(data = data, x = 'SEVERITY', palette="Set1", saturation=0.7)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```

```
Number of rows: 113250
Number of Columns 15
```

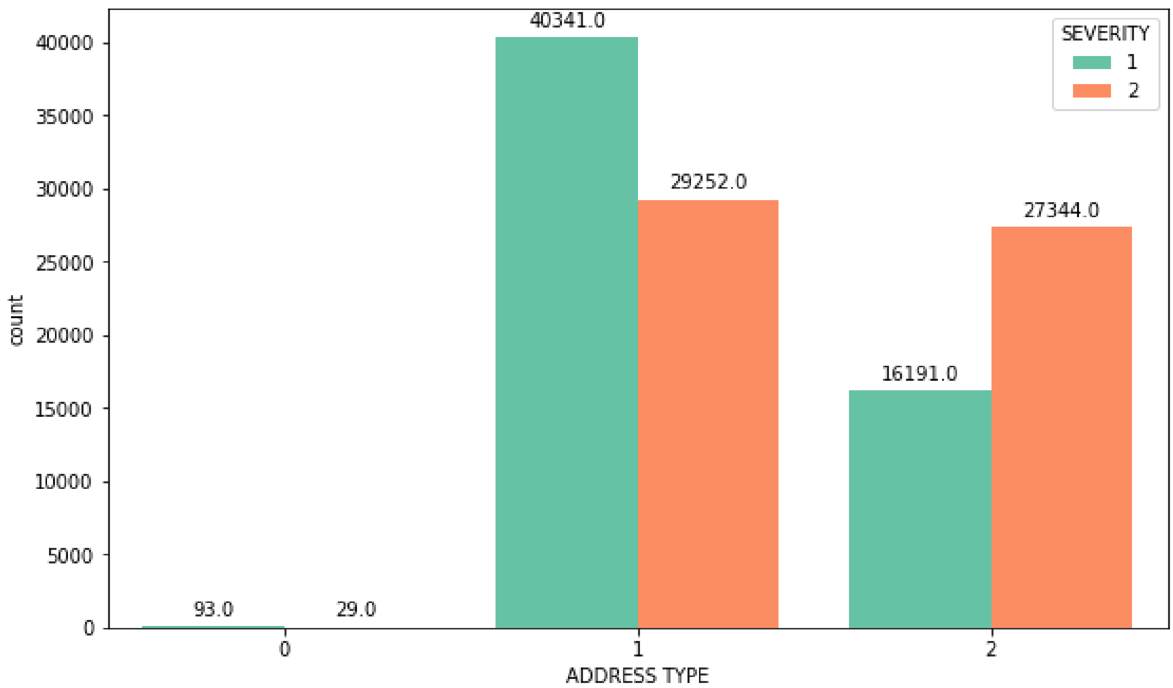


Exploratory Data Analysis

Categorical Variables

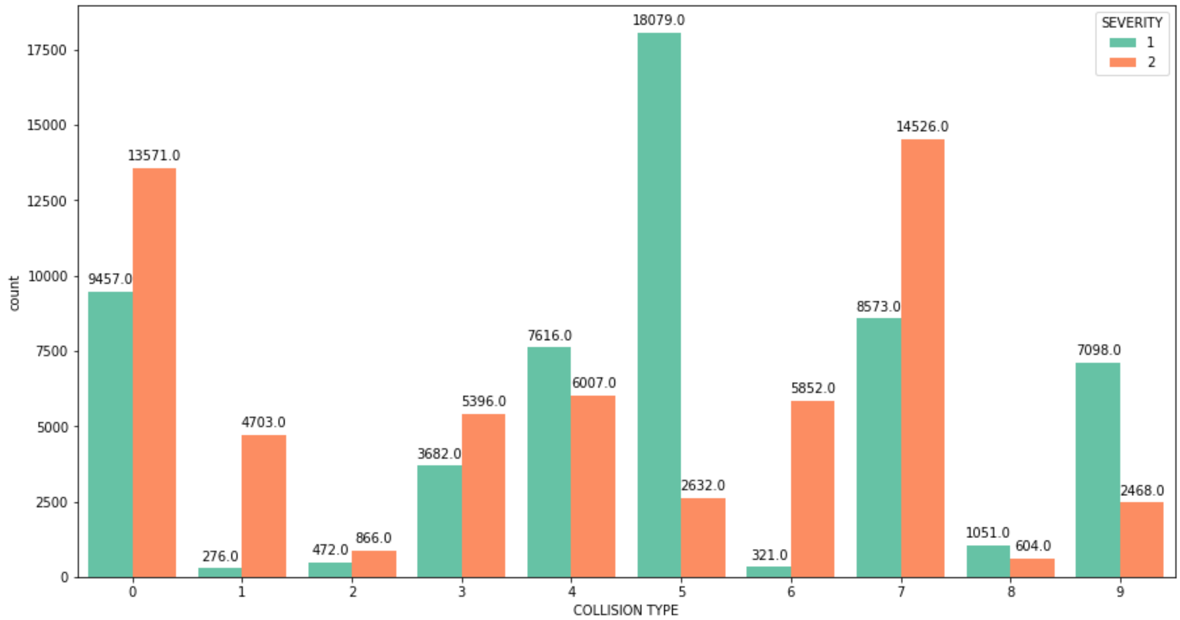
In [18]:

```
plt.figure(figsize=(10,6))
g = sns.countplot(data = data, x = 'ADDRESS TYPE', hue='SEVERITY', palette="Set2", saturat:

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



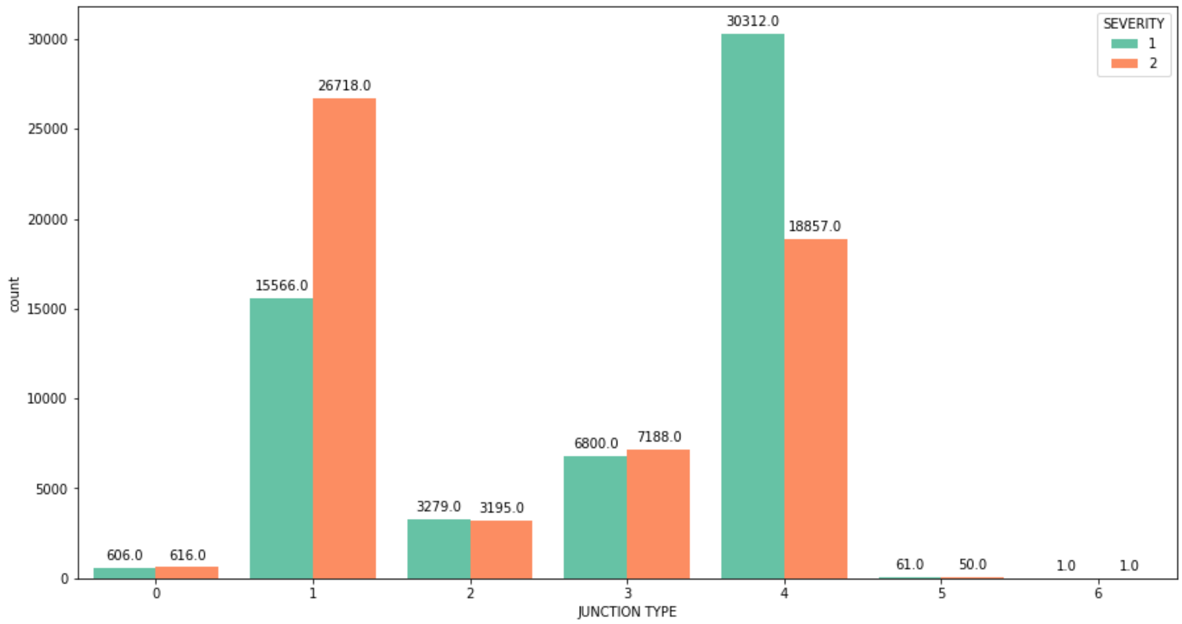
In [19]:

