A2-3 svm

February 12, 2021

```
[20]: # python
  import numpy as np
  import matplotlib.pyplot as plt

# sklearn
  from sklearn.svm import SVC
  from sklearn.pipeline import make_pipeline
  from sklearn.preprocessing import StandardScaler
  from sklearn.metrics import mean_squared_error

# stats
  import statsmodels.api as sm
```

```
[21]: ## Load Test/Train Data
      DATA = {
          "A": {
              "train": {
                  "X": np.loadtxt(open("a2-files/X_train_A.csv"), delimiter=","),
                  "Y": np.loadtxt(open("a2-files/Y_train_A.csv"), delimiter=","),
              }
          },
          "B": {
              "train": {
                  "X": np.loadtxt(open("a2-files/X_train_B.csv"), delimiter=","),
                  "Y": np.loadtxt(open("a2-files/Y_train_B.csv"), delimiter=","),
              },
              "test": {
                  "X": np.loadtxt(open("a2-files/X_test_B.csv"), delimiter=","),
                  "Y": np.loadtxt(open("a2-files/Y_test_B.csv"), delimiter=","),
              }
          },
      }
```

```
svc_regr_soft.fit(DATA["A"]["train"]["X"], DATA["A"]["train"]["Y"])
      # SVC-Hard
      svc_regr_hard = SVC(
          C=float('inf'), # regularization
          kernel='linear'
      )
      svc_regr_hard.fit(DATA["A"]["train"]["X"], DATA["A"]["train"]["Y"])
[22]: SVC(C=inf, kernel='linear')
[23]: np.shape(DATA["A"]["train"]["X"])
[23]: (2000, 50)
[24]: # SM-Soft : PerfectSeparationError: Perfect separation detected, results not
       \rightarrow available
      \# sm_logit = sm.Logit(DATA["A"]["train"]["Y"],DATA["A"]["train"]["X"]).fit()
      print("[SM]: PerfectSeparationError: Perfect separation detected, results not ⊔
       →available")
     [SM]: PerfectSeparationError: Perfect separation detected, results not available
[25]: print('w hard = ',svc regr hard.coef )
      print('b_hard = ',svc_regr_hard.intercept_)
      print('w_soft = ',svc_regr_soft.coef_)
      print('b_soft = ',svc_regr_soft.intercept_)
      print('|w_hard|_2 - |w_soft|_2 = ', (np.linalg.norm(svc_regr_hard.coef_) - np.
       →linalg.norm(svc_regr_soft.coef_)))
     w \text{ hard} = \begin{bmatrix} [-1.21665426e-01 & 3.62093715e-04 & -8.14547914e-02 & -1.30461544e-01 \end{bmatrix}
        1.03679744e-01 -1.52182440e-01 1.04733167e-01 2.37085565e-02
        1.88904300e-01 4.14259231e-01 -5.74918926e-02 2.53091455e-02
       -9.57967331e-02 2.78213946e-01 1.26402871e-02 4.24952941e-02
       -1.08058239e-01 -3.17898534e-02 3.32288614e-03 1.71401564e-01
       -6.93185355e-02 -2.85727264e-01 -1.11431511e-01 -2.81551300e-02
        7.14262962e-02 1.98803054e-01 -1.89996218e-01 9.63349060e-02
        1.20110591e-01 -5.53355480e-02 -4.29452659e-03 -1.10216493e-01
       -1.57449276e-01 3.64106600e-02 -4.35440021e-02 -1.42084333e-01
        1.30750877e-01 2.68330435e-02 6.77532548e-02 -3.01716444e-01
       -1.22263636e-02 2.15382941e-01 1.26537049e-01 2.24429271e-02
        1.34745230e-01 3.23138170e-02 1.47580798e-01 5.67770933e-02
        2.91490606e-01 -3.25700173e-02]]
     b hard = [-0.]
