Neural Network:

Importing panda and numpy:

```
In [5]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(20)
```

Importing the dataset and converting as panda framework:

```
In [6]: def import data (filename):
            This function, imports the train/test data and create the attribute matrix a
            Matrix = []
            Label = []
            with open(filename) as f:
                 for line in f:
                     sample = line.split()
                     Label.append(float(sample[0]))
                     sample.pop(0)
                     row = []
                     for s in sample:
                         feature, value = s.split(':')
                         z = len(row)
                         nz = int(feature) - (z+1)
                         for i in range (nz):
                             row.append(0)
                         row.append(float(value))
                     Matrix.append(row)
            data =[]
            M = max(len(row) for row in Matrix)
            #print("M:",M)
            for row in Matrix:
                 nz = M - (len(row))
                 for i in range (nz):
                     row.append(0)
                 data.append(row)
            Label1 = np.array(Label)
            data1= np.array(data)
             #print("aaa:",Label1, data1.shape)
            S1 = np.concatenate((data1, Label1[:,None]),axis=1)
             attributes = np.arange(1, np.size(data1,1)+2)
            #print(attributes)
             samples = range(0,np.size(data1,0))
            data2 = pd.DataFrame(S1, columns=attributes, index=samples)
            #print('label',data2[6])
            return data2
            #print("data1:",data1.shape)
```

Fold database creation:

```
In [7]: def update label(D):
            x,y = D.shape
            for i in range(x):
                 if D[y][i] ==0.0:
                     D[y][i] = -1.0
            return (D)
        def k fold(D,k):
            cols = D.columns
            D = D.to numpy()
            r_n, = D.shape
            k n = (r n//5)
            1b = (k-1)*k_n
            if k == 5:
                 ub = r n
            else:
                ub = k*k_n-1
            fk = D [lb:ub, :]
             Fk = pd.DataFrame(fk, columns=cols)
             return Fk
        def import_label (D, new_feature):
            D = D.to_numpy()
            D = D.copy()
            new feature = new feature.to numpy()
            labels = D[:, -1]
             labels = labels[:,None]
            D_out = np.append(new_feature, labels, axis=1)
            attributes = np.arange(1, np.size(D_out,1)+1)
            D out = pd.DataFrame(D out, columns=attributes)
             return D_out
```

Importing the tfidf datasets:

```
In [8]: Train_data1 = import_data('tfidf.train.libsvm')
    Train_data_tfidf = update_label(Train_data1)
    Test_data1 = import_data('tfidf.test.libsvm')
    Test_data_tfidf = update_label(Test_data1)
    Eval_data_tfidf = import_data('tfidf.eval.anon.libsvm')
```

Importing the miscellaneous datasets:

```
In [9]: misc_train = pd.read_csv ('misc-attributes-train.csv')
    train_samples, _ = misc_train.shape
    misc_test = pd.read_csv ('misc-attributes-test.csv')
    test_samples, _ = misc_test.shape
    misc_eval = pd.read_csv ('misc-attributes-eval.csv')
    eval_samples, _ = misc_eval.shape
```

In order to convert the database to one hot encoding, all the dataset are concatenated and converted to correlate the cominations.

```
In [10]:
           database = pd.concat([misc_train, misc_test, misc_eval], axis=0)
 In [7]:
           database
 Out[7]:
                  defendant_age
                                 defendant_gender num_victims
                                                                 victim_genders
                                                                                 offence_category offence_su
               0
                             62
                                                               1
                                            female
                                                                           male
                                                                                             theft
                                                                                                         theft
               1
                             17
                                              male
                                                               1
                                                                           male
                                                                                             theft
                                                                                                           ро
               2
                       not known
                                              male
                                                               1
                                                                           male
                                                                                             theft
                                                                                                           ро
               3
                       not known
                                                               1
                                                                           male
                                                                                             theft
                                              male
                                                                                                          sim
                             52
                                              male
                                                               1
                                                                          female
                                                                                             theft
                                                                                                           po
                       not known
                                                               1
            5245
                                              male
                                                                           male
                                                                                             theft
                                                                                                         theft
            5246
                       not known
                                              male
                                                               0
                                                                            NaN
                                                                                            sexual
            5247
                       not known
                                                                                             theft
                                                                                                     stealingF
                                              male
                                                               1
                                                                           male
            5248
                             26
                                              male
                                                                           male
                                                                                             theft
            5249
                             16
                                              male
                                                               1
                                                                          female
                                                                                             theft
                                                                                                          sim
           25000 rows × 6 columns
           database.dtypes
 In [8]:
 Out[8]: defendant_age
                                       object
           defendant_gender
                                       object
           num_victims
                                        int64
           victim genders
                                       object
           offence category
                                       object
           offence subcategory
                                       object
           dtype: object
```

```
In [11]: database[database.isnull().any(axis=1)]
# Converting "NaN" to no_gender in victom_genders category:
    database = database.fillna({"victim_genders": "no_gender"})
    database.head()

# convert all string data in defendant such as not known ,... to Nan and then suld database['defendant_age'] = pd.to_numeric(database.defendant_age, errors='coerce database = database.fillna({"defendant_age": 0})
    database
```