```
plt.figure(figsize=(15,8))
g = sns.countplot(data = data, x = 'COLLISION TYPE', hue='SEVERITY', palette="Set2", satur

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha = 'center', va = 'center',
                    xytext = (0, 9),
                    textcoords = 'offset points')
```



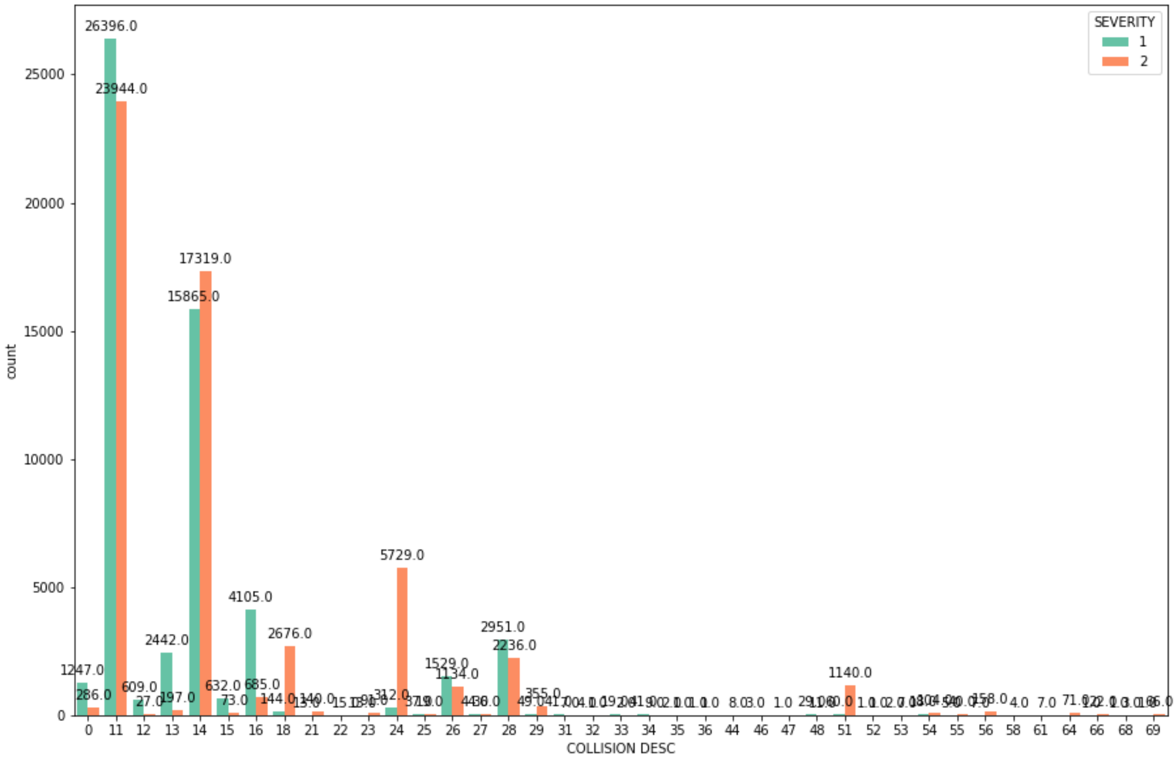
In [20]:

```
plt.figure(figsize=(15,8))
g = sns.countplot(data = data, x = 'JUNCTION TYPE', hue='SEVERITY', palette="Set2", saturat

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



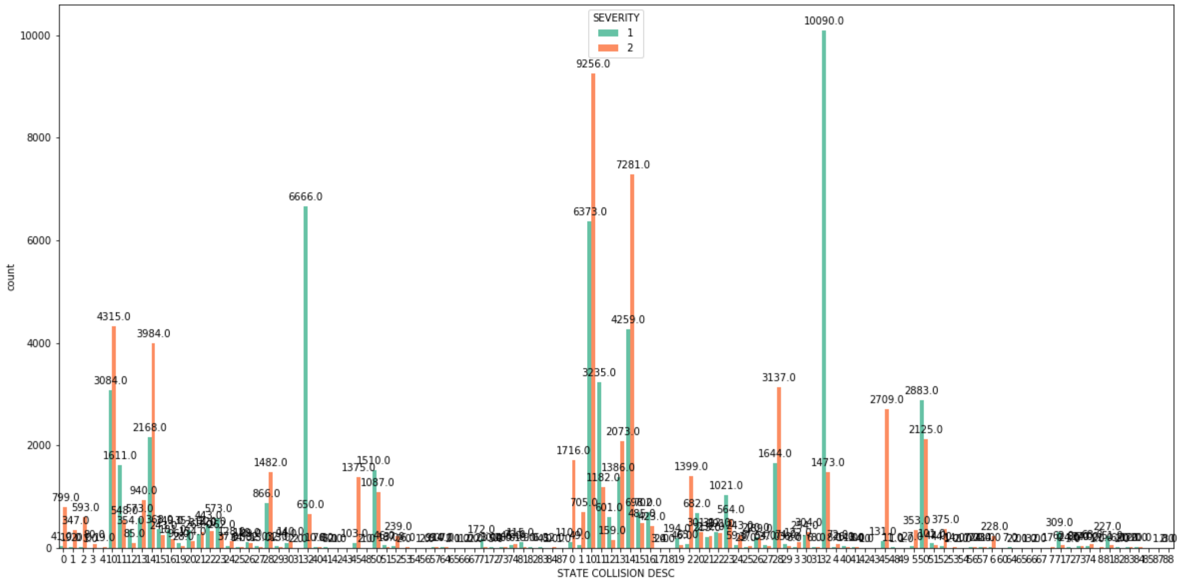
In [21]:

```
plt.figure(figsize=(15,10))
g = sns.countplot(data = data, x = 'COLLISION DESC', hue='SEVERITY', palette="Set2", saturi

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha = 'center', va = 'center',
                    xytext = (0, 9),
                    textcoords = 'offset points')
```



