INF 552 MACHINE LEARNING FOR DATA SCIENCE

HOMEWORK 6

Team member:

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Part 1:

Language used:

Python 3, GOOGLE COLABORATORY

Data structures used:

Numpy array to store data

Code-level optimization:

Data points with alpha value < 10^-4 were not considered as support vectors as they cause a very minute negligible change to the equation.

Challenges:

Solving Quadratic programming equation because proper matrix formulation is very difficult.

Choosing the proper kernel function and the degree of polynomial kernel was also difficult as there are theoretically many values and many kernel functions. Experimenting with every kernel function and comparing the accuracy was tedious

Part 2:

Library used: Scikit learn

Although the implementation gave good result and same accuracy as the library function, it can still be improved. We can experiment with different threshold set for support vectors and try out many kernel possible . also the library function uses soft margin defaultly, has coefficient factor for kernels,uses shrinking heuristics and has probability estimats enabled by default. These factors can be used in the implementation version to improve performance.

Part 3:

SVM is used to classify gene structures, protein remote homology detection and also to identify cancer.It is also used in biomarker/signature discovery where meaningful gene sequences are discovered. It is also used to predict anti-cancer drug sensitivity where is calculates response of cancer cells to drug compounds.

SVM is used in face detection where it can classify regions of face as face and non-face features and create a boundary around face.

```
#Done by SANJAY MALLASAMUDRAM SANTHANAM ; USC ID:3124715393
#PART (a)
import pandas as pd
import numpy as np
import math
import copy
import os
```

```
#load data
data=np.loadtxt('linsep.txt',delimiter=",")
```

```
len(data)
```

```
100
```

```
#separate input and label
x=data[:,0:2]
y=data[:,2]
```

```
#find number of data points and dimensions of point
N=len(x)
d=len(x[0])
y=y.reshape((N,1))
```

```
import cvxopt
from cvxopt import matrix,solvers
```

```
#Pij=(yi*yj*Xi.T*Xj)
P=matrix(np.matmul(y*x,(y*x).T), tc='d')
#q=(-1)T i.e. vector of -1
q=matrix(-1*np.ones((N,1)), tc='d')
#G is identity matrix with diagonal =-1 as we have alpha>0 <=> -alpha<0
G=matrix(-1*np.eye(N), tc='d')
#h is vector of zeros as we have RHS OF - alpha<0 as zero
h=matrix(np.zeros(N), tc='d')
#A= y as we have constraint y.T*alpha=0
A=matrix(y.reshape(-1,N),tc='d')
#b=0 as we have the RHS to be zero.
b=matrix(np.zeros(1), tc='d')
```

```
#solve eqn
sol = solvers.qp(P,q,G,h,A,b)
```

```
     pcost       dcost       gap    pres   dres
 0: -2.0636e+01 -4.3905e+01  3e+02  2e+01  2e+00
 1: -2.2372e+01 -3.7202e+01  9e+01  5e+00  5e-01
 2: -2.3112e+01 -3.8857e+01  5e+01  2e+00  2e-01
 3: -2.8318e+01 -3.3963e+01  1e+01  4e-01  4e-02
 4: -3.2264e+01 -3.3927e+01  2e+00  1e-02  1e-03
 5: -3.3568e+01 -3.3764e+01  2e-01  1e-03  1e-04
 6: -3.3737e+01 -3.3739e+01  2e-03  1e-05  1e-06
 7: -3.3739e+01 -3.3739e+01  2e-05  1e-07  1e-08
 8: -3.3739e+01 -3.3739e+01  2e-07  1e-09  1e-10
Optimal solution found.
```

```
#print all alpha values
print((sol['x']))
```

```
[ 1.16e-09]
[ 2.96e-09]
[ 4.32e-09]
[ 6.23e-10]
[ 3.97e-10]
[ 3.31e-09]
[ 9.20e-10]
[ 2.30e-09]
[ 4.69e-10]
[ 9.07e-10]
[ 3.00e-09]
[ 7.27e-10]
[ 3.94e-10]
[ 6.73e-10]
[ 1.36e-09]
[ 6.96e-10]
[ 8.36e-10]
[ 2.23e-09]
[ 2.00e-09]
[ 1.64e-09]
[ 1.03e-09]
[ 1.14e-09]
[ 1.74e-08]
[ 2.90e-09]
[ 1.51e-09]
[ 2.15e-07]
[ 2.39e-09]
[ 3.37e+01]
[ 2.83e-09]
[ 2.39e-09]
[ 4.21e-10]
[ 9.74e-10]
[ 5.47e-10]