							Į.
offence_su	offence_category	victim_genders	num_victims	defendant_gender	defendant_age		Out[11]:
theft	theft	male	1	female	62.0	0	
ро	theft	male	1	male	17.0	1	
ро	theft	male	1	male	0.0	2	
sim	theft	male	1	male	0.0	3	
ро	theft	female	1	male	52.0	4	
theft	theft	male	1	male	0.0	5245	
	sexual	no_gender	0	male	0.0	5246	
stealingF	theft	male	1	male	0.0	5247	

1

male

female

theft

theft

sim

male

male

25000 rows × 6 columns

26.0

16.0

5248

5249

In [12]: # Now that all the data are free of Nan we can convert them to one-hot encoding.
misc_transfered = pd.concat([database.defendant_age, database.num_victims, pd.ge
for dicision tree i convert all of the featres to one-hot encoding
misc_transfered_all_bin = pd.concat([pd.get_dummies(database.defendant_age), pd.get_dummies(database.defendant_age), pd.get_dummies(database.defendant_age)

In [23]: misc_transfered

Out[23]:		defendant_age	num_victims	female	indeterminate	male	female	female;female	female;fema
	0	62.0	1	1	0	0	0	0	
	1	17.0	1	0	0	1	0	0	
	2	0.0	1	0	0	1	0	0	
	3	0.0	1	0	0	1	0	0	
	4	52.0	1	0	0	1	1	0	
	5245	0.0	1	0	0	1	0	0	
	5246	0.0	0	0	0	1	0	0	
	5247	0.0	1	0	0	1	0	0	
	5248	26.0	1	0	0	1	0	0	
	5249	16.0	1	0	0	1	1	0	

25000 rows × 139 columns

(17500, 140)

```
In [13]: Train_misc_transfered = misc_transfered.iloc[:train_samples,:]
    Test_misc_transfered = misc_transfered.iloc[train_samples:train_samples+test_samples]
    Eval_misc_transfered = misc_transfered.iloc[train_samples+test_samples:,:]

In [14]: Train_misc = import_label(Train_data_tfidf, Train_misc_transfered)
    Test_misc = import_label(Test_data_tfidf, Test_misc_transfered)
    Eval_misc = import_label(Eval_data_tfidf, Eval_misc_transfered)
    print(Train_misc.shape)
```