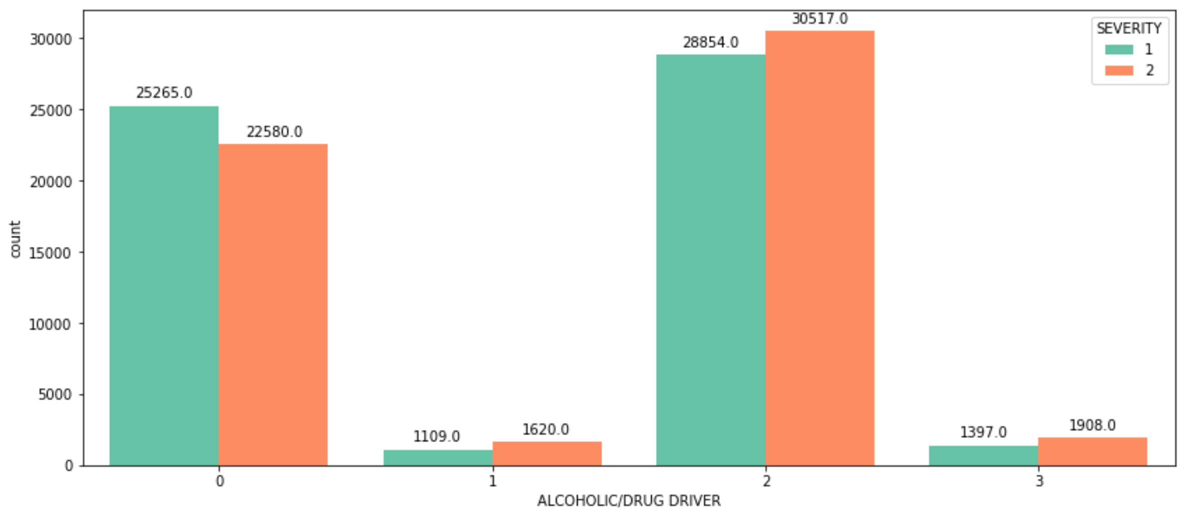
In [22]:

```
plt.figure(figsize=(20,10))
g = sns.countplot(data = data, x = 'STATE COLLISION DESC', hue='SEVERITY', palette="Set2",

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha = 'center', va = 'center',
                    xytext = (0, 9),
                    textcoords = 'offset points')
```



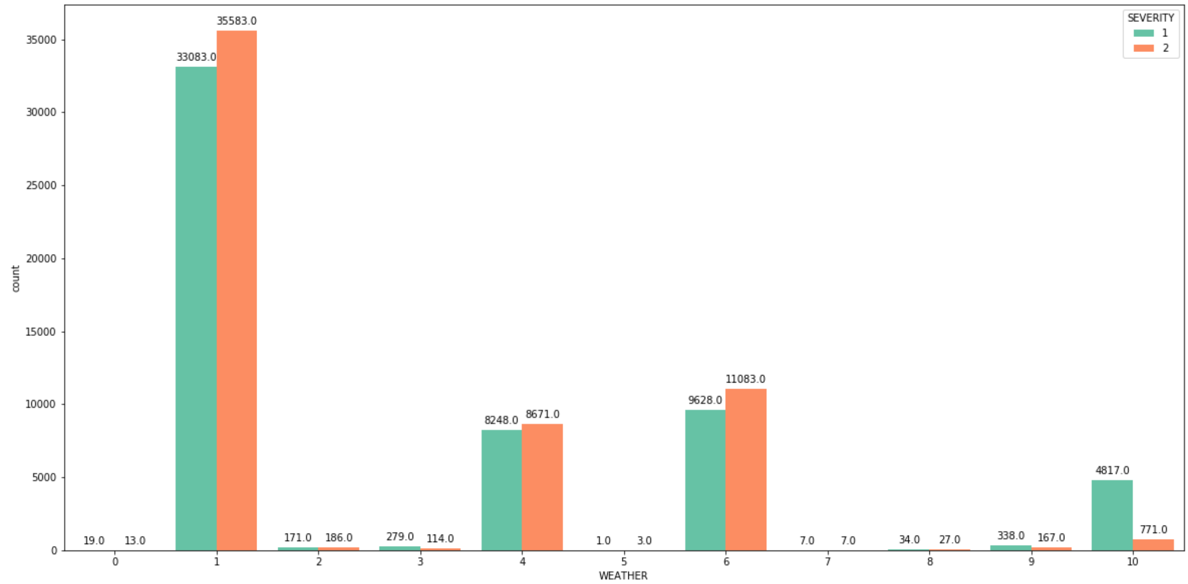
In [23]:

```
plt.figure(figsize=(14,6))
g = sns.countplot(data = data, x = 'ALCOHOLIC/DRUG DRIVER', hue='SEVERITY', palette="Set2".

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha = 'center', va = 'center',
                    xytext = (0, 9),
                    textcoords = 'offset points')
```



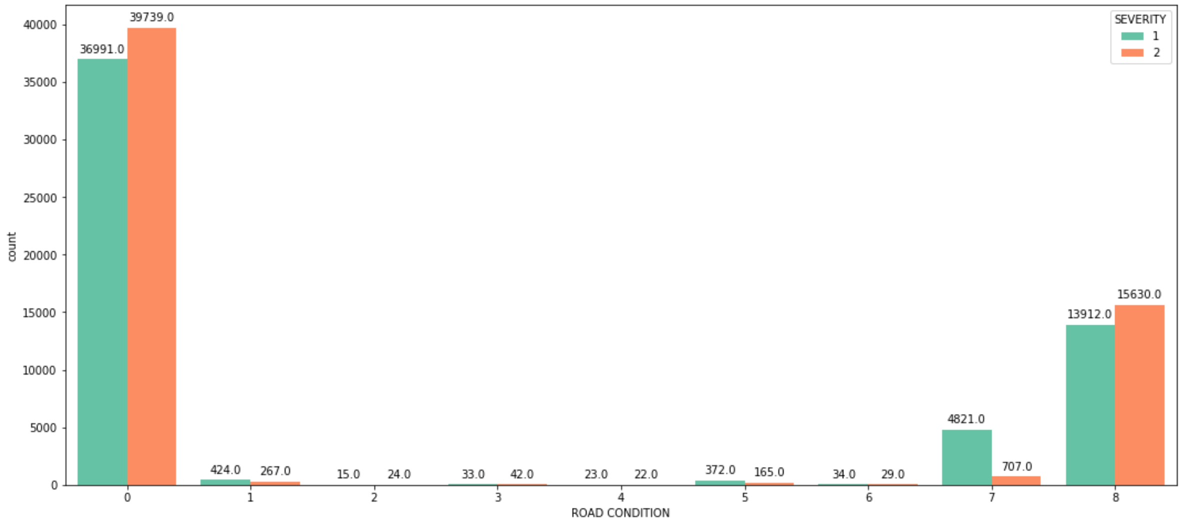
In [24]:

```
plt.figure(figsize=(20,10))
g = sns.countplot(data = data, x = 'WEATHER', hue='SEVERITY', palette="Set2", saturation=1)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



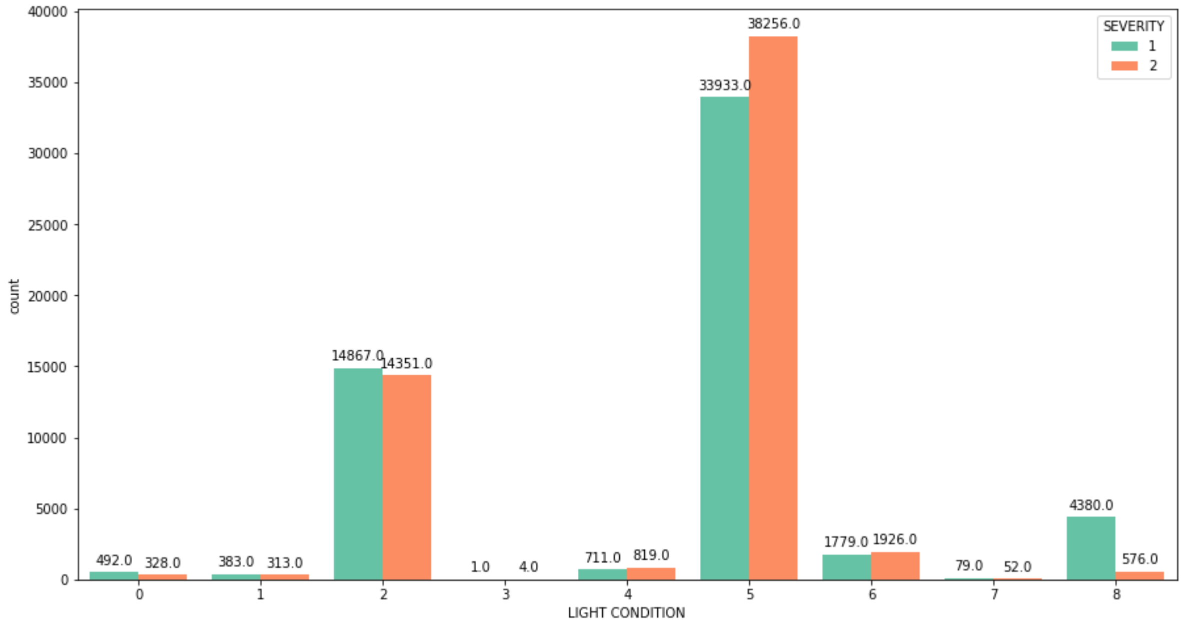
In [25]:

