7/23/2018 fuzzy-kNN

```
In [1]: from sklearn.neighbors import KNeighborsClassifier
        from sklearn.model selection import train_test_split, cross_val_score
        from sklearn import metrics
        from sklearn.preprocessing import normalize,scale
        from sklearn.decomposition import PCA
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn.decomposition import PCA as sklearnPCA
        from pandas.plotting import parallel coordinates
In [2]: #importing dataset and converting to datasframe
        header = ['pelvic_incidence', 'pelvic_tilt', 'lumbar_lordosis_angle', 'sacr
        al_slope', 'pelvic_radius', 'grade_of_spondylolisthesis', 'label']
        df = pd.read csv('./vertebral column data/column 3C.dat', sep=' ', header=N
        one, names=header)
        print(df.dtypes)
        pelvic_incidence
                                       float64
        pelvic tilt
                                       float64
        lumbar_lordosis_angle
                                       float64
        sacral slope
                                       float64
        pelvic_radius
                                       float64
        grade of spondylolisthesis
                                       float64
        label
                                        object
        dtype: object
In [3]: # extracting features and lables
        x = df.iloc[:,0:6]
        y = df.iloc[:,6]
        # split into training and test subsets
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.4)
        print(x test.shape)
        (124, 6)
In [4]: | model = KNeighborsClassifier(n neighbors=5, weights='distance')
In [5]: #10-fold cross validation
        scores = cross_val_score(model, x, y, scoring='accuracy', cv=10)
        # print scores
        print ("10-Fold Accuracy : ", scores.mean()*100)
```

10-Fold Accuracy: 83.5483870967742

7/23/2018 fuzzy-kNN

```
In [6]: #creation of the confusion matrix
        model.fit(x_train,y_train)
        print ("Testing Accuracy : ",model.score(x_test, y_test)*100)
        color_dict = {'DH' : 'cyan', 'SL' : 'magenta', 'NO' : '#1B1B1B'}
        predicted_test = model.predict(x_test)
        predicted = model.predict(x)
        predicted_test_proba = model.predict_proba(x_test)
        Testing Accuracy: 85.48387096774194
In [7]: # confusion matrix
        cm = metrics.confusion_matrix(y_test, predicted_test, labels=['DH', 'NO',
        'SL'])
        print (cm)
        print()
        print (metrics.classification_report(y_test, predicted_test))
        [[18 4 0]
         [10 28 2]
         [ 1 1 60]]
                     precision
                                  recall f1-score
                                                     support
                 DH
                          0.62
                                    0.82
                                              0.71
                                                           22
                 NO
                          0.85
                                    0.70
                                               0.77
                                                           40
                          0.97
                                    0.97
                 SL
                                              0.97
                                                           62
```