[ 1.16e-09]
[ 3.79e-10]
[ 1.66e-09]
[ 1.58e-09]
[ 8.94e-10]
[ 5.28e-10]
[ 2.00e-09]
[ 8.22e-10]
[ 5.63e-10]
[ 3.24e-09]
[ 9.98e-10]
[ 9.14e-10]
[ 4.02e-10]
[ 4.12e-10]
[ 1.76e-09]
[ 2.15e-09]
[ 1.30e-09]
[ 1.31e-09]
[ 1.16e-09]
[ 1.92e-09]
[ 1.41e-09]
[ 7.22e-10]
[ 9.69e-09]
[ 2.97e-08]
[ 4.06e-09]
[ 7.65e-10]
[ 9.54e-10]
[ 6.23e-09]
[ 3.74e-09]
[ 5.52e-10]
[ 1.20e-09]
[ 1.12e-09]
[ 1.82e-09]
[ 1.29e-09]
[ 1.09e-09]
```

```
 [ 3.32e-10]
 [ 1.52e-09]
 [ 4.68e-10]
 [ 2.07e-09]
 [ 4.95e-10]
 [ 2.86e-09]
 [ 1.52e-09]
 [ 2.76e-09]
 [ 2.56e-09]
 [ 5.67e-10]
 [ 2.74e-09]
 [ 1.11e-09]
 [ 1.11e-09]
 [ 7.11e-10]
 [ 1.51e-09]
 [ 1.29e+00]
 [ 4.90e-10]
 [ 6.93e-10]
 [ 5.68e-10]
 [ 3.24e+01]
 [ 9.68e-10]
 [ 2.77e-09]
 [ 5.45e-10]
 [ 2.47e-09]
 [ 4.33e-10]
 [ 5.64e-09]
 [ 7.79e-10]
 [ 3.20e-09]
 [ 1.17e-09]
 [ 2.52e-09]
 [ 1.82e-09]
 [ 6.09e-10]
```

```
#solution details
sol
```

```
{'dual infeasibility': 1.2144726770965757e-10,
 'dual objective': -33.738752410222155,
 'dual slack': 1.6873103881494114e-10,
 'gap': 2.4222439971708235e-07,
 'iterations': 8,
 'primal infeasibility': 1.163461785745105e-09,
 'primal objective': -33.7387521905106,
 'primal slack': 4.479968201171581e-10,
 'relative gap': 7.179411922211238e-09,
 's': <100x1 matrix, tc='d'>,
 'status': 'optimal',
 'x': <100x1 matrix, tc='d'>,
 'y': <1x1 matrix, tc='d'>,
 'z': <100x1 matrix, tc='d'>}
```

```
#Compute w
w=0
for i in range(N):
  w+=sol['x'][i]*y[i]*x[i,:]
```

```
print("W:")
print(w)
```

```
W:
[ 7.2500563  -3.86188924]
```

```
sv=(np.array(sol['x'])>0.0001).flatten()
#represents position of support vectors i.e. alphas that are >0
sv_idx=np.argwhere(sv)
```

```
sv_idx
```

```
array([[27],
       [83],
       [87]])
```

```
#non zero alpha values
print(np.array(sol['x'])[sv_idx])
```

```
[[[33.73875192]]

 [[ 1.29468506]]

 [[32.4440672 ]]]
```

```
print("Support vectors:")

print(x[sv_idx])
```

```
Support vectors:
[[[0.24979414 0.18230306]]

 [[0.3917889  0.96675591]]

 [[0.02066458 0.27003158]]]
```

```
#compute value of b
b=y[sv_idx[0]]-np.dot(x[sv_idx[0]],w)
print("b:")
print(b)
```

```
b:
[[-0.10698734]]
```

```
y_pred=np.zeros(N)
for i in range(N):
  y_pred[i]=np.sign(np.dot(w,x[i])+b)
err=0
for i in range(N):
  if(y_pred[i]!=y[i]):
    err=err+1
print("Accuracy of implementation:",(N-err)/N)
```

```
Accuracy of implementation: 1.0
```

```
from sklearn.svm import SVC
clf = SVC(kernel='linear')
clf.fit(x,y)
print("Support vectors of library functon:")
print(clf.support_vectors_)
print("Coefficients:")
print(clf.coef_)
print("Intercept:")
print(clf.intercept_)
```

```
print(clf.intercept_)
y_pred=clf.predict(x)
print("Accuracy of library function:")
print(clf.score(x,y_pred))
```

```
Support vectors of library functon:
[[0.23307747 0.86884518]
 [0.23918196 0.81585285]
 [0.14301642 0.85313079]
 [0.14586533 0.74931925]
 [0.26419794 0.91067489]
 [0.06756031 0.65812372]
 [0.17422964 0.6157447 ]
 [0.01107579 0.39873158]
 [0.15267995 0.8006936 ]
 [0.03436631 0.50247843]
 [0.3917889  0.96675591]
 [0.02066458 0.27003158]
 [0.55919837 0.70372314]
 [0.2498981  0.15693917]
 [0.65628367 0.77812372]
 [0.27872572 0.23552777]
 [0.24979414 0.18230306]
 [0.70631503 0.87261758]
 [0.22068726 0.11139981]
 [0.36354491 0.25915653]
 [0.42066002 0.43762265]
 [0.76570056 0.98727513]
 [0.45552411 0.49956489]
 [0.6798148  0.90468041]]
Coefficients:
[[ 3.59965788 -2.03198838]]
Intercept:
[0.21848298]
Accuracy of library function:
1.0
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWarning: A column-vecto
  y = column_or_1d(y, warn=True)
```

```
#part 2 nonlinear data
data=np.loadtxt('nonlinsep.txt',delimiter=",")
```