```
plt.figure(figsize=(18,8))
g = sns.countplot(data = data, x = 'ROAD CONDITION', hue='SEVERITY', palette="Set2", satur

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



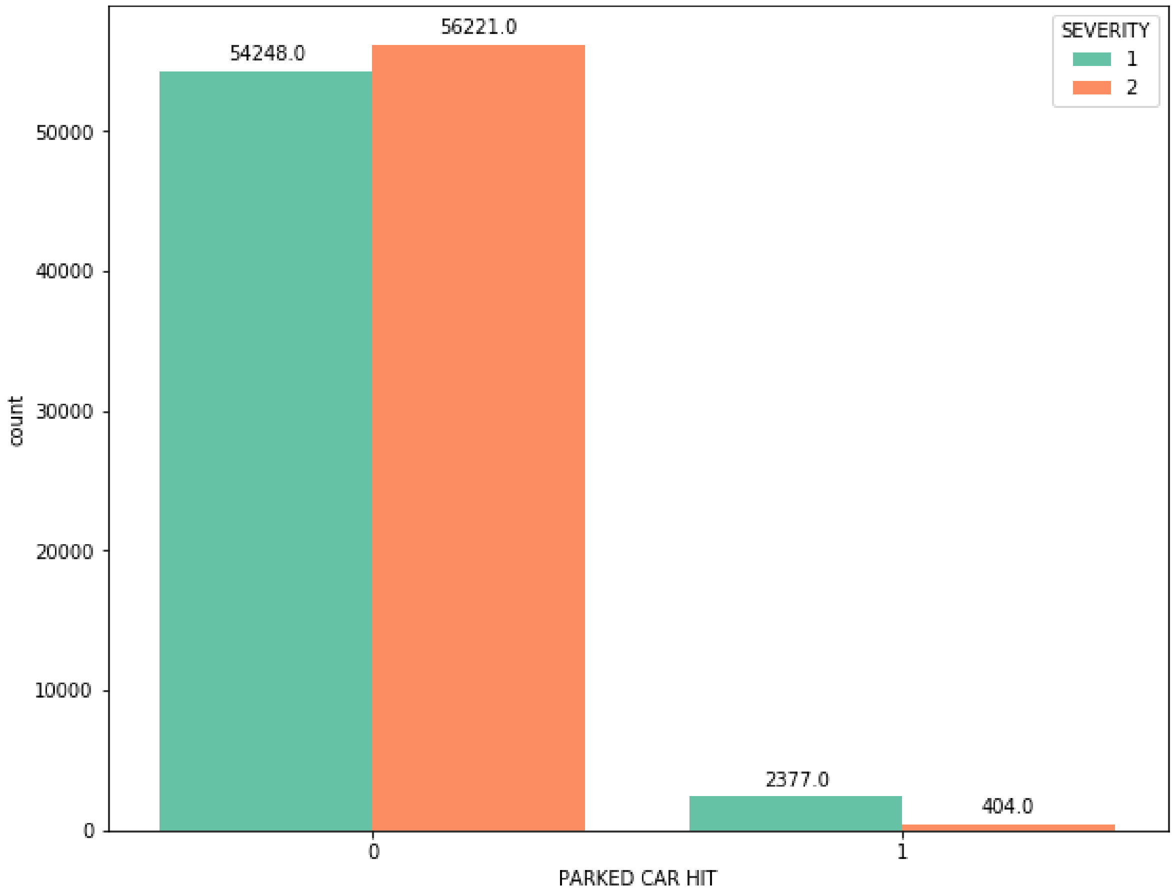
In [26]:

```
plt.figure(figsize=(15,8))
g = sns.countplot(data = data, x = 'LIGHT CONDITION', hue='SEVERITY', palette="Set2", satu

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



In [27]:

```
plt.figure(figsize=(10,8))
g = sns.countplot(data = data, x = 'PARKED CAR HIT', hue='SEVERITY', palette="Set2", saturı

