3 Domain Adaptation SVM (Code) [20pts]

Implement the domain adaptation SVM from Problem #2. A data setfor the source and target domains (both training and testing) have been uploaded to D2L. There are several ways to implement this algorithm. If I were doing this for an assignment, I would implement the SVM (both the domain adaptation SVM and normal SVM) directly using quadratic programming. You do not need to build the classifier (i.e., solve for the bias term); however, you will need to find $\mathbf{w}_T$ and $\mathbf{w}_S$. To find the weight vectors, you will need to solve a quadratic programming problem and look through the documentation to learn how to solve this optiization task. The following Python packages are recommended:

- CVXOPT(https://cvxopt.org/)
- PyCVX (https://www.cvxpy.org/install/)

Note: Your solution can (and should) use any of the packages above.

```
import numpy as np
import pandas as pd
import scipy as sp
import matplotlib.pyplot as plt
from sklearn import datasets
import cvxopt as cx
from sklearn import svm
from numpy import reshape
```

Using the following Quadratic Program

$$\begin{aligned} \min_x \quad & \frac{1}{2} x^\top P x + q^\top x \\ \text{subject to} \quad & Gx \preceq h \\ & Ax = b \end{aligned}$$

```
def split_dataset_np(source_dataset, target_dateset):
    """
    Input: two datasets
    Output: 4 dfs, x-,y-source, and x-,y-target
    """
    ysrc = source_dataset.iloc[:,-1].to_numpy()
    xsrc = source_dataset.iloc[:, 0:-1].to_numpy()
```

```python
    ytar = target_dateset.iloc[:,-1].to_numpy()
    xtar = target_dateset.iloc[:, 0:-1].to_numpy()

    return xsrc,ysrc,xtar,ytar

def kernal_phi(x):
    '''
    Standard Linear Kernal function
    '''
    kx = np.array(np.dot(x,x.T))
    return kx

def qp_svm(x,y,C_reg,B_reg,ws):
    '''
    Quadratic Program SVM function: find weighted parameters to use
for targeted data
    Solve the QP Terms (P,q, G, h, A, b)
    '''
    n = x.shape[0]

    #P = yi*yj*k(x,x)
    P = np.outer(y,y) * kernal_phi(x)
    P = cx.matrix(P, tc="d")

    #q term -1 + ByiwsTx
    f1 = -1*np.ones(n)
    if B_reg > 0:
        for i in range(n):
            f1[i] = -1+B_reg*y[i]*np.dot(ws,x[i])
    q = cx.matrix(f1,tc="d")

    #A equaility term (Ax = b)
    A = cx.matrix(y, (1, n), tc="d")
    b = cx.matrix(0.0,tc="d")

    #G inequality term (Gx <= h)
    G = cx.matrix(np.vstack((np.diag(-1 *
np.ones(n)),np.diag(np.ones(n)))),tc="d")
    h = cx.matrix(np.hstack((np.zeros(n),C_reg*np.ones(n))),tc="d")

    #alpha values
    sol = cx.solvers.qp(P,q, G, h, A, b)
    #alpha = np.ravel(sol["x"])
    alpha = sol["x"].T

    w = np.array([0.,0.])
    if B_reg > 0:
        w[0]= B_reg*ws[0] + np.sum(alpha*y*x[:,0])
        w[1]=B_reg*ws[1] + np.sum(alpha*y*x[:,1])
```

```
    else:
        w[0]=np.sum(alpha*y*x[:,0])
        w[1]=np.sum(alpha*y*x[:,1])
    print("\nC: %d, B: %d"%(C,B))
    print("Weights: ",w)
    print("\n")

    return w

def plot_svm(x,y,w,c):
    '''
    Plot the SVM Margin Lines against the Target Data to see how the
cost
    penality ajusts, as the weights do
    '''
    plt.figure

    # fit the model
    clf = svm.SVC(kernel="linear", C=c)
    clf.fit(x, y)
    plt.scatter(x[:,0],x[:,1],c = y, cmap ='Dark2',edgecolors="k")

    # plot the decision function
    ax1 = plt.gca()
    xlim = ax1.get_xlim()
    ylim = ax1.get_ylim()

    # create grid to evaluate model
    xx = np.linspace(xlim[0], xlim[1], 30)
    yy = np.linspace(ylim[0], ylim[1], 30)
    YY, XX = np.meshgrid(yy, xx)
    xy = np.vstack([XX.ravel(), YY.ravel()]).T
    Z = clf.decision_function(xy).reshape(XX.shape)

    # plot decision boundary and margins
    ax1.contour(
        XX, YY, Z, colors="k", levels=[-1, 0, 1], alpha=0.5,
linestyles=["--", "-", "--"]
    )
    # plot support vectors
    ax1.scatter(clf.support_vectors_[:, 0],clf.support_vectors_[:,
1],s=100,linewidth=1,facecolors="none",edgecolors="k")
    plt.title("Target Data ; C= %d"% c)
    plt.ylabel("x1")
    plt.xlabel("x0")
    plt.grid()
    plt.show()
```

```python
source_path = "/content/drive/MyDrive/Git/ECE523/HW3/source_train.csv"
target_path = "/content/drive/MyDrive/Git/ECE523/HW3/target_train.csv"

source_ds = pd.read_csv(source_path, header=None)
target_ds = pd.read_csv(target_path, header=None)

xsrc1,ysrc1,xtar,ytar = split_dataset_np(source_ds,target_ds)

C = 1
B = 0
# B=0, ws = np.sum(alph * y[i] * x[i])
ws = qp_svm(xsrc1,ysrc1,C,B,0)

B = 1
# B=1, wt = B*wt + np.sum(alph * y[i] * x[i])
wt = qp_svm(xtar,ytar,C,B,ws)
plot_svm(xtar,ytar,wt,C)

C=100
# B=1, wt = B*wt + np.sum(alph * y[i] * x[i])
wt = qp_svm(xtar,ytar,C,B,ws)
plot_svm(xtar,ytar,wt,C)
```