     w_{soft} = [[-1.21665426e-01 \ 3.62093715e-04 \ -8.14547914e-02 \ -1.30461544e-01]
```

```
1.03679744e-01 -1.52182440e-01 1.04733167e-01 2.37085565e-02
        1.88904300e-01 4.14259231e-01 -5.74918926e-02 2.53091455e-02
       -9.57967331e-02 2.78213946e-01 1.26402871e-02 4.24952941e-02
       -1.08058239e-01 -3.17898534e-02 3.32288614e-03 1.71401564e-01
       -6.93185355e-02 -2.85727264e-01 -1.11431511e-01 -2.81551300e-02
        7.14262962e-02 1.98803054e-01 -1.89996218e-01 9.63349060e-02
        1.20110591e-01 -5.53355480e-02 -4.29452659e-03 -1.10216493e-01
       -1.57449276e-01 3.64106600e-02 -4.35440021e-02 -1.42084333e-01
        1.30750877e-01 2.68330435e-02 6.77532548e-02 -3.01716444e-01
       -1.22263636e-02 2.15382941e-01 1.26537049e-01 2.24429271e-02
        1.34745230e-01 3.23138170e-02 1.47580798e-01 5.67770933e-02
        2.91490606e-01 -3.25700173e-02]]
     b_soft = [-0.]
     |w_{\text{hard}}|_2 - |w_{\text{soft}}|_2 = 0.0
[26]: # 3.2
      x = DATA["A"]["train"]["X"]
      y = DATA["A"]["train"]["Y"]
      w = svc regr soft.coef
      # np.dot(x, w)
      print("x: ",np.shape(x))
      print("w: ",np.shape(w))
      print("y: ",np.shape(y))
      y[y==0] = -1
      A = y * np.dot(w, np.transpose(x))
      print("A: ",np.shape(A))
      print("#A <= 1: ",np.sum(A <= 1))</pre>
     x: (2000, 50)
     w: (1, 50)
     y: (2000,)
     A: (1, 2000)
     #A <= 1: 2000
[27]: print('w_soft = ',svc_regr_soft.coef_)
      print('b_soft = ',svc_regr_soft.intercept_)
      print("Support Vector:", svc_regr_soft.support_vectors_)
      print("Support Vector Index:", svc_regr_soft.support_)
      print("SV size:", np.shape(svc_regr_soft.support_vectors_))
      print("Alpha:", svc_regr_soft.dual_coef_)
     w = [[-1.21665426e-01 \ 3.62093715e-04 \ -8.14547914e-02 \ -1.30461544e-01]
        1.03679744e-01 -1.52182440e-01 1.04733167e-01 2.37085565e-02
        1.88904300e-01 4.14259231e-01 -5.74918926e-02 2.53091455e-02
       -9.57967331e-02 2.78213946e-01 1.26402871e-02 4.24952941e-02
       -1.08058239e-01 -3.17898534e-02 3.32288614e-03 1.71401564e-01
```

```
-6.93185355e-02 -2.85727264e-01 -1.11431511e-01 -2.81551300e-02
       7.14262962e-02 1.98803054e-01 -1.89996218e-01 9.63349060e-02
       1.20110591e-01 -5.53355480e-02 -4.29452659e-03 -1.10216493e-01
       -1.57449276e-01 3.64106600e-02 -4.35440021e-02 -1.42084333e-01
        1.30750877e-01 2.68330435e-02 6.77532548e-02 -3.01716444e-01
       -1.22263636e-02 2.15382941e-01 1.26537049e-01 2.24429271e-02
        1.34745230e-01 3.23138170e-02 1.47580798e-01 5.67770933e-02
        2.91490606e-01 -3.25700173e-02]]
     b soft = [-0.]