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
               (p.get_x() + p.get_width() / 2., p.get_height()),
               ha = 'center', va = 'center',
               xytext = (0, 9),
               textcoords = 'offset points')
```



Numerical Variables

In [28]:

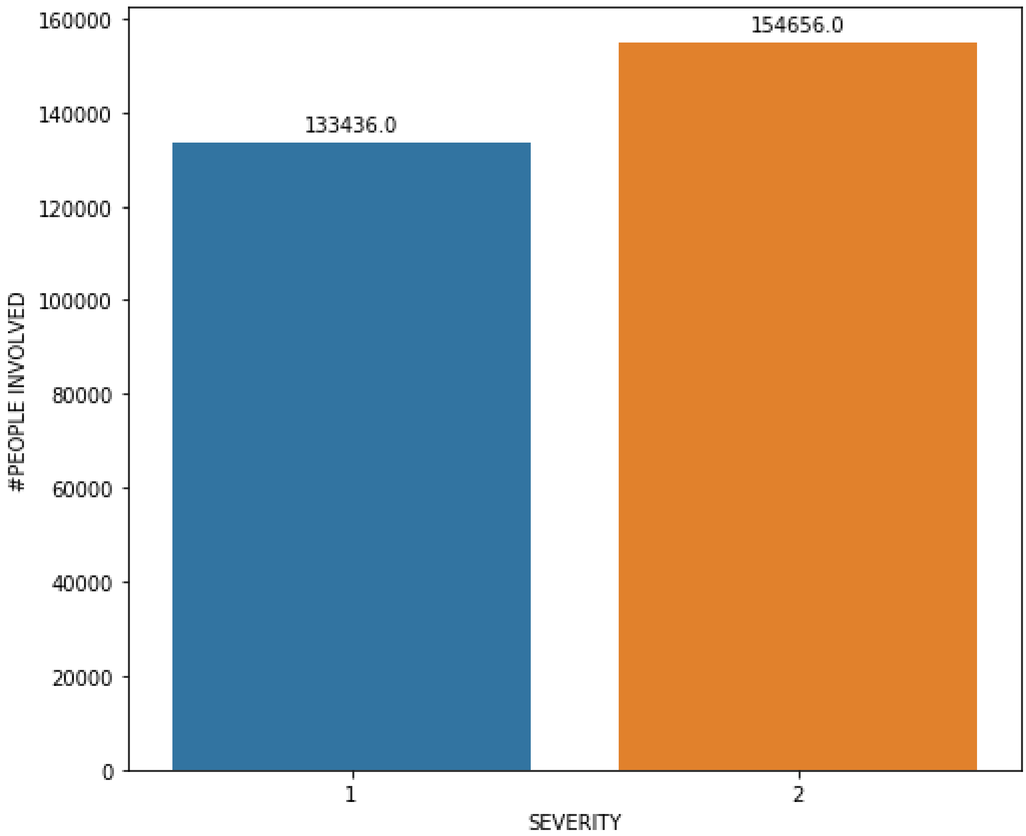
```
# aggregating by summing up numerical features grouped over 'SEVERITY'
involved = data.groupby(['SEVERITY'], as_index=False).sum()
involved
```

Out[28]:

	SEVERITY	#PEOPLE INVOLVED	#PEDESTRIANS INVOLVED	#BICYCLES INVOLVED	#VEHICLES INVOLVED
0	1	133436	342	277	113461
1	2	154656	6424	4792	107798

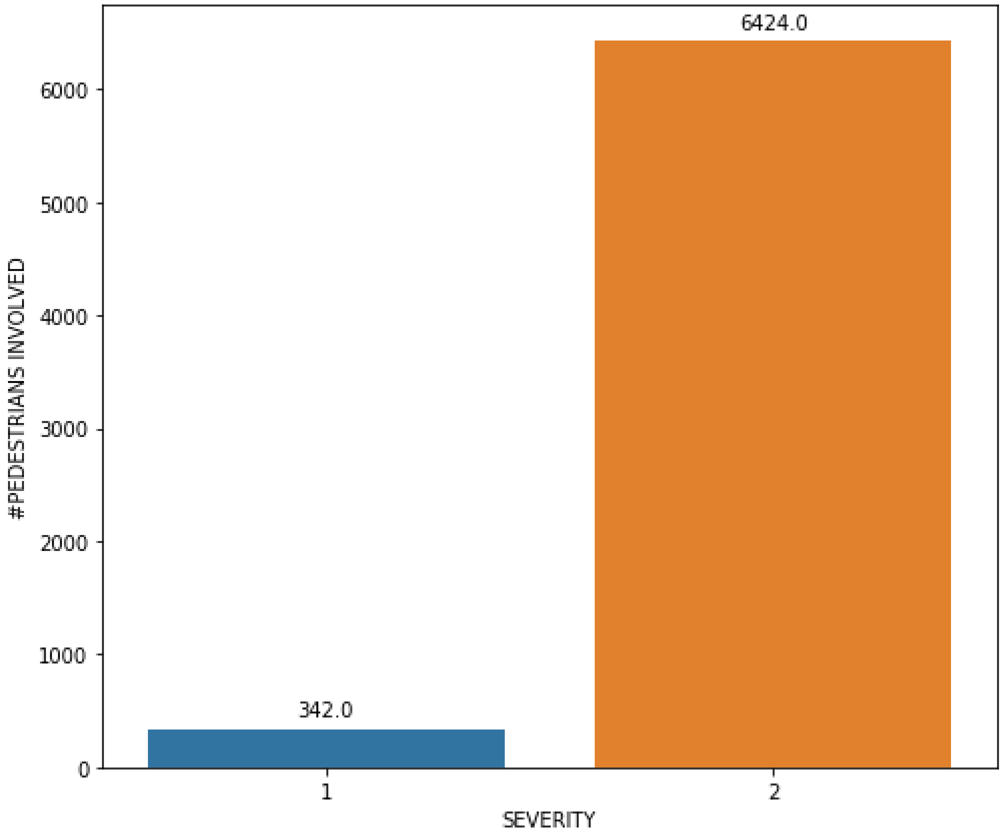
In [29]:

```
plt.figure(figsize=(8,7))
g = sns.barplot(y="#PEOPLE INVOLVED", x="SEVERITY", data=involved)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



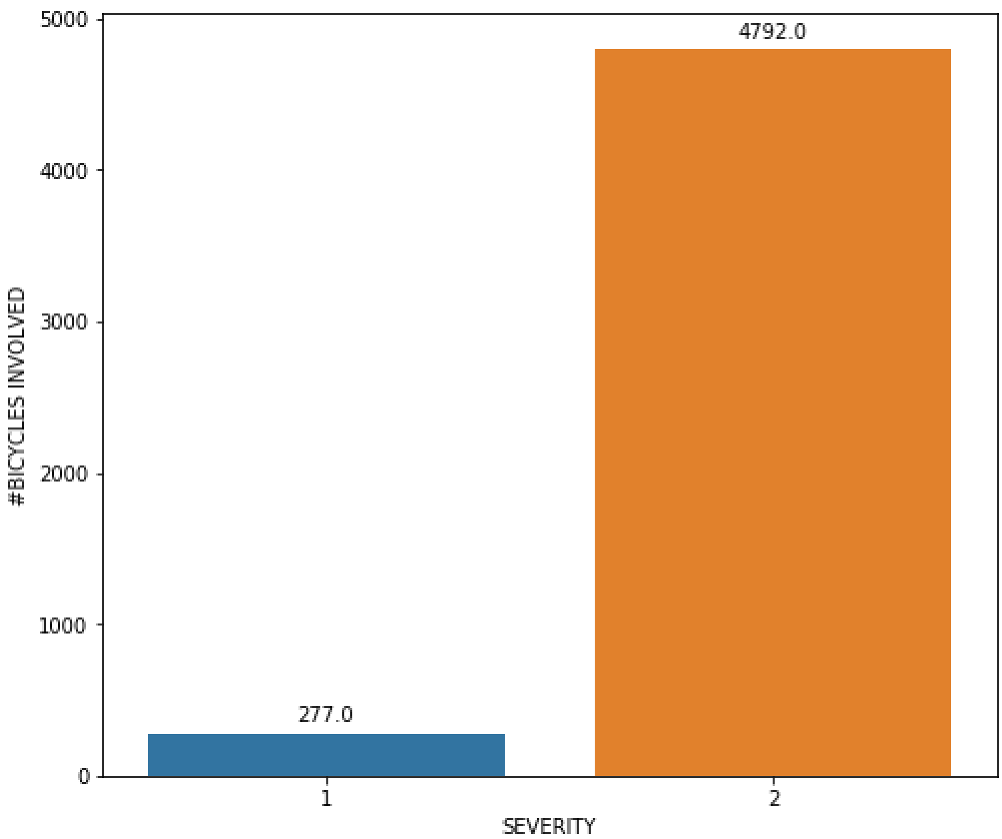
In [30]:

```
plt.figure(figsize=(8,7))
g = sns.barplot(y="#PEDESTRIANS INVOLVED", x="SEVERITY", data=involved)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha = 'center', va = 'center',
                xytext = (0, 9),
                textcoords = 'offset points')
```



