MultiLayerPerceptrop_3_train_10_test

December 17, 2017

```
In [1]: from sklearn.neural_network import MLPClassifier
        from sklearn.preprocessing import StandardScaler
        from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
        import pandas as pd
        from pandas import DataFrame,Series
        from matplotlib.colors import ListedColormap
        import numpy as np
        from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
        import matplotlib.pyplot as plt
        from pandas.plotting import scatter_matrix
        from random import sample
```

```
In [69]: multi_layer_dup_train = pd.read_csv('../FeaturesCsvFile/featuresfile.csv')
         multi_layer_dup_test = pd.read_csv('../FeaturesCsvFile/featuresfile_10.csv')
         multi_layer_train = multi_layer_dup_train.drop_duplicates(subset=['User', 'Timestamp']
         multi_layer_unique_test = multi_layer_dup_test.drop_duplicates(subset=['User', 'Timest
         multi_layer_test = multi_layer_unique_test.iloc[sample(range(len(multi_layer_unique_te

         print ('(#row,#column) of train dataset' , multi_layer_train.shape)
         print ('(#row,#column) of test dataset' , multi_layer_test.shape)
```

```
('(#row,#column) of train dataset', (406, 46))
('(#row,#column) of test dataset', (40, 46))
```

```
In [70]: X_train = multi_layer_train.values[:, 2:45]
         y_train = multi_layer_train.values[:, 45]
         X_test = multi_layer_test.values[:, 2:45]
         y_test = multi_layer_test.values[:, 45]
```

```
In [71]: scaler = StandardScaler()
         scaler.fit(X_train)
         StandardScaler(copy=True, with_mean=True, with_std=True)
         X_train = scaler.transform(X_train)
         X_test = scaler.transform(X_test)
```

```
In [59]: mlp = MLPClassifier(hidden_layer_sizes=(20,),max_iter=60)
         mlp_pred=mlp.fit(X_train,y_train)
```

```
y_pred = mlp.predict(X_test)
print(confusion_matrix(y_test,y_pred))
print(classification_report(y_test,y_pred))
print('\nAccuracy of Multi-layer Perceptron Score: %.2f' % mlp.score(X_test,y_test))
print('\nAccuracy of Accuracy Score : %.2f' % accuracy_score(y_test,y_pred))
```

```
[[22  3]
 [ 1 14]]
             precision    recall  f1-score   support

    running       0.96      0.88      0.92        25
    walking       0.82      0.93      0.87        15

avg / total       0.91      0.90      0.90        40


Accuracy of Multi-layer Perceptron Score: 0.90

Accuracy of Accuracy Score : 0.90
```

```
In [63]: for i in range(0,len(mlp.coefs_[0])):
             print mlp.coefs_[0][i]
```

```
[-0.09  0.14 -0.05 -0.01 -0.08 -0.09 -0.04  0.14 -0.17 -0.16 -0.04  0.06
  0.27  0.12 -0.14 -0.08  0.29  0.16 -0.09 -0.02]
[ 0.33  0.05 -0.05  0.32  0.16 -0.22  0.27 -0.02  0.21  0.09  0.2  -0.14
  0.26 -0.23  0.35 -0.11  0.01 -0.07  0.14 -0.12]
[-0.14 -0.08 -0.33 -0.05  0.35  0.11 -0.01 -0.29  0.24 -0.16  0.05  0.03
 -0.06  0.08  0.29 -0.2   0.17  0.28  0.23  0.08]
[-0.08 -0.08 -0.31  0.27  0.04  0.   -0.21 -0.25  0.1  -0.14 -0.    0.25
 -0.15  0.1   0.15  0.02 -0.31  0.16 -0.22  0.12]
[ 0.23  0.18  0.06 -0.24 -0.18  0.08  0.1   0.1   0.03 -0.13 -0.11  0.31
 -0.19 -0.2  -0.18 -0.04  0.22 -0.42  0.29  0.14]
[-0.22  0.19  0.03  0.01 -0.25  0.27 -0.26  0.31 -0.09  0.13 -0.15  0.34
 -0.28  0.05  0.09 -0.09 -0.06 -0.28 -0.1   0.17]
[-0.02 -0.1  -0.17  0.02  0.07 -0.07 -0.11 -0.21  0.03 -0.07  0.   -0.11
  0.2   0.1  -0.28 -0.18 -0.14 -0.18  0.04 -0.29]
[ 0.12 -0.32 -0.24  0.15 -0.15 -0.02 -0.01  0.32  0.14  0.02  0.21  0.