     Support Vector: [[-23.3061044 -9.71882945
                                                 9.34264516 -20.5378218
     -22.61745076
         0.02889478 -1.94438239 -16.76330649 -9.43733536
                                                           3.33701093
        -2.58531872 -24.78561978 18.36212309 19.90592558 -3.8111526
       -3.2063545
                    9.2496695 17.79626523 16.48625912 -15.4272087
         5.71399884
                     7.4487629
                                 7.27841757 -5.6443613
                                                          15.10283527
       11.38375049 -4.3943539 11.64219184 -16.6523856 -12.96526166
         2.42225696 -23.25482721 17.76306384 18.11354686 25.20209425
       -8.9744753 -20.56208618 0.56792822 -3.2520854 16.08640176
        17.78726158
                     1.78486979
                                  8.73822818 2.91542174 -2.06436836
       -11.22137302 -14.53169281 -14.28012612 26.60954328 16.71357943
      [-23.54943526 -9.71810526
                                  9.17973558 -20.79874489 -22.41009127
        -0.2754701
                    -1.73491606 -16.71588938 -9.05952676
                                                           4.1655294
       -2.70030251 -24.73500149 18.17052963 20.46235347 -3.78587202
        -3.12136391 9.03355302 17.73268552 16.49290489 -15.08440557
        5.57536177 6.87730838 7.05555455 -5.70067156 15.24568786
       11.7813566 -4.77434633 11.83486165 -16.41216442 -13.07593275
         2.41366791 -23.4752602 17.44816529 18.18636818 25.11500624
       -9.25864397 -20.30058443 0.62159431 -3.11657889 15.48296887
                                             2.96030759 -1.7948779
                     2.21563567
        17.76280885
                                 8.99130228
       -11.15674538 -14.23653121 -14.16657193 27.19252449 16.64843939]]
     Support Vector Index: [1999 1998]
     SV size: (2, 50)
     Alpha: [[-0.5 0.5]]
[28]: # dataset B
     # SVC-Soft
     svc_regr_soft = SVC(
         C=1.0, # regularization
         kernel='linear'
     )
     svc_regr_soft.fit(DATA["B"]["train"]["X"], DATA["B"]["train"]["Y"])
[28]: SVC(kernel='linear')
[29]: # SVC-Hard
     # svc_regr_hard = SVC(
           C=float('inf'), # regularization
```

```
kernel='linear'
      # )
      # svc_regr_hard.fit(DATA["B"]["train"]["X"], DATA["B"]["train"]["Y"])
      print("SVC-HARD: INFINITY LOOP, UNSEPARABLE")
     SVC-HARD: INFINITY LOOP, UNSEPARABLE
[30]: # SM-Soft
      sm_logit = sm.Logit(DATA["B"]["train"]["Y"],DATA["B"]["train"]["X"])
      model = sm_logit.fit()
     Optimization terminated successfully.
              Current function value: 0.030979
              Iterations 14
[31]: print('w_hard = ',svc_regr_hard.coef_)
      print('b hard = ',svc regr hard.intercept )
      print('w_soft = ',svc_regr_soft.coef_)
      print('b_soft = ',svc_regr_soft.intercept_)
      print('|w_hard|_2 - |w_soft|_2 = ', (np.linalg.norm(svc_regr_hard.coef_) - np.