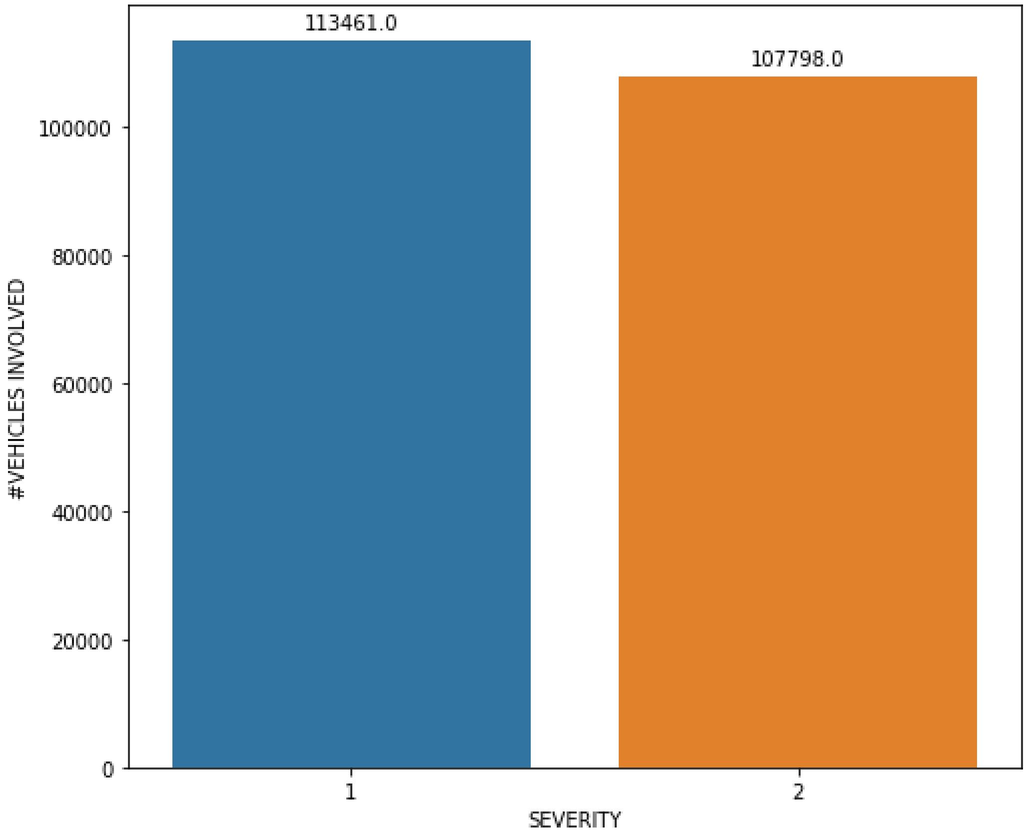
In [31]:

```
plt.figure(figsize=(8,7))
g = sns.barplot(y="#BICYCLES INVOLVED", x="SEVERITY", data=involved)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



In [32]:

```
plt.figure(figsize=(8,7))
g = sns.barplot(y="#VEHICLES INVOLVED", x="SEVERITY", data=involved)

for p in g.patches:
    g.annotate(format(p.get_height(), '.1f'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
```



In [33]:

```
# final dataset
data.head()
```

Out[33]:

	SEVERITY	ADDRESS TYPE	COLLISION TYPE	#PEOPLE INVOLVED	#PEDESTRIANS INVOLVED	#BICYCLES INVOLVED	#VEHICLE INVOLVE
20819	1	1	5	2	0	0	
114030	1	1	9	2	0	0	
137550	1	2	3	3	0	0	
32128	1	1	5	2	0	0	
52426	1	1	4	3	0	0	

Data Preparation

In [34]:

```
y = data['SEVERITY'].values
y[0:5]
```

Out[34]:

```
[1, 1, 1, 1, 1]
Categories (2, int64): [1, 2]
```

In [35]:

```
features = data.drop(columns=['SEVERITY'])
features.head()
```

Out[35]:

	ADDRESS TYPE	COLLISION TYPE	#PEOPLE INVOLVED	#PEDESTRIANS INVOLVED	#BICYCLES INVOLVED	#VEHICLES INVOLVED	JUNCTIO TYP
20819	1	5	2	0	0	2	
114030	1	9	2	0	0	2	
137550	2	3	3	0	0	3	
32128	1	5	2	0	0	2	
52426	1	4	3	0	0	3	

In [36]:

```
# normalizing dataset to get to zero mean and unit variance
from sklearn import preprocessing

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

Out[36]:

```
array([[-0.78486856,  0.23138773, -0.38496185, -0.24003531, -0.21465406,
         0.07597394,  1.00887947, -0.53788912, -1.13881327, -0.71206607,
        -0.67965636,  0.42454914, -0.11001508, -0.15866469],
       [-0.78486856,  1.62434501, -0.38496185, -0.24003531, -0.21465406,
         0.07597394,  1.00887947, -0.53788912,  0.82441877, -0.71206607,
        -0.67965636,  0.42454914, -0.7206508 , -0.15866469],
       [ 1.26259106, -0.46509091,  0.32287244, -0.24003531, -0.21465406,
         1.71765476, -1.15285513, -0.53788912,  0.82441877, -0.71206607,
        -0.67965636,  0.42454914,  0.43277223, -0.15866469],
       [-0.78486856,  0.23138773, -0.38496185, -0.24003531, -0.21465406,
         0.07597394,  1.00887947, -0.11439511, -1.13881327, -0.71206607,
        -0.67965636,  0.42454914,  0.70416588, -0.15866469],
       [-0.78486856, -0.11685159,  0.32287244, -0.24003531, -0.21465406,
         1.71765476, -0.43227693,  2.28540429, -1.13881327, -0.71206607,
        -0.67965636, -1.44281192,  0.02568175, -0.15866469]])
```

In [37]:

```
# splitting the dataset into train and test dataset
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: (90600, 14) (90600,)
Test set: (22650, 14) (22650,)
```

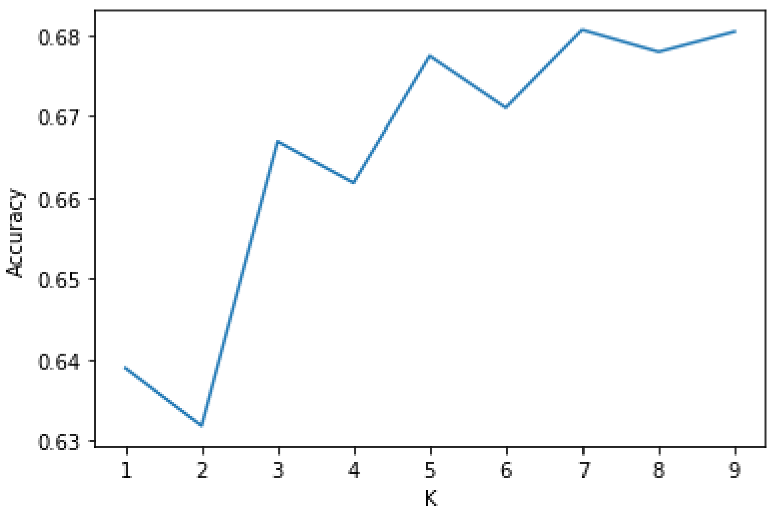
Model Building

KNN

In [38]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics

K = 10
accuracy = []

# finding the best hyperparameter
for n in range(1,K):
    knn = KNeighborsClassifier(n_neighbors = n).fit(X_train,y_train)
    y_hat=knn.predict(X_test)
    acc = round(metrics.accuracy_score(y_test, y_hat),4)
    accuracy.append(acc)

print(accuracy)

plt.plot(range(1, K), accuracy)
plt.xlabel('K')
plt.ylabel('Accuracy')
plt.show()

print("\nThe best accuracy is", round(np.max(accuracy), 4), "with k=", np.argmax(accuracy)
```