0.85

0.86

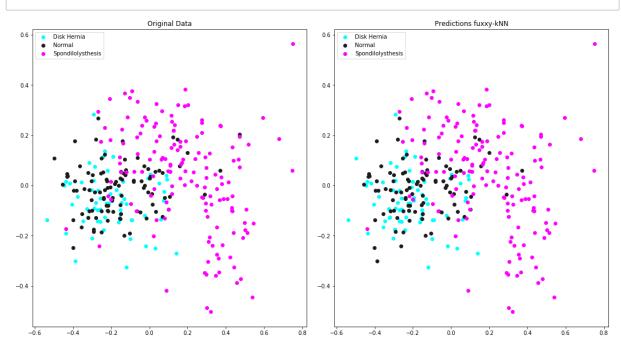
124

avg / total

0.87

7/23/2018 fuzzy-kNN

```
In [8]:
        # mean normalization and feature scaling
        x_norm = (x - x.mean())/(x.max() - x.min())
        # principle component analysis
        pca = PCA(n_components=2) #2-dimensional PCA
        # print(pca.fit_transform(x_norm))
        transformed = pd.DataFrame(pca.fit transform(x norm))
        # print(transformed.iloc[[0,1,2],:])
        # plot
        fig = plt.figure(figsize=(15,8))
        ax1 = fig.add subplot(121)
        ax1.scatter(transformed[y=='DH'][0], transformed[y=='DH'][1], label='Disk H
        ernia', c='cyan')
        ax1.scatter(transformed[y=='NO'][0], transformed[y=='NO'][1], label='Norma
        l', c='#1B1B1B')
        ax1.scatter(transformed[y=='SL'][0], transformed[y=='SL'][1], label='Spondi
        lolysthesis', c='magenta')
        ax1.legend()
        ax1.set_title('Original Data')
        ax2 = fig.add subplot(122)
        ax2.scatter(transformed[predicted=='DH'][0], transformed[predicted=='DH'][1
        ], label='Disk Hernia', c='cyan')
        ax2.scatter(transformed[predicted=='NO'][0], transformed[predicted=='NO'][1
        ], label='Normal', c='#1B1B1B')
        ax2.scatter(transformed[predicted=='SL'][0], transformed[predicted=='SL'][1
        ], label='Spondilolysthesis', c='magenta')
        ax2.legend()
        ax2.set_title('Predictions fuxxy-kNN')
        plt.tight_layout(pad=0.4, w_pad=1.5, h_pad=2.0)
        plt.show()
```



```
In [1]: from sklearn.linear_model import LogisticRegression
    from sklearn.model_selection import train_test_split, cross_val_score
    from sklearn import metrics
    from sklearn.decomposition import PCA

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]: header = ['pelvic_incidence', 'pelvic_tilt', 'lumbar_lordosis_angle', 'sacr
 al_slope', 'pelvic_radius', 'grade_of_spondylolisthesis', 'label']
 df = pd.read_csv(filepath_or_buffer='./vertebral_column_data/column_3C.dat'
 , header=None, sep=' ', names=header)
 print(df.dtypes)

```
pelvic_incidence float64
pelvic_tilt float64
lumbar_lordosis_angle float64
sacral_slope float64
pelvic_radius float64
grade_of_spondylolisthesis float64
label object
```

```
In [3]: x = df.iloc[:, 0:6]
y = df.iloc[:, 6]

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.4)
```

```
In [5]: # 10 fold cross-validation
scores = cross_val_score(model, x, y, scoring='accuracy', cv=10)
print('10 fold accuracy: {}'.format(scores.mean()*100))
```

10 fold accuracy: 83.87096774193547

```
In [6]: # creation of confusion matrix
        model = model.fit(x_train, y_train)
        print('Testing accuracy: {}'.format(model.score(x_test, y_test)*100))
        predicted = model.predict(x)
        cm = metrics.confusion_matrix(y, predicted, labels=['DH', 'NO', 'SL'])
        print(cm)
        print(metrics.classification_report(y, predicted))
        Testing accuracy: 84.67741935483872
        [[ 41 17
                    2]
         [ 17
                    2]
               81
            2
                3 145]]
                     precision
                                  recall f1-score
                                                      support
                 DH
                          0.68
                                     0.68
                                               0.68
                                                           60
                 NO
                          0.80
                                     0.81
                                               0.81
                                                          100
                 SL
                          0.97
                                     0.97
                                               0.97
                                                          150
```

0.86

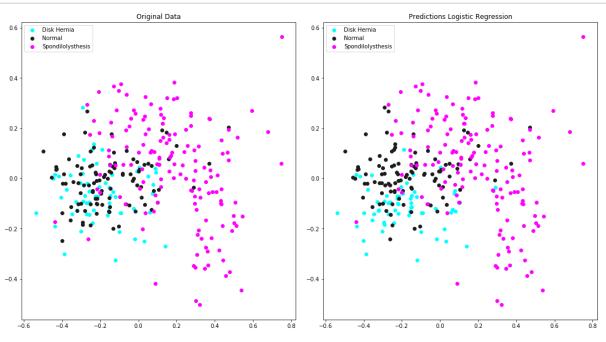
0.86

310

0.86

avg / total

```
In [11]: # mean normalization and feature scaling
         x \text{ norm} = (x - x.mean())/(x.max() - x.min())
         # principle component analysis
         pca = PCA(n_components=2) #2-dimensional PCA
         # print(pca.fit_transform(x_norm))
         transformed = pd.DataFrame(pca.fit transform(x norm))
         predicted = pd.DataFrame(predicted[:]).iloc[:, 0]
         # print(transformed[y=='DH'])
         # plot
         fig = plt.figure(figsize=(15,8))
         ax1 = fig.add subplot(121)
         ax1.scatter(transformed[y=='DH'][0], transformed[y=='DH'][1], label='Disk H
         ernia', c='cyan')
         ax1.scatter(transformed[y=='NO'][0], transformed[y=='NO'][1], label='Norma
         l', c='#1B1B1B')
         ax1.scatter(transformed[y=='SL'][0], transformed[y=='SL'][1], label='Spondi
         lolysthesis', c='magenta')
         ax1.legend()
         ax1.set_title('Original Data')
         ax2 = fig.add_subplot(122)
         ax2.scatter(transformed[predicted=='DH'][0], transformed[predicted=='DH'][1
         ], label='Disk Hernia', c='cyan')
         ax2.scatter(transformed[predicted=='NO'][0], transformed[predicted=='NO'][1
         ], label='Normal', c='#1B1B1B')
         ax2.scatter(transformed[predicted=='SL'][0], transformed[predicted=='SL'][1
         ], label='Spondilolysthesis', c='magenta')
         ax2.legend()
         ax2.set_title('Predictions Logistic Regression')
         plt.tight_layout(pad=0.4, w_pad=1.5, h_pad=2.0)
         plt.show()
```



7/23/2018 RandomForest

