#the target data path='D:/coding/divorce.csv' Data=pd.read\_csv(path) print("Selected Data Source:\n", Data) Selected Data Source: Atr1 Atr2 Atr3 Atr4 Atr5 Atr6 Atr7 Atr8 Atr9 Atr10 ... Atr46 \ 0 2 0 2 4 1 0 0 0 0 0 ... 2 4 2 1 . . . 2 2 2 2 2 3 2 3 1 1 2 1 . . . 2 3 3 2 3 2 3 3 3 3 3 3 4 2 2 1 1 1 1 0 0 0 2 . . . 165 0 0 0 0 0 0 0 0 0 0 1 166 0 0 0 0 0 0 4 0 0 0 0 . . . 0 0 1 ... 3 167 1 168 0 0 0 0 0 0 0 ... 3 0 ... 169 0 0 0 1 3 Atr51 Atr52 Atr53 Atr54 Class Atr47 Atr48 Atr49 Atr50 0 3 3 2 3 2 1 1 3 1 1 2 3 4 4 4 4 2 2 1 2 2 2 2 3 1 2 1 1 1 3 2 2 2 2 3 3 3 3 1 4 2 3 2 2 2 1 1 1 165 0 4 1 1 2 2 0 4 2 2 2 166 1 2 2 2 3 2 0 167 0 2 0 1 3 0 1 0 0 168 3 2 2 2 4 3 1 0 3 3 169 0 0 4 1 [170 rows x 55 columns] In [2]: #Transform the target to numeric array Encoder=preprocessing.LabelEncoder() Encoded\_Data=Data.apply(preprocessing.LabelEncoder().fit\_transform) print("Transformed Data:\n", Encoded\_Data) Numeric\_Array=Encoded\_Data.values print("Numeric Array\n", Numeric\_Array) Transformed Data: Atr1 Atr2 Atr3 Atr4 Atr5 Atr6 Atr8 Atr10 ... Atr46 \ Atr7 Atr9 0 2 2 1 0 0 0 0 ... 2 1 4 2 . . . 2 2 2 2 2 3 2 2 3 1 1 . . . 3 3 2 3 2 3 3 3 3 3 3 2 2 4 2 1 1 1 1 0 0 0 0 2 . 165 0 0 0 0 0 0 0 0 0 0 1 . . . 166 0 0 0 0 0 4 0 0 0 0 0 . . . 0 0 0 0 1 ... 3 167 1 0 0 0 0 0 ... 3 168 0 0 0 0 0 0 0 0 0 3 169 0 0 0 1 0 . . . Atr48 Atr49 Atr50 Atr51 Atr52 Atr53 Atr54 0 3 3 3 2 3 2 1 1 1 1 2 3 4 4 4 4 2 2 1 3 4 1 2 2 1 . . . 2 2 0 4 2 2 3 1 165 0 1 4 2 0 2 166 1 2 167 0 1 1 3 2 4 3 168 3 2 1 0 169 1 [170 rows x 55 columns] Numeric Array [[2 2 4 ... 2 1 1] [4 4 4 ... 2 2 1] [2 2 2 ... 2 2 1] [1 1 0 ... 0 0 0] [0 0 0 ... 3 1 0] [0 0 0 ... 3 1 0]] In [3]: #select samples from the transformed target data #selecting training and test sample Training\_Sample, Test\_Sample=train\_test\_split(Numeric\_Array, test\_size=0.3, random\_state=2) print("Training Sample:\n", Training\_Sample) print("Test Sample:\n", Test\_Sample) #select input attributes from training sample Training Sample: [[0 0 3 ... 0 0 0] [3 1 1 ... 0 4 0] [3 0 0 ... 1 0 0] [3 3 3 ... 3 3 1] [4 4 3 ... 4 4 1] [0 0 0 ... 3 1 0]] Test Sample: [[3 4 3 ... 4 4 1] [3 3 3 ... 4 4 1] [3 4 3 ... 4 3 1] [0 0 0 ... 0 2 0] [3 3 2 ... 3 4 1] [2 0 2 ... 2 1 0]] In [4]: | #select input attributes from training sample XTrain\_Sample=Training\_Sample[:,:-1] print("Input(Indipendent) Attributes of training sample\n", XTrain\_Sample) Input(Indipendent) Attributes of training sample [[0 0 3 ... 0 0 0] [3 1 1 ... 0 0 4] [3 0 0 ... 4 1 0] [3 3 3 ... 3 3 3] [4 4 3 ... 4 4 4] [0 0 0 ... 4 3 1]] In [5]: #select output attribute from training sample YTrain\_Sample=Training\_Sample[:,-1] print("Ouput(Dependent) Attributes of training sample\n", YTrain\_Sample) Ouput(Dependent) Attributes of training sample 1 0 1 1 1 1 1 0] In [6]: #select input attributes from test sample XTest\_Sample=Test\_Sample[:,:-1] print("Indipendent Attributes of test sample\n\n", XTest\_Sample) Indipendent Attributes of test sample [[3 4 3 ... 