```
[0.6389, 0.6318, 0.6669, 0.6618, 0.6774, 0.671, 0.6806, 0.6779, 0.6804]
```




```
The best accuracy is 0.6806 with k= 7
```

In [39]:

```
# training knn classifier with k=7
k = 7
knn = KNeighborsClassifier(n_neighbors = k).fit(X_train,y_train)
print(knn)

# predicting train accuracy
y_hat = knn.predict(X_train)
print("\nTrain set Accuracy: ", round(metrics.accuracy_score(y_train, y_hat),4))

# predicting test accuracy
y_hat = knn.predict(X_test)
print("\nTest set Accuracy: ", round(metrics.accuracy_score(y_test, y_hat),4))
```

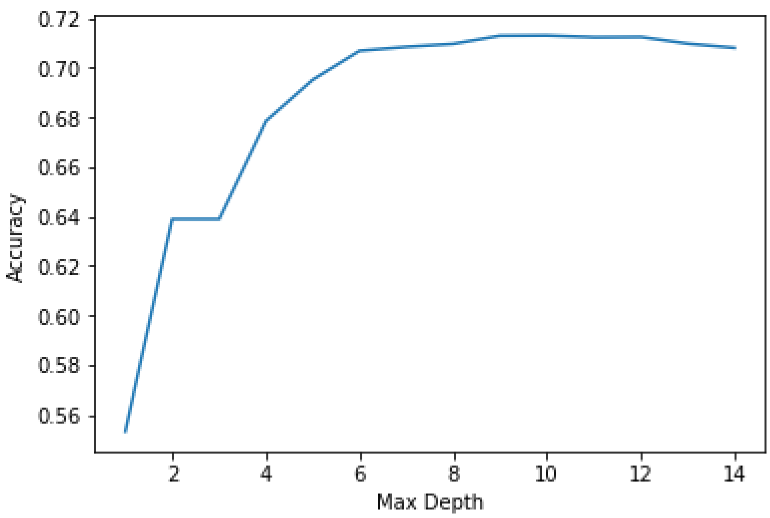
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=7, p=2,
                     weights='uniform')

Train set Accuracy:  0.7195

Test set Accuracy:  0.6806
```

Decision Tree

In [40]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics

K = 15
accuracy = []

# finding the best hyperparameter
for n in range(1,K):
    tree = DecisionTreeClassifier(criterion="entropy", max_depth = n).fit(X_train,y_train)
    y_hat = tree.predict(X_test)
    acc = round(metrics.accuracy_score(y_test, y_hat),4)
    accuracy.append(acc)

print(accuracy)

plt.plot(range(1, K), accuracy)
plt.xlabel('Max Depth')
plt.ylabel('Accuracy')
plt.show()

print("\nThe best accuracy is", round(np.max(accuracy), 4), "with max depth=", np.argmax(a
```

```
[0.5532, 0.6389, 0.6389, 0.6785, 0.6952, 0.7069, 0.7085, 0.7097, 0.713, 0.71
31, 0.7124, 0.7125, 0.7098, 0.7081]
```




```
The best accuracy is 0.7131 with max depth= 10
```

In [41]:

```
# training decision tree classifier with max depth=10
k = 10
tree = DecisionTreeClassifier(criterion="entropy", max_depth = k).fit(X_train,y_train)
print(tree)

# predicting train accuracy
y_hat = tree.predict(X_train)
print("\nTrain set Accuracy: ", round(metrics.accuracy_score(y_train, y_hat),4))

# predicting test accuracy
y_hat = tree.predict(X_test)
print("\nTest set Accuracy: ", round(metrics.accuracy_score(y_test, y_hat),4))
```

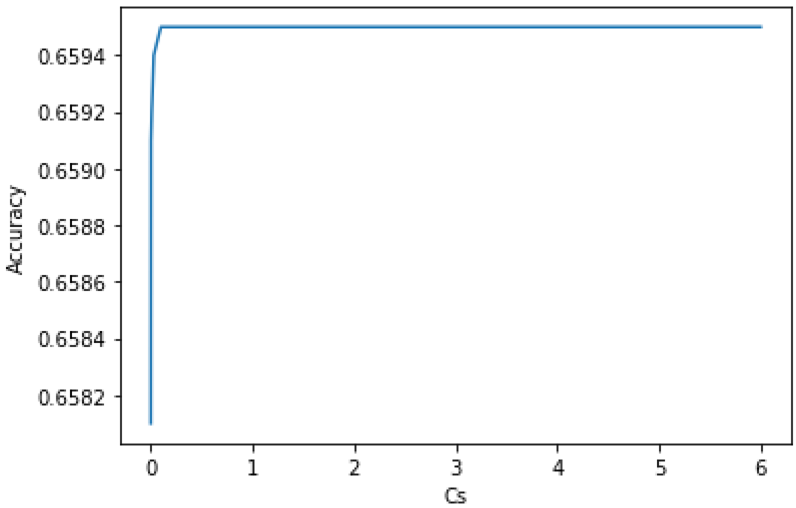
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entrop
y',
                       max_depth=10, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')

Train set Accuracy:  0.7183

Test set Accuracy:  0.7128
```

Logistic Regression

In [42]:

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

Cs = [0.001, 0.003, 0.01, 0.03, 0.1, 0.3, 1, 3, 6]
accuracy = []

# finding the best hyperparameter
for c in Cs:
    LR = LogisticRegression(C=c, solver = 'liblinear').fit(X_train, y_train)
    y_hat = LR.predict(X_test)
    acc = round(metrics.accuracy_score(y_test, y_hat),4)
    accuracy.append(acc)

print(accuracy)

plt.plot(Cs, accuracy)
plt.xlabel('Cs')
plt.ylabel('Accuracy')
plt.show()

print("\nThe best accuracy is", round(np.max(accuracy), 4), "with C=", Cs[np.argmax(accura
```

```
[0.6581, 0.6591, 0.6592, 0.6594, 0.6595, 0.6595, 0.6595, 0.6595, 0.6595]
```




```
The best accuracy is 0.6595 with C= 0.1
```

In [43]:

```
# training logistic regression classifier with C=0.1
C=0.1
LR = LogisticRegression(C=0.1, solver = 'liblinear').fit(X_train, y_train)
print(LR)

# predicting train accuracy
y_hat = LR.predict(X_train)
print("\nTrain set Accuracy: ", round(metrics.accuracy_score(y_train, y_hat),4))

# predicting test accuracy
y_hat = LR.predict(X_test)
print("\nTest set Accuracy: ", round(metrics.accuracy_score(y_test, y_hat),4))
```

```
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbos
e=0,
                   warm_start=False)

