Project: Accident data of Seattle city

Applied Data Science Capstone

Introduction

Accident data of Seattle city is considered for this project, where labeled data is already available and used for further analysis.

The attributes of the data set show different influence factors on accident probability, which will by analyzed in order to solve the problem to reduce the rate of accidents for the future. Furthermore, causes and circumstances that lead to larger accident probabilities are addressed as there are high correlations on different attributes observable.

Using the outcome of the project, improvements on traffic factors may be done and additional caution may be given to dangerous situation or traffic constellations.

Data

The labeled data in the first column describes the severity of the accidents, where different attributes are found on the remaining columns of the data set.

Data Set Basics

- Title: Collisions - All Years
- Abstract: All collisions provided by SPD and recorded by Traffic Records.
- Description: This includes all types of collisions. Collisions will display at the intersection or mid-block of a segment. Timeframe: 2004 to Present.

Attribute	Data type, length	Description
OBJECTID	ObjectID	ESRI unique identifier
SHAPE	Geometry	ESRI geometry field
INCKEY	Long	A unique key for the incident
COLDETKEY	Long	Secondary key for the incident
ADDRTYPE	Text, 12	Collision address type: Alley, Block, Intersection
NTKEY	Double	Key that corresponds to the intersection associated with a collision
LOCATION	Text, 255	Description of the general location of the collision
EXCEPTRSNCODE	Text, 10	
EXCEPTRSNDESC	Text, 300	
SEVERITYCODE	Text, 100	A code that corresponds to the severity of the collision: 3—fatality, 2b—serious injury, 2—injury, 1—prop damage, 0—unknown
SEVERITYDESC	Text	A detailed description of the severity of the collision

Attribute	Data type, length	Description
COLLISIONTYPE	Text, 300	Collision type
PERSONCOUNT	Double	The total number of people involved in the collision
PEDCOUNT	Double	The number of pedestrians involved in the collision. This is entered by the state.
PEDCYLCOUNT	Double	The number of bicycles involved in the collision. This is entered by the state.
VEHCOUNT	Double	The number of vehicles involved in the collision. This is entered by the state.
INJURIES	Double	The number of total injuries in the collision. This is entered by the state.
SERIOUSINJURIES	Double	The number of serious injuries in the collision. This is entered by the state.
FATALITIES	Double	The number of fatalities in the collision. This is entered by the state.
INCDATE	Date	The date of the incident.
INCDTTM	Text, 30	The date and time of the incident.
JUNCTIONTYPE	Text, 300	Category of junction at which collision took place
SDOT_COLCODE	Text, 10	A code given to the collision by SDOT.
SDOT_COLDESC	Text, 300	A description of the collision corresponding to the collision code.
INATTENTIONIND	Text, 1	Whether or not collision was due to inattention. (Y/N)
UNDERINFL	Text, 10	Whether or not a driver involved was under the influence of drugs or alcohol.
WEATHER	Text, 300	A description of the weather conditions during the time of the collision.
ROADCOND	Text, 300	The condition of the road during the collision.
LIGHTCOND	Text, 300	The light conditions during the collision.
PEDROWNOTGRNT	Text, 1	Whether or not the pedestrian right of way was not granted. (Y/N)
SDOTCOLNUM	Text, 10	A number given to the collision by SDOT.
SPEEDING	Text, 1	Whether or not speeding was a factor in the collision. (Y/N)
ST_COLCODE	Text, 10	A code provided by the state that describes the collision. For more information about these codes, please see the State Collision Code Dictionary.
ST_COLDESC	Text, 300	A description that corresponds to the state's coding designation.
SEGLANEKEY	Long	A key for the lane segment in which the collision occurred.
CROSSWALKKEY	Long	A key for the crosswalk at which the collision occurred.
HITPARKEDCAR	Text, 1	Whether or not the collision involved hitting a parked car. (Y/N)

Repository

- Link to Github repository: https://github.com/Guinn808/Coursera_Capstone (https://github.com/Guinn808/Coursera_Capstone)
- Notebook: https://github.com/Guinn808/Coursera_Capstone/blob/master/Coursera_Capstone.ipynb (https://github.com/Guinn808/Coursera_Capstone/blob/master/Coursera_Capstone.ipynb)
- Data: https://github.com/Guinn808/Coursera_Capstone/blob/master/Data-Collisions.rar (https://github.com/Guinn808/Coursera_Capstone/blob/master/Data-Collisions.rar)
- Metadata: https://github.com/Guinn808/Coursera_Capstone/blob/master/Metadata.pdf (https://github.com/Guinn808/Coursera_Capstone/blob/master/Metadata.pdf)

Data Preparation

The data set is loaded from csv and preprocessed in order to replace any mismatching attribute.