4 4 4] [3 3 3 ... 4 4 4] [3 4 3 ... 3 4 3] [0 0 0 ... 1 0 2] [3 3 2 ... 4 3 4] [2 0 2 ... 1 2 1]] In [7]: #select output attributes from test sample Actual\_YTest\_Sample=Test\_Sample[:,-1] print("Dependent Attributes of test sample\n\n", Actual\_YTest\_Sample) Dependent Attributes of test sample 0 0 0 0 1 1 0 1 1 0 0 0 1 0] In [8]: #Compress input attributes data training sample into two attributes # Defining PCA object for compressing the attributes  $pca = PCA(n\_components = 2)$ #use PCA objects to compress the input attributes of the Training Sample Compressed\_XTrain\_Sample = pca.fit\_transform(XTrain\_Sample) print("Compressed input atributes of Training Sample:\n", Compressed\_XTrain\_Sample) Compressed input atributes of Training Sample: [[ -9.73915962 1.64680229] [ -8.93726983 0.12789023] [ -9.00522101 0.31561341] [ -9.11596152 -3.10562409] [ -9.73766554 -1.70898361] [ -9.23089836 -0.38960601] [ -9.08013017 -0.56888428] [ 14.82904093 0.53453589] [ 11.66648172 -0.17442586] 12.17234548 -1.01359425] 10.49710716 0.57362542] [ -9.25577424 -2.27164897] [-10.78941235 -1.37280351] [ -9.33714167 -1.30376121] [ -5.25600644 -1.31520221] [ 12.13752955 -1.02250238] [ -8.99560122 -0.78554075] 5.23167028 1.10145482 [-11.1892132 -0.08702613] [ 12.90105612 -1.34448484] [ -9.09358265 0.02887838] [ -9.0404947 0.20893755] -2.16360548] [ -8.5432773 [ 12.17234548 -1.01359425] [ -9.38062186 -1.12820206] 13.41070976 2.08389658] [ 9.69546174 -3.71278306] [ -8.62210063 2.43568409] [ -8.73548325 1.68176917] [ -9.60418522 -0.0776569 ] [-10.24490909 1.45913488] [ -8.88732274 -1.25833204] [-10.27082986 1.1206134 ] 12.90105612 -1.34448484] 10.47616709 -0.11434611] 13.49022317 -0.58351494] [ -8.33187566 0.08329763] [ 7.82971052 -1.86389347] [ -9.22848552 -2.21060307] [ -9.70913472 0.2548897 [ -8.48954657 -3.38800529] -11.60273933 0.79642974] -0.9768093 [ -9.67783486 2.22834782] [-11.92280108 [ 12.92199619 -0.65651331] -8.98238799 -1.16304768] 9.65519363 -3.65358487] 9.76854444 2.74066933] -9.71110425 -0.73181061] 9.42064874 -0.65039072 5.9449173 3.91639317] 7.09729787 5.68324305] 10.31721787 3.47258051] 13.41070976 2.08389658] [ -9.10063049 -1.54327848] [-11.4716459 1.05732628] 9.19855751 -0.60362361] [-10.36437402 -0.55718083 -4.21194476 0.36470059] 9.69546174 -3.71278306] 12.09283208 1.65381727] 10.89908768 -2.37209678] 14.82904093 0.53453589 5.65883531 3.21896897] 1.05125365 6.11297595] -9.28862917 1.17123986 12.17779765 -1.08170057 12.13199979 0.79350036] -8.10561456 -3.05154524] [-10.31376017 1.94688865] 2.58745439 -0.61657836] 9.69546174 -3.71278306] [-11.22781488 1.33703909] -9.68397548 -0.35641657] -9.86454805 0.85590056] 10.31721787 3.47258051 8.04682169 1.45233907] -9.29592459 -0.10024824] -8.54450908 -1.81365585] 