Train set Accuracy:  0.6591

Test set Accuracy:  0.6595
```

Model Evaluation

In [44]:

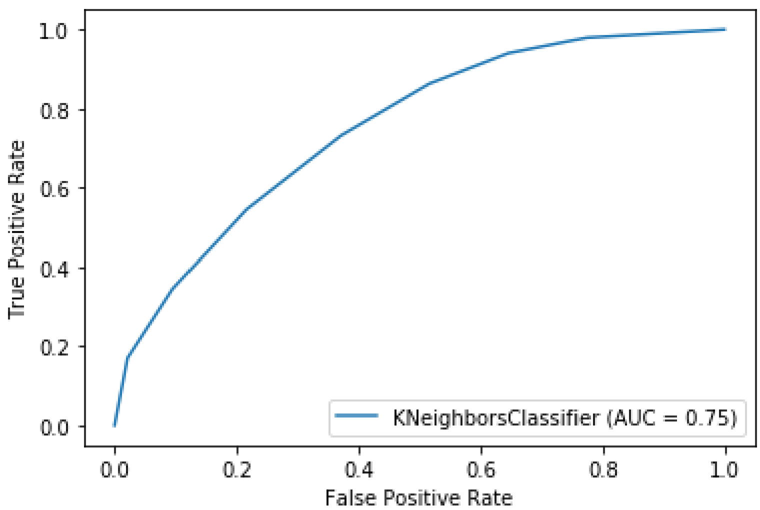
```
from sklearn.metrics import accuracy_score, log_loss, jaccard_similarity_score, \
        classification_report, f1_score, precision_score, recall_score, plot_roc_curve
```

KNN Evaluation

In [45]:

```
# KNN
y_hat = knn.predict(X_test)
print('\nKNN\n')
print('-> Jaccard Similarity Score:', round(jaccard_similarity_score(y_test, y_hat),4))
print('-> F1 Score:', round(f1_score(y_test, y_hat, average='weighted'),4))
print('-> Precision Score:', round(precision_score(y_test, y_hat),4))
print('-> Recall Score:', round(recall_score(y_test, y_hat),4), '\n')
print(classification_report(y_test, y_hat))
metrics.plot_roc_curve(knn, X_test, y_test)
plt.show()
```

```
KNN

-> Jaccard Similarity Score: 0.6806
-> F1 Score: 0.6797
-> Precision Score: 0.6991
-> Recall Score: 0.6284

              precision    recall  f1-score   support

           1       0.70      0.63      0.66     11267
           2       0.67      0.73      0.70     11383

    accuracy                           0.68     22650
   macro avg       0.68      0.68      0.68     22650
weighted avg       0.68      0.68      0.68     22650
```

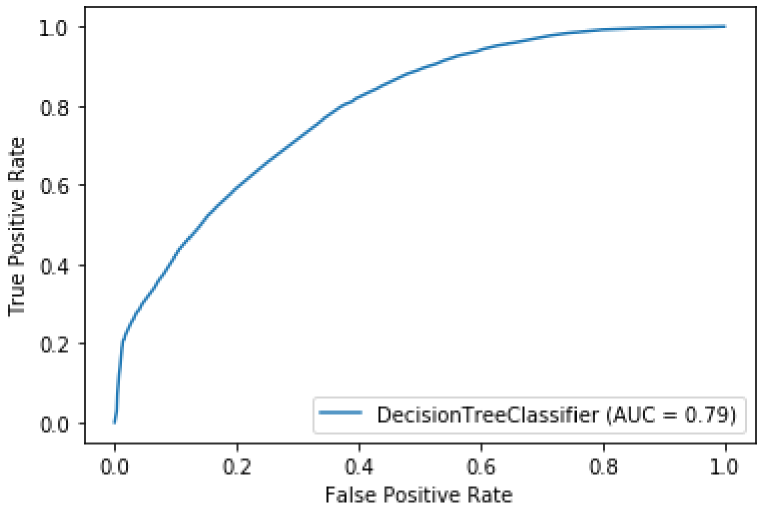


Decision Tree Evaluation

In [46]:

```
# Decision Tree
y_hat = tree.predict(X_test)
print('Decision Tree\n')
print('-> Jaccard Similarity Score:', round(jaccard_similarity_score(y_test, y_hat),4))
print('-> F1 Score:', round(f1_score(y_test, y_hat, average='weighted'),4))
print('-> Precision Score:', round(precision_score(y_test, y_hat),4))
print('-> Recall Score:', round(recall_score(y_test, y_hat),4), '\n')
print(classification_report(y_test, y_hat))
metrics.plot_roc_curve(tree, X_test, y_test)
plt.show()
```

```
Decision Tree

-> Jaccard Similarity Score: 0.7128
-> F1 Score: 0.7103
-> Precision Score: 0.7583
-> Recall Score: 0.6206

              precision    recall  f1-score   support

           1       0.76      0.62      0.68     11267
           2       0.68      0.80      0.74     11383

    accuracy                           0.71     22650
   macro avg       0.72      0.71      0.71     22650
weighted avg       0.72      0.71      0.71     22650
```

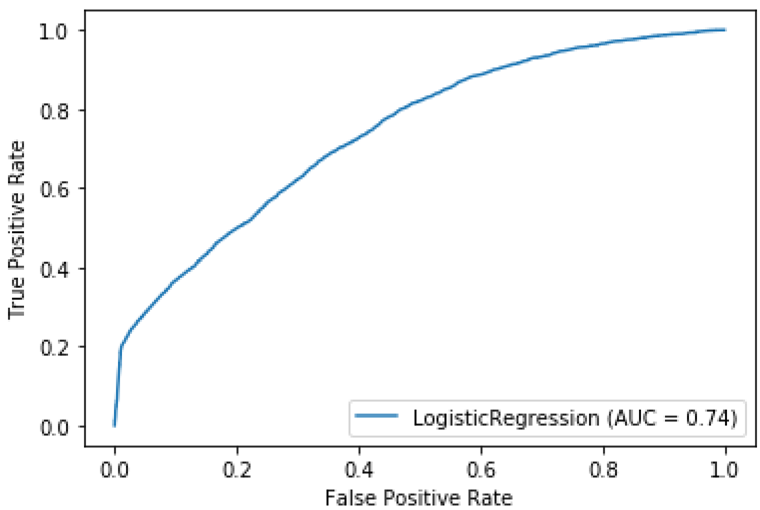


Logistic Regression Evaluation

In [47]:

```
# Logistic Regression
y_hat = LR.predict(X_test)
y_hat_prob = LR.predict_proba(X_test)
print('Logistic Regression\n')
print('-> Jaccard Similarity Score:', round(jaccard_similarity_score(y_test, y_hat),4))
print('-> F1 Score:', round(f1_score(y_test, y_hat, average='weighted'),4))
print('-> Precision Score:', round(precision_score(y_test, y_hat),4))
print('-> Recall Score:', round(recall_score(y_test, y_hat),4))
print('-> Log Loss: ', round(log_loss(y_test, y_hat_prob),4), '\n')
print(classification_report(y_test, y_hat))
metrics.plot_roc_curve(LR, X_test, y_test)
plt.show()
```

```
Logistic Regression

-> Jaccard Similarity Score: 0.6595
-> F1 Score: 0.6585
-> Precision Score: 0.6417
-> Recall Score: 0.7144
-> Log Loss:  0.5899

              precision    recall  f1-score   support

           1       0.64      0.71      0.68     11267
           2       0.68      0.61      0.64     11383

    accuracy                           0.66     22650
   macro avg       0.66      0.66      0.66     22650
weighted avg       0.66      0.66      0.66     22650
```



Results

Algorithm	Jaccard	F1-score	Precision	Recall	AUC	LogLoss
KNN	0.6806	0.6797	0.6991	0.6284	0.75	NA
Decision Tree	0.7128	0.7104	0.7582	0.6207	0.79	NA

Algorithm	Jaccard	F1-score	Precision	Recall	AUC	LogLoss
LogisticRegression	0.6595	0.6585	0.6417	0.7144	0.74	0.5899

Based on the above evaluation, it very clear that Decision Tree is the best classifiers in all the three classifiers.

In [ ]:

```

```