In [2]:

```
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn.utils import resample
from sklearn.model_selection import train_test_split


df = pd.read_csv("C:/Users/Nickel/Downloads/Data-Collisions.csv")
print("Dataset downloaded and read into a pandas dataframe!")
print("\nData Shape: ",df.shape)
print("\nMore data info:")
print(df.head())
print(df.info())
print("\nStatistics:")
print(df.describe(include="all"))


data_sel = df[["WEATHER","SPEEDING","LIGHTCOND","ROADCOND","JUNCTIONTYPE","PERSONCOUNT","VE
data_sel.head()
data_sel = data_sel[data_sel.WEATHER !="Unknown"]
data_sel = data_sel[data_sel.WEATHER !="Other"]
data_sel['WEATHER'].fillna(data_sel['WEATHER'].mode()[0], inplace=True)
print("\nWeather attributes:")
print(data_sel.WEATHER.value_counts(dropna=False))

data_sel['SPEEDING'] = data_sel['SPEEDING'].fillna('N')

data_sel = data_sel[data_sel.LIGHTCOND !="Unknown"]
data_sel = data_sel[data_sel.LIGHTCOND !="Other"]
data_sel['LIGHTCOND'].fillna(data_sel['LIGHTCOND'].mode()[0], inplace=True)
print("\nLight attributes:")
print(data_sel.LIGHTCOND.value_counts(dropna=False))

data_sel = data_sel[data_sel.ROADCOND !="Unknown"]
data_sel = data_sel[data_sel.ROADCOND !="Other"]
data_sel['ROADCOND'].fillna(data_sel['LIGHTCOND'].mode()[0], inplace=True)
print("\nRoad attributes:")
print(data_sel.ROADCOND.value_counts(dropna=False))

data_sel['SEVERITYCODE'].fillna(data_sel['SEVERITYCODE'].mode()[0], inplace=True)
print("\nSeverity attributes:")
print(data_sel.SEVERITYCODE.value_counts(dropna=False))

print("\nData types (before convertion):")
print(data_sel.info())
w_list = data_sel['WEATHER'].unique()
w_dict = dict(zip(w_list, range(len(w_list))))
s_list = data_sel['SPEEDING'].unique()
s_dict = dict(zip(s_list, range(len(s_list))))
l_list = data_sel['LIGHTCOND'].unique()
l_dict = dict(zip(l_list, range(len(l_list))))
r_list = data_sel['ROADCOND'].unique()
r_dict = dict(zip(r_list, range(len(r_list))))
j_list = data_sel['JUNCTIONTYPE'].unique()
j_dict = dict(zip(j_list, range(len(j_list))))
data_sel = data_sel.replace({'WEATHER': w_dict, 'SPEEDING': s_dict, 'LIGHTCOND': l_dict, 'R
print("\nData types (after convertion to integer):")
```

```
print(data_sel.info())
```

```
C:\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3020: Dtyp
eWarning: Columns (33) have mixed types. Specify dtype option on import or
set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Data Selection and Evalutation

Specific data attributes (e.g. weather conditions and speeding) are selected for prediction of severity of accidents.

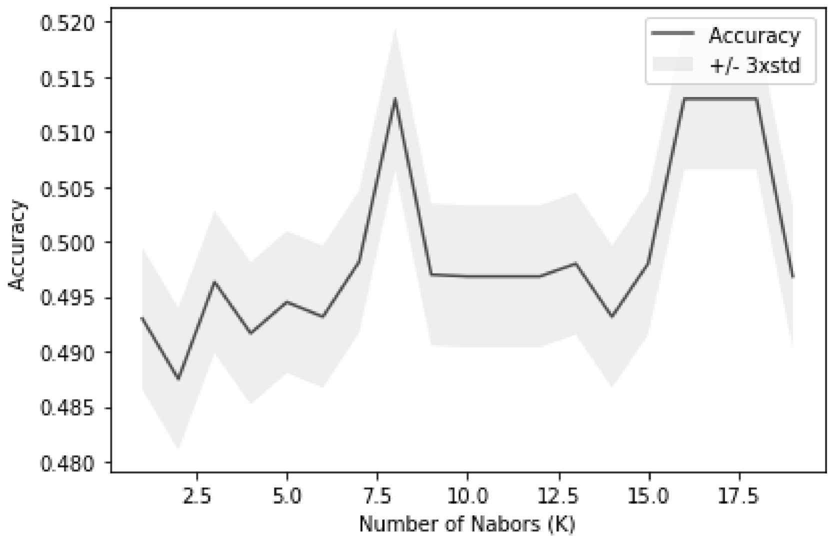
K Nearest Neighbor(KNN)

First, the value of K is optimized and the accuracy is determined.

In [4]:

```
x = data_sel[["WEATHER","SPEEDING","LIGHTCOND","ROADCOND","JUNCTIONTYPE","PERSONCOUNT","VEH
y = data_sel[["SEVERITYCODE"]].values

sev_1 = data_sel[data_sel.SEVERITYCODE == 1]
sev_2 = data_sel[data_sel.SEVERITYCODE == 2]
print("\nSHAPE 1: ",sev_1.shape)
print("SHAPE 2: ",sev_2.shape)

sev_max =min([sev_1.shape[0],10000])
sev_1_res = resample(sev_1,replace=True,n_samples=sev_max,random_state=17)
sev_2_res = resample(sev_2,replace=True,n_samples=sev_max,random_state=17)
data_sel_res = pd.concat([sev_1_res, sev_2_res])
data_sel_res.reset_index(inplace = True,drop=True)
print("\nShape after resampling: ",data_sel_res.shape)
print("\nData info:")
print(data_sel_res.head())

featureNames = ["WEATHER","SPEEDING"]#,"LIGHTCOND","ROADCOND","JUNCTIONTYPE"]
X = data_sel_res[featureNames].values
Y = data_sel_res["SEVERITYCODE"]
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=3)

# Severity as target variable

from sklearn.model_selection import train_test_split
print ('Train set:', x_train.shape,  y_train.shape)
print ('Test set:', x_test.shape,  y_test.shape)

from sklearn.neighbors import KNeighborsClassifier
k = 20
neigh = KNeighborsClassifier(n_neighbors = k).fit(x_train,y_train)
yhat = neigh.predict(x_test)

from sklearn import metrics
import matplotlib.pyplot as plt
print("Train set Accuracy: ", metrics.accuracy_score(y_train, neigh.predict(x_train)))
print("Test set Accuracy: ", metrics.accuracy_score(y_test, yhat))
Ks = 20
mean_acc = np.zeros((Ks-1))
std_acc = np.zeros((Ks-1))
ConfustionMx = [];
for n in range(1,Ks):
    #Train Model and Predict
    neigh = KNeighborsClassifier(n_neighbors = n).fit(x_train,y_train)
    yhat=neigh.predict(x_test)
    mean_acc[n-1] = metrics.accuracy_score(y_test, yhat)
    std_acc[n-1]=np.std(yhat==y_test)/np.sqrt(yhat.shape[0])
plt.plot(range(1,Ks),mean_acc,'g')
plt.fill_between(range(1,Ks),mean_acc - 1 * std_acc,mean_acc + 1 * std_acc, alpha=0.10)
plt.legend(('Accuracy ', '+/- 3xstd'))
plt.ylabel('Accuracy ')
plt.xlabel('Number of Nabors (K)')
plt.tight_layout()
plt.show()
print( "The best accuracy was with", mean_acc.max(), "with k=", mean_acc.argmax()+1)
```

```
SHAPE 1:  (118401, 8)
SHAPE 2:  (56815, 8)

Shape after resampling:  (20000, 8)