  0.25  0.25  0.1   0.07  0.13 -0.15 -0.07 -0.39]
[ 0.22  0.17  0.18  0.08  0.16 -0.14 -0.02 -0.11  0.12 -0.03  0.27  0.15
 -0.15 -0.18  0.17  0.03  0.06  0.13  0.11 -0.08]
[-0.23 -0.31  0.19  0.28  0.19  0.03 -0.28 -0.26 -0.25  0.09  0.16 -0.08
  0.12  0.18 -0.17  0.29 -0.15 -0.15 -0.26 -0.17]
[ 0.27 -0.26  0.03 -0.03 -0.07 -0.03  0.2   0.06 -0.18  0.25 -0.25  0.1
 -0.05  0.1   0.15 -0.15  0.27  0.11  0.25  0.24]
[ 0.15 -0.34 -0.14  0.13  0.09 -0.03 -0.11 -0.25 -0.03 -0.16  0.29  0.13
 -0.13  0.08  0.22  0.1   0.16 -0.08 -0.21 -0.11]
```

```
[ 0.18 -0.01 -0.28  0.06  0.23 -0.18  0.04 -0.17  0.19 -0.18  0.23  0.02
  0.12  0.28  0.02 -0.23  0.17  0.4  -0.04 -0.03]
[-0.27  0.2   0.04 -0.11 -0.11 -0.09 -0.24  0.2  -0.05  0.15 -0.15  0.19
  0.01  0.15  0.3   0.29 -0.29 -0.23  0.15  0.03]
[-0.31 -0.02  0.21  0.17 -0.33  0.35 -0.05  0.28  0.22  0.12 -0.13 -0.11
 -0.1  -0.02  0.06  0.21 -0.18  0.12 -0.23 -0.06]
[ 0.23  0.24 -0.33  0.    0.23 -0.3   0.09  0.23  0.19  0.04 -0.13 -0.33
 -0.19  0.04 -0.28  0.28  0.06  0.23 -0.05  0.13]
[-0.17 -0.24 -0.17 -0.09  0.23 -0.21  0.05 -0.11  0.1   0.06 -0.26 -0.11
  0.01  0.1   0.18  0.12 -0.15  0.13 -0.27  0.08]
[-0.21  0.28 -0.25  0.12 -0.08  0.02 -0.11  0.32 -0.01 -0.26 -0.   -0.19
 -0.34  0.03 -0.15 -0.35 -0.24  0.16 -0.27  0.25]
[ 0.3  -0.14 -0.1   0.1   0.06 -0.01 -0.04  0.19 -0.05  0.17  0.24 -0.11
 -0.08 -0.09  0.23 -0.11 -0.1  -0.21 -0.23  0.27]
[-0.13  0.   -0.21 -0.3  -0.31 -0.18 -0.33  0.23  0.13 -0.15 -0.26  0.15
  0.03 -0.3  -0.24 -0.12 -0.04 -0.39  0.15  0.15]
[ 0.03  0.18  0.03  0.19  0.02  0.16 -0.16 -0.1  -0.08 -0.02  0.19  0.33
  0.2  -0.01 -0.11  0.32 -0.14 -0.08 -0.21 -0.12]
[-0.12  0.26  0.3  -0.22 -0.32 -0.14  0.14  0.06  0.04  0.1   0.09 -0.14
 -0.06 -0.13 -0.2  -0.22 -0.12 -0.17 -0.21 -0.16]
[-0.22  0.12  0.35  0.29  0.17  0.06  0.09  0.18  0.22  0.24 -0.26 -0.11
  0.08 -0.18  0.19 -0.13 -0.31 -0.26 -0.23 -0.05]
[ 0.2  -0.27 -0.2  -0.09 -0.19  0.03  0.13 -0.27  0.27  0.18  0.19  0.13
  0.26  0.26 -0.24 -0.2   0.06  0.23 -0.23  0.05]
[ 0.16 -0.16 -0.16  0.1   0.19 -0.26 -0.16 -0.06 -0.25 -0.01 -0.29 -0.24
 -0.12  0.15  0.2  -0.17  0.02 -0.15  0.05 -0.23]
[-0.17  0.14  0.17 -0.18 -0.12  0.19 -0.04 -0.18 -0.28 -0.1  -0.23  0.06
  0.24 -0.1   0.06  0.23 -0.06  0.07 -0.14  0.12]
[-0.36  0.23 -0.18  0.23 -0.12 -0.06 -0.33  0.14 -0.02 -0.39 -0.3   0.04
  0.13 -0.22  0.12 -0.    0.09 -0.18 -0.2   0.32]