```
In [1]: from sklearn.preprocessing import LabelEncoder, StandardScaler
    from sklearn.model_selection import train_test_split
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.metrics import confusion_matrix
    from sklearn import metrics

import numpy as np
import pandas as pd
```

```
In [2]: dataset = pd.read_csv('./vertebral_column_data/column_3C.dat', delimiter =
    ' ', header = None)
    X = dataset.iloc[:,0:-1].values
    Y = dataset.iloc[:,-1].values
```

```
In [3]: le = LabelEncoder()
    Y = le.fit_transform(Y)
    #Y = np.reshape(Y,(310,1))
    #onehotencoder = OneHotEncoder(categorical_features=[0])
    #Y = onehotencoder.fit_transform(Y).toarray()

X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.2,random_state = 0)
```

```
In [4]: sc = StandardScaler()
    X_train = sc.fit_transform(X_train)
    X_test = sc.transform(X_test)

classifier = RandomForestClassifier(n_estimators=10, criterion = 'entropy',
    random_state = 0)
    classsifier = classifier.fit(X_train,Y_train)
```

7/23/2018 RandomForest

```
In [5]: Y_pred = classifier.predict(X_test)
        reverse = dict(zip(range(3),['DH','NO','SL']))
        Y_test = np.vectorize(reverse.get)(Y_test)
        Y_pred = np.vectorize(reverse.get)(Y_pred)
        cm = confusion_matrix(Y_test, Y_pred)
        print(cm)
        print(metrics.classification_report(Y_test, Y_pred))
        [[ 3 9 1]
         [ 1 16 2]
         [ 0 1 29]]
                     precision
                                  recall f1-score
                                                      support
                          0.75
                                    0.23
                                               0.35
                 DH
                                                           13
                 NO
                          0.62
                                    0.84
                                               0.71
                                                           19
                 SL
                          0.91
                                    0.97
                                               0.94
                                                           30
        avg / total
                          0.78
                                    0.77
                                               0.74
                                                           62
```

Using TensorFlow backend.

```
In [2]: dataset = pd.read_csv('./vertebral_column_data/column_3C.dat', delimiter =
    ' ', header = None)
    X = dataset.iloc[:,0:-1].values
    Y = dataset.iloc[:,-1].values

le = LabelEncoder()
    Y = le.fit_transform(Y)
    Y = np.reshape(Y,(310,1))
    onehotencoder = OneHotEncoder(categorical_features=[0])
    Y = onehotencoder.fit_transform(Y).toarray()
```

In [4]: classifier.fit(X_train,Y_train,epochs = 100, batch_size = 10)

```
Epoch 1/100
cc: 0.4718
Epoch 2/100
cc: 0.4839
Epoch 3/100
cc: 0.4839
Epoch 4/100
cc: 0.4839
Epoch 5/100
cc: 0.4839
Epoch 6/100
cc: 0.4839
Epoch 7/100
cc: 0.5081
Epoch 8/100
cc: 0.6210
Epoch 9/100
cc: 0.6774
Epoch 10/100
248/248 [============= ] - 0s 150us/step - loss: 0.8507 - a
cc: 0.7016
Epoch 11/100
cc: 0.7177
Epoch 12/100
248/248 [=============== ] - 0s 117us/step - loss: 0.7513 - a
cc: 0.7097
Epoch 13/100
cc: 0.6895
Epoch 14/100
248/248 [============= ] - 0s 121us/step - loss: 0.6892 - a
cc: 0.6935
Epoch 15/100
700 - 0s 135us/step - loss: 0.6687 - acc: 0.6895
Epoch 16/100
cc: 0.6935
Epoch 17/100
cc: 0.6976
Epoch 18/100
248/248 [=============== ] - 0s 131us/step - loss: 0.6279 - a
cc: 0.7016
Epoch 19/100
cc: 0.7016
```

