4/14/2020 HW2 Problem1

```
import numpy as np
In [464]:
           import pandas as pd
           from sklearn.model selection import train test split
In [465]:
           #Importing the data
           pima=pd.read csv("diabetes.csv")
In [466]:
           pima
Out[466]:
                Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction
                         6
                                                                       33.6
              0
                                148
                                               72
                                                            35
                                                                                             0.6
              1
                         1
                                 85
                                               66
                                                            29
                                                                    0
                                                                       26.6
                                                                                             0.3
                         8
              2
                                183
                                                             0
                                                                    0
                                                                       23.3
                                                                                             0.6
                                               64
              3
                                 89
                                                            23
                                                                   94
                                                                       28.1
                                                                                             0.1
                                               66
                         0
                                137
                                               40
                                                            35
                                                                   168 43.1
                                                                                             2.2
                         ...
                                 ...
                                                             ...
            763
                        10
                                101
                                               76
                                                            48
                                                                   180 32.9
                                                                                             0.1
                         2
                                               70
                                                                       36.8
            764
                                122
                                                            27
                                                                    0
                                                                                             0.3^{4}
            765
                         5
                                121
                                               72
                                                            23
                                                                   112
                                                                       26.2
                                                                                             0.2
            766
                         1
                                126
                                               60
                                                             0
                                                                    0 30.1
                                                                                             0.3
            767
                                 93
                                               70
                                                            31
                                                                    0 30.4
                                                                                             0.3
           768 rows × 9 columns
In [467]:
          #Taking required features for training into a list
           features=["Glucose", "BloodPressure", "SkinThickness", "Outcome"]
           #Creating a DataFrame with the list features
           X temp=pima[features]
           #Spliting the Datasets into 2 parts i.e Training Set and Test Set
           X train,X test = train test split(X temp, test size=0.5)
           #defining two DataFrames for two Classes A("Outcome"==0) and B("Outcome"==1)
           X_trainA=X_train[X_train["Outcome"]==0]
           X trainB=X train[X train["Outcome"]==1]
In [468]:
           #calculating the prior probability of the classes
           prior prob A=X trainA.shape[0]/(X trainA.shape[0]+X trainB.shape[0])
           prior_prob_B=X_trainB.shape[0]/(X_trainA.shape[0]+X_trainB.shape[0])
In [469]:
           y trainA=X trainA[["Outcome"]]
           y_trainB=X_trainB[["Outcome"]]
           #Removing Outcome Column Feature from Both DataFrames
           X_trainA=X_trainA[["Glucose","BloodPressure","SkinThickness"]]
```

X trainB=X trainB[["Glucose","BloodPressure","SkinThickness"]]

```
In [470]: #function for calculating the mean
          def mean(x):
              return sum(x)/x.shape[0]
In [471]:
          #mean of the features of classA
          meanVarA1=mean(X_trainA.iloc[:,0])
          meanVarA2=mean(X trainA.iloc[:,1])
          meanVarA3=mean(X_trainA.iloc[:,2])
In [472]:
          #mean of the features of classB
          meanVarB1=mean(X trainB.iloc[:,0])
          meanVarB2=mean(X trainB.iloc[:,1])
          meanVarB3=mean(X trainB.iloc[:,2])
In [473]: #function which takes "mean" and "covariance" as the parameters and returns th
          e likelihood of the Feature Vector
          def likelihood(x,mu,co):
              #inverse of the covariance matrix
              inv=np.linalg.inv(co)
              p1=1/(np.sqrt(((2*np.pi)**3)*np.linalg.det(co)))
              p2=np.exp(-0.5*np.dot(np.dot((x-mu).T,inv),(x-mu)))
              p=p1*p2
              return p
In [474]:
          #defining the meanVector which stacked all the means of the taken Features
          MeanVectorA=np.array([[meanVarA1,meanVarA2,meanVarA3]])
          MeanVectorB=np.array([[meanVarB1,meanVarB2,meanVarB3]])
In [475]:
          #calculating the covariance matrix for both classes(A and B)
          covA=np.cov(X trainA.T)
          covB=np.cov(X trainB.T)
In [494]:
          ##Testing one test sample on the classsifier
          a=X test.iloc[381,0:3].to numpy().reshape(X test.shape[1]-1,1)
          postA=likelihood(a,MeanVectorA.T,covA)*prior_prob_A
          postB=likelihood(a,MeanVectorB.T,covB)*prior_prob_B
          if(postA<postB):</pre>
              print("Class B")
          else:
              print("Class A")
```

Class A

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```
In [477]: #Accuracy of the Total Test Set
          predicted outcome=[]
          for k in range(X test.shape[0]):
              #Changing the test sample from Pandas Series to numpy Array and reshaping
           it
              a=X_test.iloc[k,0:3].to_numpy().reshape(X_test.shape[1]-1,1)
              #Calculating the posterior probabilities
              postA=likelihood(a,MeanVectorA.T,covA)*prior prob A
              postB=likelihood(a,MeanVectorB.T,covB)*prior prob B
              #Whichever Posterior Probability is more, the test sample is labelled with
          the class label
              if(postA<postB):</pre>
                  predicted_outcome.append(1)
              else:
                  predicted outcome.append(0)
          XTest=X test.copy()
          XTest["predictedOutcome"]=predicted outcome
          correct=0
          wrong=0
          #Checking how many did the classifier correctly labelled
          for k in range(XTest.shape[0]):
              if(XTest.iloc[k,3]==XTest.iloc[k,4]):
                  correct+=1
              else:
                  wrong+=1
          print("Total no of correctly predicted values:" +str(correct))
          Accuracy=correct/X_test.shape[0]
          print("Accuracy: "+str(ratio))
          Total no of correctly predicted values:299
          Accuracy: 0.78125
          Total no of wrongly predicted values:85
          Mean: 0.22135416666666666
          #storing the accuracy of 10 iterations in a list
In [478]:
          ListAccuracy=[]
In [479]:
          ListAccuracy.append(Accuracy)
In [480]: ListAccuracy
Out[480]: [0.7473958333333334,
           0.71614583333333334,
           0.77083333333333334,
           0.7473958333333334,
           0.75,
           0.7083333333333334,
           0.7395833333333334,
           0.734375,
           0.77864583333333334]
```

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```
In [481]: #mean accuracy
Mean=sum(ListAccuracy)/len(ListAccuracy)
print(Mean)

0.7424242424242423
```

```
In [482]: import math
std_dev=0
for p in range(len(ListAccuracy)):
    std_dev+=(ListAccuracy[p]-Mean)**2
std_destd_dev/(len(ListAccuracy)-1)
std_deviation=math.sqrt(std_d)
```

```
In [483]: #Standard Deviation of the accuracy
print(std_deviation)
```

0.020520256490892612