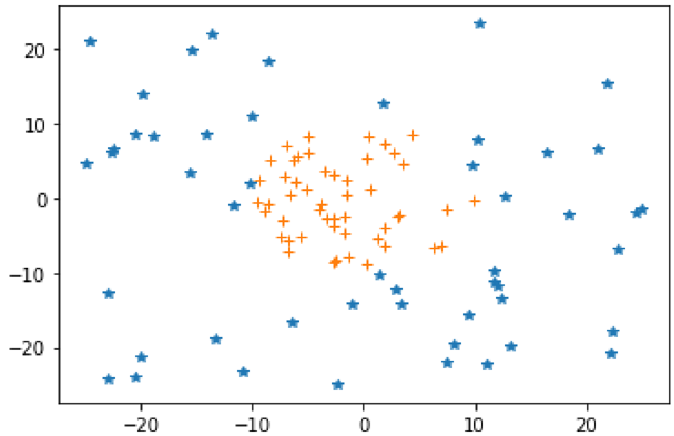
```
x=data[:,0:2]
y=data[:,2]
```

```
#find positive and negative class for plotting
pos_x=[]
neg_x=[]
for i in range(len(x)):
  if(y[i]>0):
    pos_x.append(list(x[i]))
  else:
    neg_x.append(list(x[i]))
```

```
pos_x=np.array(pos_x)
neg_x=np.array(neg_x)
```

```
#plot graph
import matplotlib.pyplot as plt
plt.plot(pos_x[:,0],pos_x[:,1],'*')
plt.plot(neg_x[:,0],neg_x[:,1],'+')
```

```
[<matplotlib.lines.Line2D at 0x7f476ebc82b0>]
```




```
N=len(x)
d=len(x[0])
y=y.reshape((N,1))
```

```
import numpy.linalg as la
from numpy import linalg
print("****************************************************************************************************")
print("****************************************************************************************************")
print("****************************************************************************************************")
print("\n\n\n")
print("Kernel used is polynomial kernel \nFrom the above plot it is clear the equation of curve is a circle")
print("\n\n\n")
print("****************************************************************************************************")
print("****************************************************************************************************")
print("****************************************************************************************************")


def kernel(x, y, p=2):
    return (1 + np.dot(x, y)) ** p
```

```
****************************************************************************************************
****************************************************************************************************
****************************************************************************************************




Kernel used is polynomial kernel
From the above plot it is clear the equation of curve is a circle




****************************************************************************************************
****************************************************************************************************
****************************************************************************************************
```

```
#Calculate Pij=(yi*yj*Kernel(Xi,Xj))
P=np.zeros((N,N))
for i in range(N):
  for j in range(N):
    P[i][j]=y[i]*y[j]*kernel(x[i],x[j])
```

```
P=matrix(P, tc='d')



#q=(-1)T i.e. vector of -1
q=matrix(-1*np.ones((N,1)), tc='d')
#G is identity matrix with diagonal =-1 as we have alpha>0 <=> -alpha<0
G=matrix(-1*np.eye(N), tc='d')
#h is vector of zeros as we have RHS OF - alpha<0 as zero