localhost:8889/notebooks/Box/machine learning/Project/Project material/4_NN.ipynb

```
In [30]:
          print(Train misc)
                   1
                         2
                              3
                                    4
                                          5
                                               6
                                                     7
                                                           8
                                                                9
                                                                      10
                                                                                 131
                                                                                      132
                                                                                            133
          0
                  62.0
                         1.0
                              1.0
                                    0.0
                                          0.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                 0.0
                                                                                      0.0
                                                                                            0.0
                              0.0
          1
                  17.0
                         1.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                 0.0
                                                                                      0.0
                                                                                            0.0
          2
                   0.0
                         1.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                 0.0
                                                                                      0.0
                                                                                            0.0
          3
                   0.0
                         1.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                 1.0
                                                                                       0.0
                                                                                            0.0
          4
                  52.0
                         1.0
                              0.0
                                    0.0
                                          1.0
                                               1.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                      0.0
                                                                                            0.0
                                                                                 0.0
                                    . . .
                                                                      . . .
          17495
                   0.0
                         1.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                 0.0
                                                                                      0.0
                                                                                            0.0
          17496
                   0.0
                         0.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                 0.0
                                                                                      0.0
                                                                                            0.0
          17497
                   0.0
                         1.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                                      0.0
                                                                                            0.0
                                                                      0.0
                                                                                 0.0
          17498
                   0.0
                         0.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                           0.0
                                                                0.0
                                                                      0.0
                                                                                 0.0
                                                                                      0.0
                                                                                            0.0
          17499
                   0.0
                         1.0
                              0.0
                                    0.0
                                          1.0
                                               0.0
                                                     0.0
                                                          0.0
                                                                0.0
                                                                      0.0
                                                                                            0.0
                                                                                 0.0
                                                                                      0.0
                                              139
                  134
                        135
                             136
                                   137
                                        138
                                                    140
          0
                  0.0
                        1.0
                             0.0
                                   0.0
                                        0.0
                                              0.0 -1.0
          1
                  0.0
                        0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0 -1.0
          2
                  0.0
                        0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0
                                                    1.0
          3
                  0.0
                        0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0
                                                    1.0
          4
                  0.0
                        0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0 -1.0
                  0.0
          17495
                        1.0
                             0.0
                                   0.0
                                        0.0
                                              0.0
                                                    1.0
          17496
                  0.0
                        0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0
                                                   1.0
          17497
                  0.0
                       0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0
                                                   1.0
          17498
                  0.0
                        0.0
                             0.0
                                   0.0
                                        0.0
                                              0.0 - 1.0
          17499
                                              0.0 1.0
                  0.0
                       0.0
                             0.0
                                   0.0
                                        0.0
          [17500 rows x 140 columns]
          # generating 5-fold dataset:
In [15]:
          Data1 = Train misc
          cols = Data1.columns
          Data1 = Data1.to numpy()
          np.random.shuffle(Data1)
          Data1 = pd.DataFrame(Data1, columns=cols)
          f1 = k fold(Data1,1)
          f2 = k \text{ fold(Data1,2)}
          f3 = k \text{ fold(Data1,3)}
          f4 = k fold(Data1,4)
          f5 = k fold(Data1,5)
          from sklearn.preprocessing import StandardScaler
In [21]:
          from sklearn.neural network import MLPClassifier
```

from sklearn.metrics import classification_report, confusion_matrix

from sklearn.metrics import accuracy score

```
In [39]:
         Train misc1 = Train misc.to numpy()
         Train_misc_x = Train_misc1[:,:-1]
         Train_misc_y = Train_misc1[:,-1]
         Test misc1 = Test misc.to numpy()
         Test_misc_x = Test_misc1[:,:-1]
         Test_misc_y = Test_misc1[:,-1]
         Eval misc1 = Eval misc.to numpy()
         Eval_misc_x = Eval_misc1[:,:-1]
         Eval_misc_y = Eval_misc1[:,-1]
In [40]: | predictions = mlp.predict(Test_misc_x)
 In [ ]: print(confusion matrix(y test,predictions))
         print(classification_report(y_test,predictions))
In [44]:
         predictions_train = mlp.predict(Train_misc_x)
         print(accuracy_score(predictions_train, Train_misc_y))
         predictions test = mlp.predict(Test misc x)
         print(accuracy_score(predictions_test, Test_misc_y))
         0.7976
         0.488888888888889
```

Cross validation procedure:

```
In [30]:
         def cross val(f1, f2, f3, f4, f5, hiddenLayers, learningRate):
             The function calculates the mean accuracy and std based on the 5-fold cross
             #train data = pd.DataFrame(columns = f1.columns)
             dataset = []
              acc = []
              loss = []
             for i in range (1,6):
                  valid_data = eval("f"+str(i))
                  train_name =[]
                  val_name = ["f"+str(i)]
                  #print(i,val name)
                  #print(valid_data)
                  for j in range(1,6):
                      if j != i:
                          #print(j)
                          train name.append ("f"+str(j))
                          dataset.append(eval("f"+str(j)))
                  train_data = pd.concat(dataset, ignore_index=True)
                  dataset = []
                  train_data1 = train_data.to_numpy()
                  valid data1 = valid data.to numpy()
                  Train x = train data1[:,:-1]
                  Train y = train data1[:,-1]
                  val_x = valid_data1[:,:-1]
                  val y = valid data1[:,-1]
                  mlp = MLPClassifier(solver='adam', hidden_layer_sizes=hiddenLayers, random
                                      learning_rate="invscaling",learning_rate_init = lear
                  #print(train data)
                  mlp.fit(Train_x,Train_y)
                  predictions = mlp.predict(val_x)
                  ac = accuracy_score(predictions, val_y)
                  acc.append (ac)
             Mean_acc = np.mean(acc)
              return Mean_acc
```

```
# Evaluating the network accuracy based on different values for learning rates as
In [32]:
          .....
         learning rates = [0.1, 1e-2, 1e-3, 1e-4]
         hiddenLayers = [(10), (50), (100), (10,10), (50,50), (10,10,10), (50,50,50)]
         #hiddenLayers = \lceil (10) \rceil
         acc mean = []
         loss mean = []
         result = []
         for lr in learning_rates:
              for hl in hiddenLayers:
                  mean ac = cross val(f1, f2, f3, f4, f5, h1, 1r)
                  #print(mean ac)
                  acc mean.append(mean ac)
                  result.append([lr, hl, mean_ac])
                  #print(lr, u)
         result = np.array(result)
         Best lr = result[np.argmax(result[:,2]), 0]
         Best c = result[np.argmax(result[:,2]), 1]
         best_acc = result[np.argmax(result[:,2]), 2]
          print('Cross validation results for different Learning rates and loss tradeoff:'
          result = pd.DataFrame(result, columns=['Learning rate', 'hiddenLayer', 'accuracy
         pd.set option('display.max rows', None)
         print(result.to string(index = False))
          print('Best learning rate:', Best_lr)
         print('Best Cost:', Best c)
         report1 = [{'Best learning rate':Best_lr, 'hiddenLayer':Best_c, 'Best accuracy':|
          report1 = pd.DataFrame.from records(report1)
          print(report1.to string(index = False))
```