```
Epoch 20/100
cc: 0.7056
Epoch 21/100
cc: 0.7056
Epoch 22/100
cc: 0.7097
Epoch 23/100
cc: 0.7097
Epoch 24/100
cc: 0.7137
Epoch 25/100
cc: 0.7218
Epoch 26/100
cc: 0.7218
Epoch 27/100
cc: 0.7258
Epoch 28/100
cc: 0.7258
Epoch 29/100
cc: 0.7339
Epoch 30/100
cc: 0.7419
Epoch 31/100
cc: 0.7379
Epoch 32/100
cc: 0.7419
Epoch 33/100
cc: 0.7460
Epoch 34/100
cc: 0.7460
Epoch 35/100
cc: 0.7460
Epoch 36/100
cc: 0.7581
Epoch 37/100
248/248 [================ ] - 0s 135us/step - loss: 0.4662 - a
cc: 0.7621
Epoch 38/100
cc: 0.7661
```

```
Epoch 39/100
cc: 0.7702
Epoch 40/100
cc: 0.7742
Epoch 41/100
cc: 0.7782
Epoch 42/100
cc: 0.7823
Epoch 43/100
cc: 0.7823
Epoch 44/100
cc: 0.7823
Epoch 45/100
cc: 0.7823
Epoch 46/100
cc: 0.7823
Epoch 47/100
cc: 0.7863
Epoch 48/100
cc: 0.7863
Epoch 49/100
cc: 0.7863
Epoch 50/100
cc: 0.7863
Epoch 51/100
cc: 0.7863
Epoch 52/100
cc: 0.7863
Epoch 53/100
cc: 0.7863
Epoch 54/100
cc: 0.7863
Epoch 55/100
c: 0.7863
Epoch 56/100
cc: 0.7863
Epoch 57/100
cc: 0.7863
```

```
Epoch 58/100
cc: 0.7863
Epoch 59/100
cc: 0.7903
Epoch 60/100
cc: 0.7863
Epoch 61/100
cc: 0.8024
Epoch 62/100
cc: 0.8065
Epoch 63/100
cc: 0.8065
Epoch 64/100
cc: 0.8024
Epoch 65/100
cc: 0.8065
Epoch 66/100
cc: 0.8145
Epoch 67/100
cc: 0.8185
Epoch 68/100
cc: 0.8185
Epoch 69/100
cc: 0.8145
Epoch 70/100
cc: 0.8226
Epoch 71/100
248/248 [============ ] - 0s 112us/step - loss: 0.3752 - a
cc: 0.8185
Epoch 72/100
cc: 0.8226
Epoch 73/100
cc: 0.8266
Epoch 74/100
cc: 0.8226
Epoch 75/100
cc: 0.8266
Epoch 76/100
cc: 0.8266
```

```
Epoch 77/100
cc: 0.8266
Epoch 78/100
cc: 0.8266
Epoch 79/100
cc: 0.8226
Epoch 80/100
cc: 0.8226
Epoch 81/100
cc: 0.8266
Epoch 82/100
cc: 0.8387
Epoch 83/100
cc: 0.8306
Epoch 84/100
cc: 0.8266
Epoch 85/100
cc: 0.8306
Epoch 86/100
cc: 0.8347
Epoch 87/100
cc: 0.8347
Epoch 88/100
cc: 0.8387
Epoch 89/100
cc: 0.8387
Epoch 90/100
cc: 0.8427
Epoch 91/100
cc: 0.8387
Epoch 92/100
cc: 0.8468
Epoch 93/100
cc: 0.8508
Epoch 94/100
248/248 [=============== ] - 0s 121us/step - loss: 0.3285 - a
cc: 0.8589
Epoch 95/100
cc: 0.8710
```

Out[4]: <keras.callbacks.History at 0x7fc05b9ded68>

```
In [5]: Y_pred = classifier.predict(X_test)
Y_pred = (Y_pred>0.5).astype(float)
print(Y_pred)
```

[[0. 1. 0.] [0. 0. 1.] [1. 0. 0.] [0. 0. 1.] [1. 0. 0.] [0. 1. 0.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [1. 0. 0.] [0. 1. 0.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [1. 0. 0.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.] [1. 0. 0.] [0. 0. 1.] [0. 1. 0.] [0. 1. 0.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 1. 0.] [0. 1. 0.] [0. 0. 1.] [0. 1. 0.] [0. 0. 1.] [0. 0. 1.]

[0. 1. 0.] [0. 0. 1.]

[0. 0. 1.] [0. 1. 0.] [1. 0. 0.] [0. 1. 0.] [0. 1. 0.]]