h=matrix(np.zeros(N), tc='d')
#A= y as we have constraint y.T*alpha=0
A=matrix(y.reshape(-1,N),tc='d')
#b=0 as we have the RHS to be zero.
b=matrix(np.zeros(1), tc='d')
```

```
sol = solvers.qp(P,q,G,h,A,b)
#solve for equation
```

```
     pcost       dcost       gap    pres   dres
 0: -4.0666e+01 -1.0206e+02  5e+02  2e+01  3e+00
 1: -1.5924e+02 -2.2789e+02  3e+02  1e+01  1e+00
 2: -2.9280e+02 -3.6244e+02  3e+02  1e+01  1e+00
 3: -5.7710e+02 -6.0303e+02  4e+02  9e+00  1e+00
 4: -1.2873e+03 -1.2409e+03  5e+02  9e+00  1e+00
 5: -1.2647e+03 -1.0924e+03  7e+02  8e+00  9e-01
 6: -6.9076e+02 -4.0802e+02  1e+03  5e+00  6e-01
 7: -1.8688e+02 -2.9779e+01  4e+02  1e+00  2e-01
 8: -3.4731e+00 -5.2038e-02  1e+01  3e-02  4e-03
 9: -3.5053e-02 -3.8447e-02  1e-01  3e-04  3e-05
10: -2.1413e-02 -2.7448e-02  6e-03  1e-17  2e-13
11: -2.6166e-02 -2.6328e-02  2e-04  5e-18  2e-13
12: -2.6293e-02 -2.6295e-02  2e-06  5e-18  1e-13
13: -2.6295e-02 -2.6295e-02  2e-08  4e-18  1e-13
Optimal solution found.
```

```
#print all alpha calues
print(sol['x'])
```

```
[ 3.14e-12]
[ 8.72e-12]
[ 3.34e-12]
[ 3.56e-12]
[ 1.29e-11]
[ 1.25e-02]
[ 1.55e-11]
[ 6.94e-12]
[ 1.98e-12]
[ 7.51e-12]
[ 1.31e-11]
[ 4.36e-12]
[ 1.81e-12]
[ 2.93e-12]
[ 1.99e-11]
[ 3.66e-12]
[ 3.77e-12]
[ 2.54e-12]
[ 8.59e-12]
[ 2.91e-12]
[ 2.19e-12]
[ 5.27e-12]
[ 7.01e-12]
[ 3.96e-12]
[ 3.03e-12]
[ 1.92e-12]
[ 7.83e-12]
[ 1.01e-11]
[ 5.73e-12]
[ 4.41e-12]
[ 4.45e-12]
[ 3.96e-12]
[ 2.06e-12]
[ 3.02e-12]
[ 6.01e-12]
[ 2.70e-12]
[ 1.50e-02]
[ 3.56e-12]
[ 1.81e-11]
[ 2.36e-12]
[ 3.27e-12]
[ 3.03e-12]
[ 5.93e-12]
[ 3.25e-12]
[ 2.18e-12]
[ 8.37e-12]
[ 3.71e-12]
[ 2.48e-12]
[ 7.29e-12]
[ 2.38e-12]
[ 4.66e-12]
[ 6.64e-03]
[ 4.31e-12]
[ 2.74e-12]
[ 7.33e-12]
[ 4.66e-03]
[ 2.21e-12]
[ 6.45e-12]
[ 8.33e-12]
[ 6.87e-10]
[ 5.51e-12]
[ 8.83e-12]
[ 5.90e-12]
[ 5.62e-12]
[ 6.83e-12]
[ 6.12e-12]
[ 6.15e-12]
[ 8.25e-12]
```

```
 [ 5.62e-12]
 [ 2.04e-11]
 [ 7.11e-12]
 [ 4.95e-11]
 [ 6.86e-12]
 [ 8.47e-12]
 [ 9.10e-12]
 [ 6.36e-12]
 [ 8.38e-12]
 [ 1.25e-11]
 [ 7.32e-12]
 [ 6.38e-12]
 [ 9.99e-12]
 [ 7.81e-12]
 [ 5.81e-12]
 [ 7.59e-12]
 [ 8.65e-12]
 [ 6.36e-12]
 [ 7.75e-12]
 [ 6.59e-12]
 [ 6.02e-12]
 [ 6.94e-12]
 [ 7.05e-12]
 [ 6.23e-12]
 [ 6.27e-12]
 [ 1.96e-11]
 [ 7.41e-03]
 [ 6.39e-03]
 [ 1.76e-11]
 [ 8.01e-12]
 [ 7.60e-12]
 [ 1.31e-11]
```

```
sol
```

```
{'dual infeasibility': 1.4009764698038531e-13,
 'dual objective': -0.02629468169231002,
 'dual slack': 2.7068456092004104e-08,
 'gap': 1.6155817802359547e-08,
 'iterations': 13,
 'primal infeasibility': 4.422694427346993e-18,