Data info:
   WEATHER  SPEEDING  LIGHTCOND  ROADCOND  JUNCTIONTYPE  PERSONCOUNT  \
0        2         0          1         1             1            2
1        0         0          1         0             0            2
2        1         1          0         0             0            3
3        2         0          0         1             1            2
4        1         1          3         0             1            1

   VEHCOUNT  SEVERITYCODE
0         2             1
1         2             1
2         2             1
3         2             1
4         1             1
Train set: (14000, 2) (14000,)
Test set: (6000, 2) (6000,)
Train set Accuracy:  0.513
Test set Accuracy:  0.513
```




```
The best accuracy was with 0.513 with k= 8
```

Conclusion for K Nearest Neighbor(KNN)

It can be observed, that the optimization of K does not lead to significant improvements. The accuracy is always in the order of 50% (0.48-0.52) - this is NOT a good result w.r.t. using the selected attributes in order to predict the severity.

Support Vector Machine (SVN)

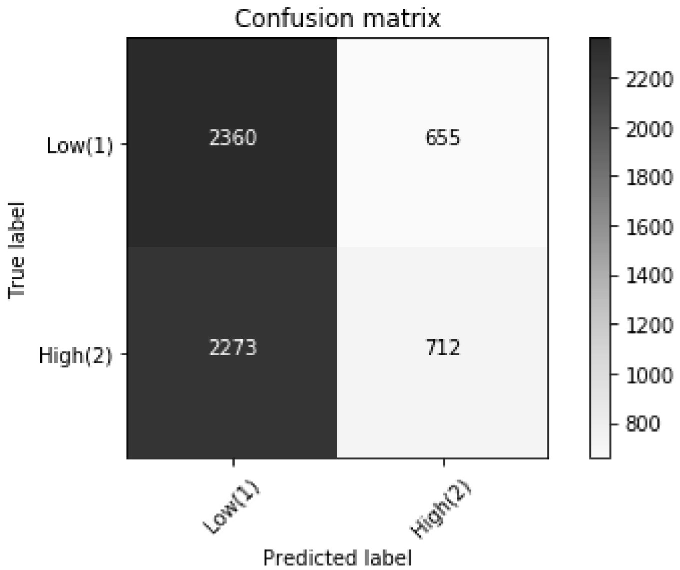
In order to achieve better results, the SVN method is applied.

In [7]:

```
from sklearn import svm
clf = svm.SVC(kernel='rbf')
clf.fit(x_train, y_train)
yhat = clf.predict(x_test)
yhat [0:5]

from sklearn.metrics import classification_report, confusion_matrix
import itertools


def plot_confusion_matrix(cm, classes, normalize=False, title='Confusion matrix', cmap=plt.
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')
    print(cm)
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')


# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, yhat, labels=[1,2])
np.set_printoptions(precision=2)

print (classification_report(y_test, yhat))

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Low(1)','High(2)'],normalize= False,  title='Co
```

```
C:\Anaconda3\lib\site-packages\sklearn\svm\base.py:196: FutureWarning: The d
efault value of gamma will change from 'auto' to 'scale' in version 0.22 to
account better for unscaled features. Set gamma explicitly to 'auto' or 'sca
le' to avoid this warning.
  "avoid this warning.", FutureWarning)

              precision    recall  f1-score   support

           1       0.51      0.78      0.62      3015
           2       0.52      0.24      0.33      2985
```

```
   micro avg       0.51      0.51      0.51      6000
   macro avg       0.52      0.51      0.47      6000
weighted avg       0.52      0.51      0.47      6000

Confusion matrix, without normalization
[[2360  655]
 [2273  712]]
```



Conclusion for SVN

Using SVN for estimation of severity, we observe a similar precision of about 0.51-0.52 for estimation of low-1 or high-2 severity. Nevertheless, the recall is much higher (0.78) for low-1 severity than for high-2 severity (0.24). The values show us, that it is NOT very good to predict the severity of an accident only given the state of the weather and the speeding. Due to the general larger occurany of low severity than high severity, it is right the way clear, that the recall is much larger for low severity.

Conclusions

Using the existing dataset of the course, some remarkable insights have been obtained. At the beginning it was guessed, that the severity of an accident could be predicted by the weather or speeding conditions. Using different methods for estimation of the severity based on the existing dataset it could be observed, that only small amount of information can be gained by predictions.