11.48272496 0.20487585] 10.93390361 -2.36318865] -8.31201894 1.06541536] 0.36089645 -9.56251117 11.01333943 -3.28270376] 10.79318203 -0.32455047 4.05731289 0.33000113] -8.57781905 -1.17344172] -9.1000003 1.86780482] 3.7888494 -8.17572873 10.93390361 -2.36318865] [-11.17318394 3.70768998] 8.48206856 6.28354758] 9.55474016 -1.67414488] -8.49578496 1.05063627] -0.22520345] 10.16484727 12.03715367 -0.79095881] -0.52248693] 11.40393228 -10.18198424 -0.18156532] -2.1997514 10.8389799 -9.88524073 -1.68804592] -6.24265101 1.17700055] [-10.36889837 -1.04080745] 11.40393228 -0.52248693] -9.87953469 -0.8096858 -9.68796468 -0.34125188] -8.75848166 -0.70325954] 12.17226789 0.73430217] 9.69546174 -3.71278306] 10.89363551 -2.30399046] [ -8.52647287 1.05177021] [-10.48947775 -0.57739814] 2.69832461 5.19941512] -0.33981104] 10.34435887 7.00334106 6.42549352] 10.93390361 -2.36318865] 12.64718319 2.40587904] 8.42950117 1.53436159] [ 13.49022317 -0.58351494] [ -8.40945997 -2.97377109]] In [9]: Compressed\_XTest\_Sample = pca.fit\_transform(XTest\_Sample) print("Compressed input atributes of Training Sample:\n", Compressed\_XTest\_Sample) Compressed input atributes of Training Sample: [[ 14.16629338 -0.05995038] [ 12.99382033 -0.75665428] 11.71918267 0.99597938] [ 12.99382033 -0.75665428] -9.58199849 -0.78641563] [ 14.16629338 -0.05995038] 12.32389914 -1.15294086] -8.19299882 -0.71591504] -10.23450067 1.82988715] 11.75997199 -2.30624576] -8.80270584 -2.61302463] 5.23464671 3.62721322] 5.13483065 1.94414035] -7.89872074 0.48010672] 10.1910608 -0.87288274] -8.52849823 4.12597099] 11.75997199 -2.30624576] 2.62376989 2.91416351] 12.93244504 -1.60954186] -7.65578024 1.52468389] -8.04934025 0.4535768 -8.67181543 -2.93447043] -8.40019397 -3.73916046] 11.37665701 -0.52202141] -5.62853808 0.99741447] -9.66348834 -1.87306591] -8.48603505 -4.44982959] 11.68144699 -1.36444005] -7.81959962 1.50938761] -1.51367262] [ 13.09981437 -8.52557524 4.27412802] 10.39616581 1.58340592] -9.17827565 -2.27925261 -8.27886214 -0.02448487] -7.74276906 0.69421357] 6.20054778 7.28643739] -8.95279771 1.4134299 -9.42549258 2.63434722] -9.59760903 -2.82627282] -7.7279913 -0.57628747] -8.67181543 -2.93447043] 5.54893173 6.61077088] 14.01709153 0.02216284] [-11.19719254 -0.44111276] -2.30624576] [ 11.75997199 -1.9529604 9.0884359 -9.65624072 0.40065463] -8.94538002 0.12672066] -8.23304253 -1.53242044 10.21852984 -0.68809536] [ -7.64034151 0.50588985]] In [10]: |#Classification phase #develop a NaiveBayes Classifier from sklearn.naive\_bayes import GaussianNB Classifier\_object = GaussianNB() #train the classifier object to develop a classifier NBayes\_classifier=Classifier\_object.fit(Compressed\_XTrain\_Sample,YTrain\_Sample) In [11]: from mlxtend.plotting import plot\_decision\_regions from sklearn.metrics import confusion\_matrix, plot\_confusion\_matrix import matplotlib.pyplot