 'primal objective': -0.02629466553649222,
 'primal slack': 1.8082528872251508e-12,
 'relative gap': 6.144142727329316e-07,
 's': <100x1 matrix, tc='d'>,
 'status': 'optimal',
 'x': <100x1 matrix, tc='d'>,
 'y': <1x1 matrix, tc='d'>,
 'z': <100x1 matrix, tc='d'>}
```

```
#Find non zero alpha positions
sv=(np.array(sol['x'])>0.0001).flatten()
sv_idx=np.argwhere(sv)
```

```
sv_idx
```

```
array([[ 5],
       [36],
       [51],
       [55],
       [94],
       [95]])
```

```
#support vector
sup_vec=x[sv_idx]
```

```
len(sup_vec)
```

```
6
```

```
print("Support vector:")
print(sup_vec)
```

```
Support vector:
[[[ -8.47422847   5.15621613]]

 [[-10.260969     2.07391791]]

 [[  1.3393313  -10.29098822]]

 [[  9.67917724   4.3759541 ]]

 [[ -6.80002274  -7.02384335]]

 [[  9.90143538  -0.31483149]]]
```

```
sup_vec.flatten().reshape(len(sv_idx),d)
```

```
array([[ -8.47422847,   5.15621613],
       [-10.260969  ,   2.07391791],
       [  1.3393313 , -10.29098822],
       [  9.67917724,   4.3759541 ],
       [ -6.80002274,  -7.02384335],
       [  9.90143538,  -0.31483149]])
```

```
#non zero alpha values
sup_vec_alpha=np.array(sol['x'])[sv_idx]
```

```
sup_vec_alpha
```

```
array([[[0.0125012 ]],

       [[0.0149904 ]],

       [[0.00664213]],

       [[0.00466215]],

       [[0.00740837]],

       [[0.00638511]]])
```

```
#labels of support vectors
sup_vec_y=y[sv_idx]
```

```
sup_vec_y
```

```
array([[[-1.]],

        [[ 1.]],

        [[ 1.]],

        [[ 1.]],

        [[-1.]],

        [[-1.]]])
```

```
#Calculate b value using a random support vector as m value
b=y[sv_idx[0]]
for i in range(len(sup_vec)):
  b-=sup_vec_alpha[i]*sup_vec_y[i]*kernel(x[sv_idx[i]],x[sv_idx[0]].T)
```

```
print("b:")
print(b)
```

```
b:
[[-16.66005249]]
```

```
y_pred=np.zeros(N)
for i in range(N):
  s=0
  for j in range(len(sv_idx)):
    s+=sup_vec_alpha[j]*sup_vec_y[j]*kernel(x[sv_idx[j]],x[i])
  y_pred[i]=np.sign(s+b)
err=0
for i in range(N):
  if(y_pred[i]!=y[i]):
    err=err+1
print("Accuracy of implementation:",(N-err)/N)
```

```
Accuracy of implementation: 1.0
```

```
from sklearn.svm import SVC
clf = SVC(kernel='poly')
clf.fit(x,y)
print("Support vectors of library functon:")
print(clf.support_vectors_)

print("Intercept:")
print(clf.intercept_)
y_pred=clf.predict(x)
print("Accuracy of library function:")
print(clf.score(x,y_pred))
```

```
Support vectors of library functon:
[[ -8.47422847   5.15621613]
 [  1.31699547  -5.38274816]
 [ -2.7471552   -8.47244873]
 [  2.97968693  -2.49860433]
 [ -2.52922727  -8.29282482]
 [  7.38012912  -1.36077284]