[-0.18 -0.17  0.31 -0.08  0.19 -0.   -0.25  0.14 -0.23  0.25 -0.08  0.01
  0.2  -0.1  -0.2  -0.1   0.19 -0.21 -0.03 -0.15]
[ 0.23 -0.18 -0.22 -0.03 -0.13 -0.05  0.19 -0.05  0.18  0.08  0.2  -0.31
 -0.18  0.11 -0.23 -0.07 -0.06 -0.09 -0.24 -0.16]
[ 0.25 -0.28  0.16  0.14 -0.24  0.23 -0.11  0.1  -0.17 -0.29  0.22 -0.24
 -0.02  0.11 -0.09  0.22 -0.05 -0.    0.08 -0.01]
[-0.4   0.09  0.02  0.02 -0.31 -0.03  0.05  0.06 -0.17  0.39 -0.29  0.32
 -0.15  0.15  0.13  0.06  0.13 -0.07  0.31 -0.02]
[ 0.01 -0.09 -0.16 -0.02 -0.28  0.2   0.19 -0.21  0.16  0.33 -0.04 -0.11
 -0.41 -0.11 -0.12 -0.08  0.18 -0.24  0.3   0.29]
[ 0.07 -0.1   0.33 -0.09  0.13  0.11 -0.4   0.18 -0.31  0.05 -0.09  0.35
 -0.11 -0.17 -0.45 -0.15  0.03  0.09 -0.18  0.11]
[-0.11  0.08 -0.18 -0.1   0.27 -0.38 -0.14 -0.37  0.4  -0.24 -0.03 -0.2
  0.03  0.09  0.38  0.25  0.16  0.29 -0.08  0.07]
[ 0.09 -0.01  0.08  0.16  0.05 -0.18  0.37 -0.41  0.06  0.18  0.29 -0.27
  0.42 -0.29  0.09  0.07  0.38  0.21  0.05 -0.11]
[-0.07  0.17 -0.26  0.12 -0.09 -0.16  0.05 -0.37 -0.2  -0.17 -0.12  0.1
 -0.02 -0.27 -0.13 -0.15  0.34  0.08 -0.27 -0.31]
```

```
[ 0.27 -0.19 -0.05  0.09  0.27 -0.01 -0.31  0.    0.2  -0.21 -0.03  0.31
  0.06  0.23 -0.44 -0.03 -0.24 -0.36 -0.19 -0.22]
[-0.11  0.24  0.07 -0.25  0.17 -0.08 -0.39 -0.17 -0.18  0.13  0.17  0.42
 -0.4  -0.03 -0.39  0.12  0.12 -0.42  0.16 -0.16]
[ 0.1   0.17 -0.38  0.21 -0.17 -0.15  0.    0.01  0.17 -0.05  0.36 -0.34
  0.05  0.07  0.29  0.03  0.14 -0.09  0.11  0.03]
[ 0.29 -0.11 -0.18  0.35  0.17 -0.34  0.18  0.09 -0.16  0.01  0.03  0.03
 -0.01  0.19 -0.04  0.09  0.04 -0.18 -0.29 -0.39]
[ 0.32  0.05  0.2   0.26  0.12 -0.07  0.28 -0.37  0.22  0.06 -0.05  0.13
  0.13 -0.24  0.17  0.38  0.34  0.26  0.13  0.06]
[ 0.3  -0.33 -0.15  0.   -0.18  0.09 -0.03 -0.23  0.17  0.19 -0.06 -0.27
  0.34 -0.1  -0.1  -0.03 -0.09 -0.18 -0.11 -0.28]
[-0.13 -0.03  0.24 -0.24  0.2  -0.27 -0.15  0.2   0.2   0.03 -0.1  -0.26
 -0.22 -0.11  0.14 -0.19 -0.25  0.08  0.01 -0.19]
```

```
In [68]: avg_weight = []
         for i in range(0,len(mlp.coefs_[0])):
             avg_weight.append(np.mean(mlp.coefs_[0][i]))
         print ('Important features (featureName, weigh of important, #column)')
         header = list(multi_layer_train.head(1))
         important_feature = []
         for i in range(0,len(avg_weight)):
              important_feature.append((header[i+2],avg_weight[i],i+2))