Cross validation results for different Learning rates and loss tradeoff: Learning rate Loss tradeoff accuracy mean

```
0.1
                  10
                           0.78035
 0.1
                  50
                          0.781378
  0.1
                100
                           0.78435
 0.1
           (10, 10)
                           0.77812
 0.1
           (50, 50)
                          0.779149
 0.1 (10, 10, 10)
                          0.781436
 0.1
      (50, 50, 50)
                          0.782522
 0.01
                  10
                          0.787494
 0.01
                 50
                          0.783379
 0.01
                100
                          0.784293
0.01
           (10, 10)
                          0.786523
0.01
           (50, 50)
                          0.784922
      (10, 10, 10)
 0.01
                          0.786922
0.01
       (50, 50, 50)
                          0.784065
0.001
                  10
                          0.787494
```

```
0.001
                                   50
                                           0.783893
                 0.001
                                  100
                                           0.784351
                 0.001
                             (10, 10)
                                           0.785779
                 0.001
                             (50, 50)
                                           0.782578
                 0.001
                        (10, 10, 10)
                                           0.786237
                        (50, 50, 50)
                 0.001
                                           0.784065
                 0.0001
                                   10
                                           0.781207
                0.0001
                                   50
                                           0.789094
                0.0001
                                  100
                                           0.787951
                0.0001
                             (10, 10)
                                            0.78738
                0.0001
                             (50, 50)
                                           0.787894
                0.0001 (10, 10, 10)
                                           0.788694
                0.0001
                        (50, 50, 50)
                                            0.78738
         Best learning rate: 0.0001
         Best Cost: 50
          Best learning rate Best Loss tradeoff Best accuracy
                      0.0001
                                               50
                                                        0.789094
In [40]: mlp = MLPClassifier(solver='adam', hidden layer sizes=Best c, random state=1, max
                                      learning_rate="invscaling",learning_rate_init = Best
         mlp.fit(Train misc x,Train misc y)
Out[40]: MLPClassifier(activation='relu', alpha=0.0001, batch size='auto', beta 1=0.9,
                        beta 2=0.999, early stopping=False, epsilon=1e-08,
                        hidden_layer_sizes=50, learning_rate='invscaling',
                        learning rate init=0.0001, max iter=1000, momentum=0.9,
                        n iter no change=10, nesterovs momentum=True, power t=0.5,
                        random state=1, shuffle=True, solver='adam', tol=0.0001,
                        validation fraction=0.1, verbose=False, warm start=False)
In [42]:
         prediction train = mlp.predict(Train misc x)
         train ac = accuracy score(prediction train, Train misc y)
         prediction test = mlp.predict(Test misc x)
         test ac = accuracy score(prediction test, Test misc y)
         print(train ac, test ac)
         0.7909142857142857 0.79822222222223
In [60]:
         prediction eval = mlp.predict(Eval misc x)
         prediction eval[prediction eval==-1] = 0
         #print(prediction eval.shape)
         pred =[]
         for i in range (len(prediction_eval)):
              pred.append([i, prediction_eval[i]])
         Pred = pd.DataFrame(pred, columns=['example id', 'label'])
In [61]:
         #pred1 = prediction (Eval misc, w1[best epoch-1][:], b1[best epoch-1])
         #print(pred1)
         Pred.to_csv ('nn_misc_labels.csv', index = False, header=True)
```