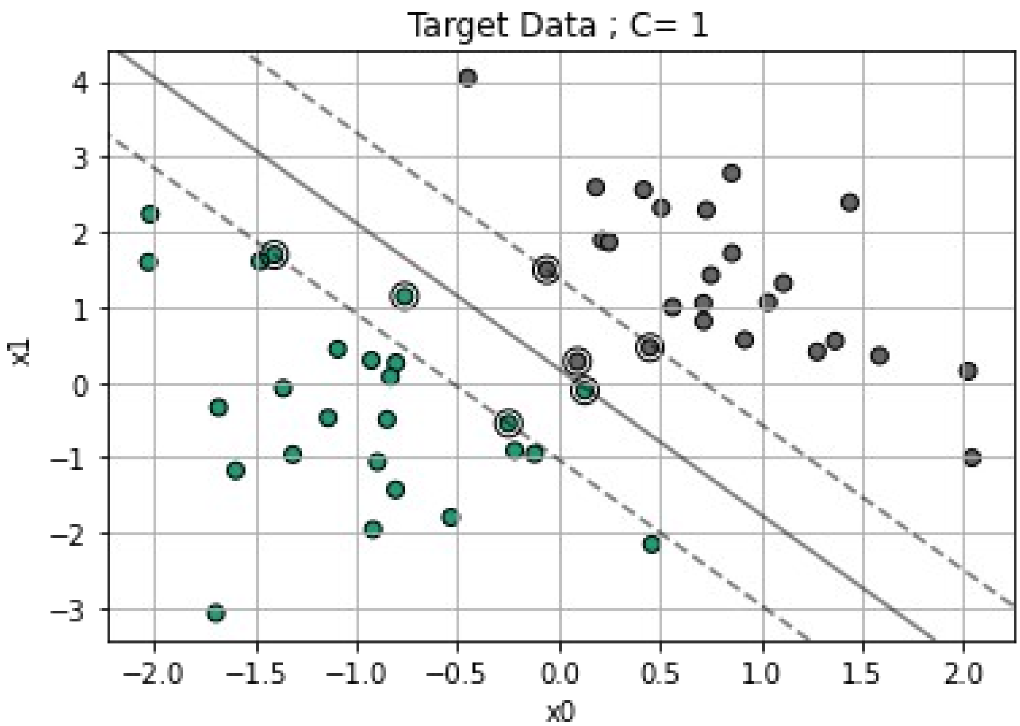
```
     pcost       dcost       gap    pres   dres
 0: -5.4527e+01 -4.1324e+02  2e+03  3e+00  4e-15
 1: -3.5700e+01 -2.3871e+02  4e+02  3e-01  4e-15
 2: -2.5093e+01 -5.7172e+01  5e+01  3e-02  5e-15
 3: -2.5903e+01 -3.2574e+01  9e+00  6e-03  2e-15
 4: -2.7004e+01 -2.8976e+01  2e+00  1e-03  2e-15
 5: -2.7351e+01 -2.8080e+01  9e-01  4e-04  3e-15
 6: -2.7552e+01 -2.7690e+01  2e-01  6e-05  3e-15
 7: -2.7589e+01 -2.7628e+01  4e-02  1e-05  3e-15
 8: -2.7603e+01 -2.7607e+01  5e-03  1e-06  3e-15
 9: -2.7605e+01 -2.7605e+01  5e-05  1e-08  3e-15
10: -2.7605e+01 -2.7605e+01  5e-07  1e-10  3e-15
Optimal solution found.

C: 1, B: 0
Weights:  [1.92786559 1.82082169]


     pcost       dcost       gap    pres   dres
 0: -1.0443e+01 -1.1542e+02  7e+02  3e+00  4e-16
 1: -5.5520e+00 -6.7448e+01  1e+02  4e-01  4e-16
 2: -7.2201e-01 -1.2869e+01  2e+01  4e-02  2e-15
 3: -1.2286e+00 -2.6601e+00  2e+00  3e-03  7e-16
 4: -1.5711e+00 -1.8573e+00  3e-01  5e-04  2e-16
 5: -1.6714e+00 -1.6775e+00  7e-03  6e-06  3e-16
 6: -1.6736e+00 -1.6737e+00  7e-05  6e-08  3e-16
 7: -1.6736e+00 -1.6736e+00  7e-07  6e-10  3e-16
```