as plt In [ ]: In [12]: #test it can classify new data and visualize the classifier #use predict() function to predict classes of Test Sample Predicted\_YTest\_Sample = NBayes\_classifier.predict(Compressed\_XTest\_Sample) #visualize the testing results using Decision boundaries plot\_decision\_regions(Compressed\_XTest\_Sample, Predicted\_YTest\_Sample, clf=Classifier\_object,legend=2) plt.title('Classification Test Results') Legend=plt.legend() Legend.get\_texts()[0].set\_text('Divorce\_prediction') Legend.get\_texts()[1].set\_text('Divorce\_prediction') plt.show() #visualize Testing results using a Data Frame Both\_YTest\_Sample={ 'Actual\_Classes': Actual\_YTest\_Sample, 'Predicted\_Classes': Predicted\_YTest\_Sample Tabulated\_Test\_Results = pd.DataFrame(Both\_YTest\_Sample, columns=['Actual\_Classes', 'Predicted\_Classes']) print("Classification Test results\n", Tabulated\_Test\_Results) Classification Test Results ■ Divorce\_prediction ▲ Divorce\_prediction -10 -5 10 15 Classification Test results Actual\_Classes Predicted\_Classes 0 1 1 1 1 1 2 1 1 3 1 1 4 0 0 5 1 1 6 1 0 7 8 0 0 9 1 1 10 0 11 1 1 12 1 1 13 0 0 14 1 15 0 16 1 1 17 1 1 18 19 0 0 20 0 0 21 0 22 23 1 1 24 1 1 25 0 26 27 1 1 28 0 29 1 30 31 1 32 0 33 0 34 35 1 36 0 37 0 38 39 0 40 0 41 1 42 1 43 0 44 1 45 1 46 47 0 48 49 50 In [ ]: In [16]: | from sklearn.metrics import confusion\_matrix Test\_Results =pd.DataFrame(Both\_YTest\_Sample) from sklearn.metrics import accuracy\_score Confusion\_Matrix = confusion\_matrix(Test\_Results['Actual\_Classes'], Test\_Results['Predicted\_Classes']) print(Confusion\_Matrix) import seaborn as sns #visualize the validation results using a heat map confusion\_matrix1=pd.crosstab(Test\_Results['Actual\_Classes'], Test\_Results['Predicted\_Classes'], rownames=['Actual\_Classes'], colnames=['Predicted\_Classes']) ax= plt.subplot() sns.heatmap(confusion\_matrix1, annot=True, ax=ax); ax.set\_xlabel('predictions');ax.set\_ylabel('Actual cases'); ax.set\_title('Confusion Matrix Heatmap'); ax.xaxis.set\_ticklabels(['No', 'Yes']);ax.yaxis.set\_ticklabels(['Np', 'Yes']); plt.show() [[27 0] [ 0 24]] Confusion Matrix Heatmap - 25 27 윤 Actual cases 24 Æ No predictions

In [17]: **from sklearn import** metrics

gnb = GaussianNB()

Accuracy: 98.04

In [ ]:

#Create a Gaussian Classifier

gnb.fit(XTrain\_Sample, YTrain\_Sample)
y\_pred = gnb.predict(XTest\_Sample)

print("Accuracy: %.2f" % (accuracy\*100))

# Model Accuracy, how often is the classifier correct?

accuracy = metrics.accuracy\_score(Actual\_YTest\_Sample, y\_pred)

In [1]: #select necesary libraries
import numpy as np

import pandas as pd

from sklearn.metrics import accuracy\_score

from sklearn.preprocessing import Normalizer

from sklearn.model\_selection import train\_test\_split

from sklearn import preprocessing

from sklearn.decomposition import PCA