         sorted_list = sorted(important_feature,key=lambda important_feature: important_feature
         for j in range(0,len(sorted_list)):
                 first_imp_fea = sorted_list[0]
                 second_imp_fea = sorted_list[1]
                 print sorted_list[j]
```

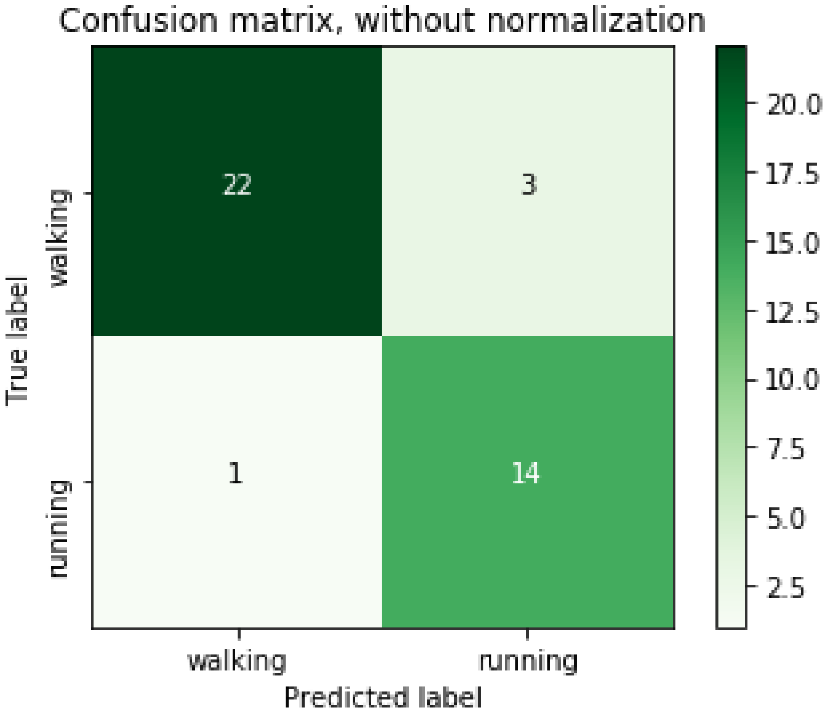
```
Important features (featureName, weigh of important, #column)
('StdDev-y', 0.11856774245202002, 42)
('Bin2,x', 0.070739032320360315, 3)
('AvgAbsDiff-y', 0.062513738529986443, 36)
('Bin9,x', 0.057268960437239516, 10)
('Bin1,y', 0.05130342349274266, 12)
('Bin3,y', 0.041779064470997697, 14)
('Bin1,z', 0.031269696890251851, 22)
('Bin3,x', 0.029507054837830716, 4)
('AvgAcc-z', 0.028498096435685367, 40)
('Bin8,x', 0.019793966854913043, 9)
('Bin6,y', 0.019664466343774677, 17)
('Bin4,z', 0.015621769570225688, 25)
('Bin9,y', 0.015421246134956965, 20)
('TimeDiffPeaks-x', 0.014885141168728588, 32)
('Bin3,z', 0.01265772405696342, 24)
('Bin5,y', 0.0099705655485033094, 16)
('AvgAbsDiff-x', 0.0095896804296363748, 35)
```

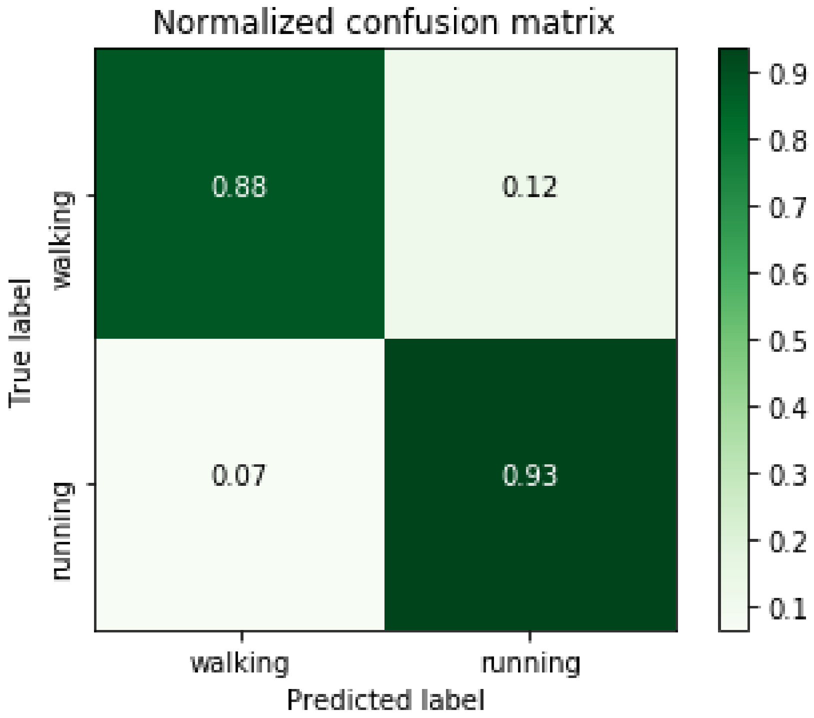
```
('Bin4,y', 0.009261059237709839, 15)
('Bin1,x', 0.004880553488554896, 2)
('Bin5,x', 0.002525417702741833, 6)
('Bin10,z', -4.815816869455898e-05, 31)
('Bin6,x', -0.009749265623426649, 7)
('TimeDiffPeaks-y', -0.011371135092482762, 33)
('StdDev-x', -0.011582157834018248, 41)
('Bin2,y', -0.012092007357850505, 13)
('Bin6,z', -0.014548667184813019, 27)
('Bin8,z', -0.02499960499567027, 29)
('Bin4,x', -0.027295806781554594, 5)
('TimeDiffPeaks-z', -0.029502712054923431, 34)
('Bin7,y', -0.03741234696079667, 18)
('Bin10,x', -0.039573191463880983, 11)
('AvgAcc-x', -0.042129079649980722, 38)
('AvgAcc-y', -0.049046067574073378, 39)
('Bin9,z', -0.05019909791376107, 30)
('AvgResAcc', -0.051772577236402675, 44)
('StdDev-z', -0.052366643249193066, 43)
('Bin7,z', -0.052915845151429927, 28)
('Bin2,z', -0.060534247260531512, 23)
('Bin8,y', -0.06483474958925442, 19)
('Bin5,z', -0.069967243144852406, 26)
('Bin7,x', -0.07371541552481807, 8)
('AvgAbsDiff-z', -0.086473916510525911, 37)
('Bin10,y', -0.10565482723871462, 21)
```

```
In [67]: from sklearn import metrics
         def plot_roc_curve(Y_predict,Y_test,name_graph):
             num_predns = []
             for i in range(0,len(Y_predict)):
                 if Y_predict[i] == "walking":
                     num_predns.append(0)
