

svm

September 9, 2018

1 Importing the libraries

```
In [1]: import numpy as np
import cvxpy as cp
```

2 Loading the dataset

```
In [2]: x = np.genfromtxt('Xsvm.csv' , delimiter = ",")
y = np.genfromtxt('ysvm.csv' , delimiter = ",")
print(x.shape,y.shape)
```

(500, 2) (500,)

```
In [3]: z = np.append(y.reshape(500,1),y.reshape(500,1),axis = 1)
print(z.shape)
xy = x*z ##for sigma_over_n(y*x_bar)
# print(x[1:10],y[1:10],xy[1:10])
```

(500, 2)

3 Finding the optimal alphas

```
In [4]: alpha = cp.Variable(500)
a = cp.vstack([alpha , alpha])
#equation to be maximixed ()cost
objective = cp.Maximize(sum(alpha) - 0.5 * cp.sum_squares(cp.sum(cp.multiply(a.T , xy) ,
constraints = [ 0 <= alpha , np.transpose(y)*alpha == 0]
problem = cp.Problem(objective,constraints)
result = problem.solve() #maximizing the equation
print(result) #optimal cost function
print(alpha.value) #values of alphas
```

69.43702993663008

```
[ 1.38626419e-17  5.24868059e-17  5.26283784e-17  5.78074802e-17
 1.61518808e-17  2.55653038e-17  5.65591735e-17  1.48276379e-17
```

5.51148152e-17	3.49510018e-17	2.73489998e-17	2.36342925e-17
2.21433752e-17	5.41669588e-17	3.17332423e-17	4.42179939e-17
5.89161152e-17	2.70534277e-17	4.57736605e-17	2.59124319e-17
4.49198513e-17	4.09828421e-17	3.43082225e-17	3.11899435e-17
5.24993073e-17	3.43353275e-17	5.16031307e-17	5.70039545e-17
2.83925444e-17	4.92502948e-17	2.61272565e-17	2.13214521e-17
5.30666900e-17	3.53511117e+00	1.67121931e-17	2.47977366e-17
4.76503906e-17	4.74302145e-17	5.14331684e-17	3.96208486e-17
4.75067954e-17	4.37054008e-18	3.91125934e-17	5.00833641e-17
2.81030686e-17	4.81433739e-17	1.96172831e-17	3.55957126e-17
5.61383300e-17	5.56787940e-17	3.24219194e-17	9.11161835e-18
2.43233981e-17	1.51517254e-17	4.78068832e-17	6.83216775e-18
4.96590503e-17	1.95291682e-17	5.06952734e-17	2.41641559e-17
9.35632594e-18	2.30494606e-17	4.17486298e-18	5.47945067e-17
2.21249413e-17	5.61615740e-17	4.87975681e-18	5.56144173e-17
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2.67482703e-17	3.62317931e-17	4.99532190e-17	4.83492815e-17
1.71913807e-17	2.37381900e-17	5.12216474e-17	5.48159123e-17
4.45342741e-17	2.80672837e-17	4.21799993e-17	4.99144254e-17
6.07248295e-17	2.61055554e-17	5.58712798e-17	5.79659762e-17
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5.58284756e-17	3.57539267e-17	6.40653370e-18	3.37864502e-17
3.98241010e-17	5.31144128e-17	2.25345724e-17	1.09555241e-17
1.57681849e-17	1.55718537e-17	2.01390554e-17	3.00662815e-17
4.51794217e-17	5.28014408e-17	5.31987468e-17	4.47165634e-17
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4.33342056e-18	2.36620766e-17	5.23357443e-17	4.30953897e-17
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3.45115104e-17	1.50320758e-17	5.49335632e-17	4.97387227e-17
1.08393722e-17	4.16793540e-17	4.18389542e-17	4.88510923e-17
5.12794142e-17	6.11577273e-17	1.43250212e-17	8.51568004e-18
4.95312326e-17	1.63513965e-17	5.43210798e-17	5.84669128e-17
4.75089980e-17	5.12160812e-17	4.37283665e-17	4.46570770e-17
4.97896068e-17	2.91379334e-17	5.18924465e-17	3.49858489e-17
4.06237002e-17	2.99102762e-17	4.00612703e-17	5.14314770e-17
5.24444587e-17	4.35562915e-17	5.08831687e-17	5.52830194e-17
5.33122666e-17	5.16138371e-17	3.25630800e-17	3.03576608e-17
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4.16130346e-17	5.55000891e-17	2.94191483e-17	5.62265290e-17
5.75247595e-17	2.72168627e-17	2.77022404e-17	5.36373610e-17
2.17145366e-17	3.73019850e-17	1.93868901e-17	4.10641573e-17
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2.85441311e-17	4.70915993e-17	5.21393056e-17	5.03324785e-17
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5.27905754e-17	5.41384964e-17	5.18601414e-17	1.07640947e-17
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1.16230854e-17	2.46667663e-17	5.29426282e-17	3.95144018e-17
6.12372922e-18	3.68069018e-17	4.95258065e-17	5.22334490e-17
2.56854271e-17	5.83323340e-17	6.62295061e-18	1.16162098e-17
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3.87636269e-18	2.93920433e-17	5.02341915e-17	4.99708921e-17
5.18807410e-17	4.28530909e-17	1.67407592e-17	5.22413130e-17
3.27496819e-17	4.35530810e-17	1.86787706e-17	5.54814912e-17
5.48964747e-17	5.05268434e-17	4.94457993e-17	5.83735178e-17
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5.42310878e-17	4.78160358e-17	5.30293914e-17	1.57789439e-17
8.22061472e-18	2.04957075e-18	2.14650699e-17	4.07931067e-17
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3.47351271e-17	5.93177883e-17	5.78921895e-17	3.51552554e-17
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5.36393520e-17	5.05456174e-17	5.19713290e-17	5.12517074e-17
1.67136541e-17	5.11221787e-17	4.66003646e-17	5.07794211e-17
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5.59002706e-17	8.45723167e-18	4.37579353e-17	5.70751441e-17
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2.28177005e-17	3.69145182e-17	5.47237725e-17	4.41541335e-17
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5.20871350e-17	4.85514311e-17	5.27259330e-17	3.69170840e-17
5.77346532e-17	4.40677095e-17	2.86215219e-17	5.70096905e-17
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3.48028897e-17	5.37770929e-17	4.75954487e-17	2.11091351e-17
5.76983306e-17	5.26453607e-17	5.78376755e-17	1.48891451e-17
5.02294744e-17	7.79722670e-18	4.96929495e-17	2.16613581e-17
5.29587173e-17	2.30867300e-17	2.39250435e-17	5.24719368e-17
1.05632876e-17	5.24794221e-17	5.51228264e-17	3.74273385e-17

```

5.18840585e-17  5.69388523e-17  1.16585615e-17  4.39610810e-17
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1.70766383e-17  4.62978202e-17  2.41043837e-18  5.95576820e-17
7.98613470e-18  5.44863468e-17  1.23023065e-17  4.68235128e-17
6.12127290e-17  4.74509074e-17  4.17966126e-17  4.41845219e-17
5.04490918e-17  5.17955104e-17  2.50436481e-17  3.71135956e-17
2.56617102e-17  4.76313339e-17  5.51782621e-17  2.32798535e-17
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5.19876466e-17  1.10419215e-17  4.69349608e-17  9.20047187e-18
9.22927099e-18  3.16416979e-17  4.21077019e-17  4.52838149e-17
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5.65444460e-17  2.34239960e-17  3.42503582e-17  3.64536705e-17
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4.46083382e-17  5.40403997e-17  3.23015076e-17  5.10311979e-17
5.26866871e-17  4.43005064e-17  1.76901808e-17  4.92068481e-17
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3.85162822e-17  2.17822993e-17  3.72207316e-17  3.92774568e-17
5.02789152e-17  8.37715585e-18  2.92802349e-17  1.26504459e-17
4.79777818e-17  9.81831195e-18  7.36495148e-18  4.65800358e-17
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3.03530233e-17  2.99518303e-17  5.98009874e-17  4.76899455e-17
3.76399956e-18  5.99613419e-17  9.64377295e-18  3.39694093e-17
2.95038163e-17  1.64019460e-17  5.60905218e-18  2.47740196e-17]