 [ -3.97598846  -1.57588443]
 [ -5.6641213   -5.15957119]
 [ -6.90647562   7.14833849]
 [  0.62777463   1.24416427]
 [ -1.40132717  -7.89496002]
 [  3.25517668  -2.17320191]
 [ -1.56822041   0.54897313]
 [ -2.75451922  -3.66892412]
 [  0.19284408   5.28058385]
 [ -1.73942447  -2.49247814]
 [ -7.47227246  -5.09869845]
 [ -1.62434502   2.54344738]
 [ -6.58460709   0.49263571]
 [ -9.46760885   2.36139525]
 [ -6.11267832   2.260214  ]
 [ -6.01390512   5.64535541]
 [ -5.11486937   1.21194674]
 [ -6.28466148   5.23802834]
 [  6.3666283   -6.49712918]
 [ -6.82939503  -5.58508942]
 [ -2.66451453  -2.5921847 ]
 [  0.20162846  -8.81260121]
 [ -7.22017042  -2.99311063]
 [ -2.70069925   3.22027052]
 [  3.49129216   4.55141497]
 [ -7.07467953   2.99084456]
 [ -3.27127183  -2.69337135]
 [ -3.47027963   3.62524904]
 [ -1.73910738  -4.7002146 ]
 [ -3.91819679  -0.75834033]
 [  1.90112006  -3.96946184]
 [  6.99249663  -6.41143087]
 [ -6.80002274  -7.02384335]
 [  9.90143538  -0.31483149]
 [ -4.98349411   8.31816584]
 [ -5.06083035   6.04187381]
 [  1.92405932  -6.33525986]
 [ 13.14703274 -19.8118231 ]
 [ 10.24592717   7.95373492]
 [-20.56769507   8.68464484]
 [-13.58465635  21.94036504]
 [-14.23121874   8.57661163]
 [-15.64719728   3.32039056]
 [ 10.42163247  23.45279171]
 [-11.64621294  -0.87217731]
 [ 12.74780931   0.19913032]
 [-24.68241909  21.16594535]
 [-22.47779916   6.69516468]
 [-10.02833317  11.09354511]
 [ 22.19384568 -20.81599498]
 [  9.4073989  -15.80141025]
 [-22.63814659   6.10417437]
 [ 21.9265387   15.53137584]
 [ 12.09288782 -11.65283671]
 [  3.28969027 -14.15854536]
 [ 22.42614347 -17.79484871]
 [  2.91722251 -12.27214032]
 [ 11.79487022 -11.3924611 ]
 [ -8.50961599  18.4104395 ]
 [ -6.41766882 -16.57062517]
 [ 12.29630776 -13.58191606]
```

```
 [-20.08588052 -21.4203383 ]
 [ 24.55963843  -1.9636474 ]
 [ -1.08933763 -14.10562483]
 [  8.12850656 -19.5567185 ]
 [-10.260969     2.07391791]
 [-15.50532883  19.94336178]
 [  1.66404809  12.68562818]
 [-23.03961851 -24.17915876]
 [-19.9566285   13.84906795]
 [ 24.93834167  -1.51189247]
 [ 22.88511672  -6.75299078]
 [-22.96901354 -12.67010547]
 [ 18.4228554   -2.20783009]
 [ 21.03826634   6.53015579]
 [-18.81914596   8.31142157]
 [  1.3393313  -10.29098822]
 [ 16.42108453   6.07221393]
 [-24.88943066   4.62448412]
 [ 11.75880948  -9.85890377]
 [  9.67917724   4.3759541 ]]
Intercept:
[-0.90769788]
Accuracy of library function:
1.0
/usr/local/lib/python3.6/dist-packages/sklearn/utils/validation.py:760: DataConversionWarning: A column-vect
  y = column_or_1d(y, warn=True)
```