      →linalg.norm(svc_regr_soft.coef_)))
      # 3.2
      x = DATA["B"]["train"]["X"]
      y = DATA["B"]["train"]["Y"]
      w = svc regr soft.coef
      # np.dot(x, w)
      print("x: ",np.shape(x))
      print("w: ",np.shape(w))
      print("y: ",np.shape(y))
      y[y==0] = -1
      A = y * np.dot(w, np.transpose(x))
      print("A: ",np.shape(A))
      print("#A <= 1: ",np.sum(A <= 1))</pre>
      print('w_soft = ',svc_regr_soft.coef_)
      print('b_soft = ',svc_regr_soft.intercept_)
      print("Support Vector:", svc_regr_soft.support_vectors_)
      print("SV size:", np.shape(svc_regr_soft.support_vectors_))
      print("Alpha:", svc_regr_soft.dual_coef_)
     w \text{ hard} = \begin{bmatrix} -1.21665426e-01 & 3.62093715e-04 & -8.14547914e-02 & -1.30461544e-01 \end{bmatrix}
        1.03679744e-01 -1.52182440e-01 1.04733167e-01 2.37085565e-02
        1.88904300e-01 4.14259231e-01 -5.74918926e-02 2.53091455e-02
       -9.57967331e-02 2.78213946e-01 1.26402871e-02 4.24952941e-02
       -1.08058239e-01 -3.17898534e-02 3.32288614e-03 1.71401564e-01
       -6.93185355e-02 -2.85727264e-01 -1.11431511e-01 -2.81551300e-02
        7.14262962e-02 1.98803054e-01 -1.89996218e-01 9.63349060e-02
        1.20110591e-01 -5.53355480e-02 -4.29452659e-03 -1.10216493e-01
       -1.57449276e-01 3.64106600e-02 -4.35440021e-02 -1.42084333e-01
```

```
1.30750877e-01 2.68330435e-02 6.77532548e-02 -3.01716444e-01
 -1.22263636e-02 2.15382941e-01 1.26537049e-01 2.24429271e-02
  1.34745230e-01 3.23138170e-02 1.47580798e-01 5.67770933e-02
  2.91490606e-01 -3.25700173e-02]]
b hard = [-0.]
w = [-0.14883452 -1.33157854 -2.62109121 -0.14008824 -0.01591273]
-2.36571773
  -0.11301085 -0.33174302 1.25422302 0.12226576 0.71048243 -1.99753926
  0.59084758 1.56039593 0.2022904 -0.16566907 0.96702447 1.19357528
  1.66424776 -1.98261002 0.46273767 3.02203225 -0.45076031 -1.15875928
 -0.57344131 -1.52304994 1.23503273 -0.66182995 -0.0203479
                                                               2.09304347
  2.14280852 -0.46211822 2.15805064 0.61019298 0.01783408 -0.33238668
 -1.60256375 0.25252616 0.08694866 0.36201239 -0.38220834 1.01984528
 -0.58570554 0.41533726 -0.73605655 -1.77306584 0.77725884 -0.6126139
  -1.89797582 -0.12823335]]
b_soft = [-0.05146275]
|w_{\text{hard}}|_2 - |w_{\text{soft}}|_2 = -7.659534185945252
x: (2000, 50)
w: (1, 50)
y: (2000,)
A: (1, 2000)
#A <= 1: 161
w = [-0.14883452 -1.33157854 -2.62109121 -0.14008824 -0.01591273]
-2.36571773
 -0.11301085 -0.33174302 1.25422302 0.12226576 0.71048243 -1.99753926
  0.59084758 \quad 1.56039593 \quad 0.2022904 \quad -0.16566907 \quad 0.96702447 \quad 1.19357528
  1.66424776 -1.98261002 0.46273767 3.02203225 -0.45076031 -1.15875928
 -0.57344131 -1.52304994 1.23503273 -0.66182995 -0.0203479 2.09304347
  2.14280852 -0.46211822 2.15805064 0.61019298 0.01783408 -0.33238668
 -1.60256375 0.25252616 0.08694866 0.36201239 -0.38220834 1.01984528
 -0.58570554 0.41533726 -0.73605655 -1.77306584 0.77725884 -0.6126139
  -1.89797582 -0.12823335]]
b soft = [-0.05146275]
Support Vector: [[ 2.46332952 -0.77978006 -0.27155939 ... 0.13239303
-1.96125867
   1.388048377
 [-1.42552454 -2.16288447 -0.88451354 ... -0.41396881 -0.74861742
 -0.111407697
 [-0.13560691 -0.2559248 \quad 0.69591211 \dots -0.72321138 -0.07651619
 -0.779469417
 [-0.55038792 1.6337104 0.84330336 ... -0.26088387 -0.93452198
  1.06213669]
 [-0.19594668 -0.74682712 \ 0.79477568 ... -0.04955724 \ 0.05319692
  0.1507748 ]
 [-1.18788362 0.98410019 0.95051311 ... -0.61773492 0.64569337
 -1.12892607]]
SV size: (192, 50)
```

```
-0.46579615 -0.65113809 -1.