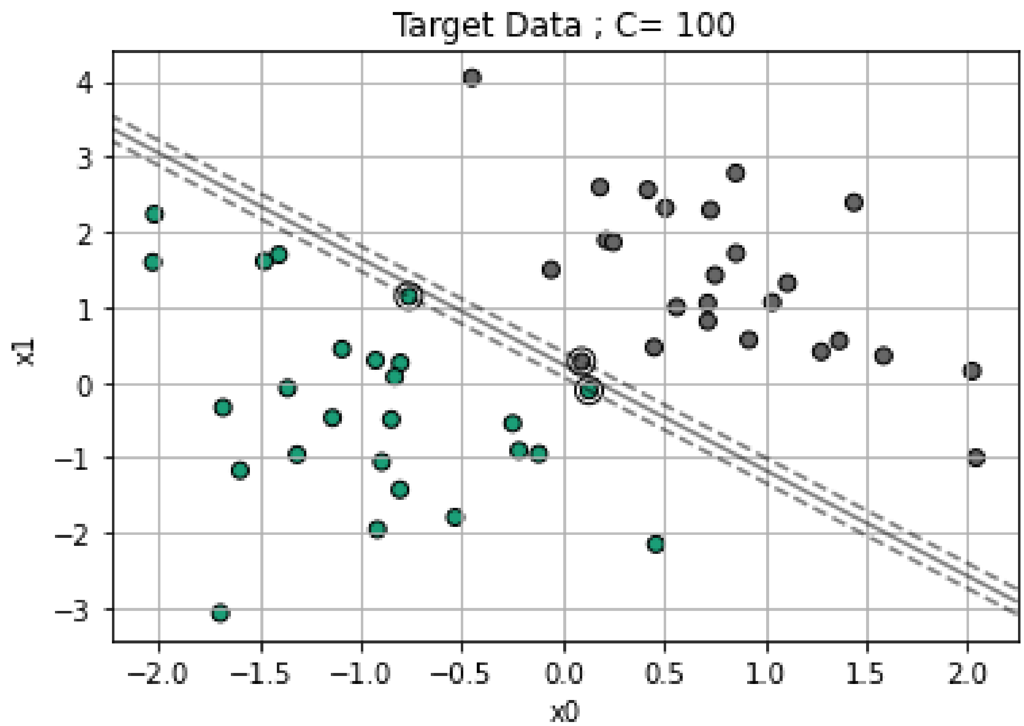
```
Optimal solution found.

C: 1, B: 1
Weights:  [2.64808185 1.78022468]
```




```
     pcost       dcost       gap    pres   dres
 0:  2.0578e+03 -3.1988e+05  9e+05  8e-01  2e-14
 1:  6.2843e+03 -7.7704e+04  1e+05  5e-02  5e-14
 2:  3.0741e+03 -7.4076e+03  1e+04  3e-03  3e-14
 3:  5.7636e+02 -8.0813e+02  1e+03  4e-05  1e-14
 4:  7.7728e+01 -9.6799e+01  2e+02  4e-15  6e-15
 5:  7.5585e+00 -3.8024e+01  5e+01  3e-14  2e-15
 6: -2.3555e+01 -3.6451e+01  1e+01  2e-14  2e-15
 7: -3.0006e+01 -3.0180e+01  2e-01  3e-14  3e-15
 8: -3.0097e+01 -3.0099e+01  2e-03  2e-14  2e-15
 9: -3.0098e+01 -3.0098e+01  2e-05  9e-16  2e-15
Optimal solution found.

C: 100, B: 1
Weights:  [8.4547185 6.0156039]
```



Note: As the cost increase, so do the weights