```

4 Finding the values of W

```

In [5]: v = np.append(alpha.value.reshape(500,1),alpha.value.reshape(500,1),axis = 1)
        print(v.shape)
        w = np.sum(v * xy , axis = 0)
        print(w)

(500, 2)
[-0.11844048  11.78388865]

```

5 Finding W

```

In [6]: for i in range(0,500):
        if alpha.value[i] > 0.1:
            w0 = y[i] - np.matmul(w,np.transpose(x[i]))
            print(w0)

```

```
0.10229992556221768
0.10229992556221679
0.10229992556222078
```

6 Testing the Model

```
In [7]: x_test = np.array([[2,0.5],[0.8,0.7],[1.58,1.33], [0.008,0.001]])
        # print(x_test.shape)
        print("Predictions:")
        for i in range(0,4):
            y_test = w0 + np.matmul(w , np.transpose(x_test[i]))
            if(y_test >= 0):
                print("1")
            else:
                print("0")
```

Predictions:

```
1
1
1
1
```

7 Visualization

```
In [9]: import matplotlib.pyplot as plt
```

```
x_train_1 = []
x_train_0 = []
for i in range(0,500):
    if y[i] == 1:
        x_train_1.append(x[i])
    else:
        x_train_0.append(x[i])
x_train_1 = np.asarray(x_train_1)
x_train_0 = np.asarray(x_train_0)
print(x_train_1.shape)
print(x_train_0.shape)

plt.plot(x_train_1[:,0],x_train_1[:,1],'o',label = 'label = 1')
plt.plot(x_train_0[:,0],x_train_0[:,1],'o', label = 'Label = -1')
plt.plot(x_test[:,0],x_test[:,1],'ro',label = 'Test Sample')
plt.legend()
plt.show()
```

(228, 2)

(272, 2)