                                                         -1.
                                                                      -1.
       -1.
                                -0.28149788 -1.
                                                         -1.
                                                                     -1.
       -0.13851952 -1.
                                             -1.
                                                         -0.6550175 -0.90999031
       -0.8893523 -0.41517747 -1.
                                             -1.
                                                         -1.
                                                                     -0.12184268
       -0.5046161 -1.
                                -0.72350645 -1.
       -1.
                    -1.
                                -0.84901527 -1.
                                                         -0.19431178 -1.
       -1.
                    -1.
                                                         -0.27641444 -1.
                                -1.
       -1.
                    -1.
                                             -1.
                                -1.
                                                         -1.
       -1.
                    -1.
                                -1.
                                             -1.
                                                         -1.
                                                                     -1.
       -0.28400342 -1.
                                -1.
                                             -0.7332253 -1.
                                                                     -1.
       -1.
                    -0.79840101 -1.
                                             -1.
                                                         -1.
                                                                      -1.
                                                         -0.76305116 -1.
                    -1.
       -1.
                                -1.
                                             -1.
       -1.
                    -1.
                                -1.
                                                         -1.
                                             -1.
                                                                      -1.
                    -1.
                                                         -1.
                                                                      -0.63660558
       -1.
                                -1.
                                             -1.
       -1.
                    -1.
                                 0.65196242  0.42485213  0.35353782  1.
        0.94539376 1.
                                 0.3388051
                                             1.
                                                                       1.
                                                          1.
        0.43223143 1.
                                                          0.90793149 1.
                                 1.
                                              1.
        1.
                     1.
                                 0.04970768 1.
                                                                       1.
        1.
                     0.97289561 1.
                                              1.
                                                          0.9196539
                     0.93216669 1.
                                              1.
                                                          0.51862456 0.7570981
        0.06533931 0.11250122
                                             0.65794784
                                                                       0.49810779
                                             0.37562404 1.
                                                                       0.03267648
                                 1.
                                                                       0.65694822
        1.
                     1.
                                              1.
                                                          1.
        0.51235981 1.
                                 1.
                                              1.
                                                          1.
                                                                       1.
        1.
                     1.
                                 1.
                                              1.
                                                                       1.
        0.29611049 0.08661775 1.
                                              1.
                                                          0.20712176 0.08321326
        0.74696912 0.20421004 1.
                                              1.
                                                          0.8872863
        1.
                     1.
                                 1.
                                              1.
                                                                       0.49311911
        1.
                     1.
                                                                       0.33433675
                     1.
                                 0.76428281 0.0078512
                                                                       0.42621879
        1.
                                                          1.
        1.
                                             0.81932003
                                                                                 ]]
[32]: result_right = sum(DATA["B"]["test"]["Y"] == svc_regr_soft.
       →predict(DATA["B"]["test"]["X"]))
      empirical_accuracy = (result_right)/len(DATA["B"]["test"]["Y"])
      print("Soft-SVM Test Performance (Empirical Accuracy): {}%".
       →format(empirical_accuracy*100))
     Soft-SVM Test Performance (Empirical Accuracy): 97.15%
[33]: result_right = sum(DATA["B"]["test"]["Y"] == np.round(model.
       →predict(DATA["B"]["test"]["X"])))
      empirical_accuracy = (result_right)/len(DATA["B"]["test"]["Y"])
      print("Logit Test Performance (Empirical Accuracy): {}%".
       →format(empirical_accuracy*100))
```

-1.

-1.

-1.

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Logit Test Performance (Empirical Accuracy): 96.95%

Alpha: [[-0.18154043 -1.