                 else:
                     num_predns.append(1)
             num_labels = []
             for i in range(0,len(Y_test)):
                 if Y_test[i] == "walking":
                     num_labels.append(0)
                 else:
                     num_labels.append(1)

             predns = np.array(num_predns)
             labels = np.array(num_labels)
             fpr, tpr, thresholds = metrics.roc_curve(labels, predns)
             roc_auc = metrics.auc(fpr, tpr)
             plt.title('Area under ROC Curve')
             plt.plot(fpr, tpr, 'grey', label = 'AUC = %0.2f' % roc_auc)
             plt.legend(loc = 'lower right')
             plt.plot([0, 1], [0, 1],'r--')
             plt.xlim([0, 1])
             plt.ylim([0, 1])
             plt.ylabel('True Positive Rate')
             plt.xlabel('False Positive Rate')
         #     plt.show()
             plt.savefig('./image/roc_multipc.png', dpi=100)

         plot_roc_curve(y_pred,y_test,"Area_under_roc_pc")

In [66]: import itertools
         import numpy as np
         import matplotlib.pyplot as plt

         def plot_confusion_matrix(cm, classes,
                                   normalize=False,
                                   title='Confusion matrix',
                                   cmap=plt.cm.Greens):
             """
             This function prints and plots the confusion matrix.
             Normalization can be applied by setting `normalize=True`.
             """
             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)
             plt.yticks(tick_marks, classes, rotation=90)

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

```
cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
# plt.figure()
class_names = ["walking", "running"]
plot_confusion_matrix(cnf_matrix, classes=["walking", "running"],
                      title='Confusion matrix, without normalization')
plt.savefig('./image/confusion_matrix_multipc.png', dpi=100)
# plt.savefig('H:/mastersProject/activity_analyzer/LogisticRegression/cm_lr', dpi=100

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[22  3]
 [ 1 14]]
Normalized confusion matrix
[[ 0.88  0.12]
 [ 0.07  0.93]]
```




Normalized confusion matrix
True label
walking
running
0.88
0.12
0.07
0.93
walking
running
Predicted label
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1