Support Vector Machines

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***Abstract*—This manual provides an introduction to SVM.**

1 Reflection

1.1 Find the distance of $\mathbf{x}_1 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$ from the line

$$\begin{pmatrix} 3 & 4 \end{pmatrix} \mathbf{x} + 5 = 0 \tag{1.1}$$

1.2 Show that the distance of the point $\mathbf{x}_1$ from the line

$$\mathbf{n}^T \mathbf{x} + c = 0, \quad \|\mathbf{n}\| = 1 \tag{1.2}$$

is

$$M = \left|\mathbf{n}^T \mathbf{x}_1 + c\right| \tag{1.3}$$

1.3 Find the reflection $\mathbf{x_2}$ of $\mathbf{x_1}$.

1.4 Define

$$f(\mathbf{x}) = \mathbf{n}^T \mathbf{x} + c \tag{1.4}$$

1.5 Compute $f(\mathbf{x_1})$ and $f(\mathbf{x_2})$. Comment.

2 Optimization Problem

2.1 Suppose $(\mathbf{x_1}, y_1)$ and $(\mathbf{x_2}, y_2)$ are i/o data for a system where $y_1, y_2 \in \{1, -1\}$. If you want to find $\mathbf{n}, c$ from the given dataset, how will formulate the equivalent optimization problem?

Solution: Consider the optimization problem

$$\max_{\mathbf{n},c} M \tag{2.1}$$

$$\text{s.t} \quad y_1 \left(\mathbf{x}_1^T \mathbf{n} + c\right) \ge M \tag{2.2}$$

$$y_2 \left(\mathbf{x}_2^T \mathbf{n} + c\right) \ge M \tag{2.3}$$

$$\|\mathbf{n}\| = 1 \tag{2.4}$$

2.2 The *signum* function is defined as

$$\text{sgn}(z) = \begin{cases} 1 & z > 0 \\ 0 & z = 0 \\ -1 & z < 0 \end{cases} \tag{2.5}$$

Show that

$$\text{sgn}(\mathbf{x}^T \mathbf{n} + c) = \text{sgn}(\mathbf{x}^T \mathbf{w} + d) \tag{2.6}$$

where

$$\mathbf{w} = \frac{\mathbf{n}}{M}, d = \frac{c}{M}, M > 0 \tag{2.7}$$

2.3 Show that (2.1)-(2.4) can be reformulated as

$$\min_{\mathbf{w},d} \frac{1}{2} \|\mathbf{w}\|^2 \tag{2.8}$$

$$\text{s.t} \quad y_i \left(\mathbf{x}_i^T \mathbf{w} + d\right) \ge 1 \tag{2.9}$$

Solution: From (2.7),

$$\mathbf{w} = \frac{\mathbf{n}}{M} \implies \|\mathbf{w}\| = \frac{\|\mathbf{n}\|}{M} \tag{2.10}$$

$$\implies M = \frac{1}{\|\mathbf{w}\|} \because \|n\| = 1 \tag{2.11}$$

Thus,

$$\max_{\mathbf{n},c} M = \max_{\mathbf{w},d} \frac{1}{\|\mathbf{w}\|} = \min_{\mathbf{w},d} \|\mathbf{w}\|. \tag{2.12}$$

Also, (2.2)-(2.3) become

$$y_i \left(\mathbf{x}_i^T \mathbf{w} + d\right) \ge 1 \tag{2.13}$$

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3 Solver

3.1 Solve (2.8) using *cvxpy/cvxopt* for $\mathbf{x}_1 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}, y_1 = 1$ and $\mathbf{x}_2 = \begin{pmatrix} 0.8 \\ -0.6 \end{pmatrix}, y_2 = -1$.
Solution: From the given information, the constraints in (2.8) become

$$\begin{pmatrix} 2 & 1 \end{pmatrix} \mathbf{w} + d \geq 1 \tag{3.1}$$

$$\begin{pmatrix} 0.8 & -0.6 \end{pmatrix} \mathbf{w} + d \leq -1 \tag{3.2}$$

The following code results in

$$\mathbf{w}_{opt} = \begin{pmatrix} 0.6 & 0.8 \end{pmatrix}, d_{opt} = 1, \left\|\mathbf{w}_{opt}\right\|^2 = 1 \tag{3.3}$$

```
import cvxpy as cp

w = cp.Variable(2)
d = cp.Variable()

probconst = ([2*w[0]+w[1]+d>=1,0.8*w
    [0]-0.6*w[1]+d<=-1])
probobj = cp.Minimize(0.5*cp.square(cp.
    norm(w)))

prob = cp.Problem(probobj,probconst)
prob.solve()

print (prob.value)
print (w.value)
print (d.value)
```

3.2 Provide a graphical representation for (2.8)
Solution: The following code plots Fig. 3.2. The constraint lines in (3.1)-(3.2) are plotted for $d = 0, 0.5$ and 1. The circles $\|\mathbf{w}\|^2 = r^2$ are plotted for $r = 1, 2$ and 3. The smalles circle that satisfies the constraints is obtained when $d = 1$

```
wget https://raw.githubusercontent.com/
    gadepall/EE1390/master/manuals/svm/
    codes/svm_graph.py
```

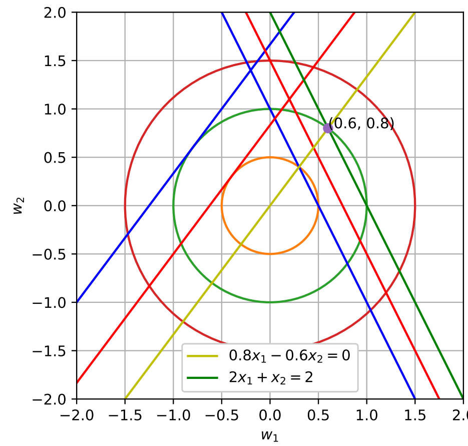

Fig. 3.2

4 KKT Solution

4.1 Show that the Lagrangian for (2.8) can be expressed as

$$L_p(\mathbf{w}, \boldsymbol{\alpha}, d) = \frac{1}{2}\|\mathbf{w}\|^2 - \boldsymbol{\alpha}^T \left(\begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix}^T \mathbf{w} + d \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right) \tag{4.1}$$

where

$$\boldsymbol{\alpha} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} \tag{4.2}$$

are the Lagrange multipliers.
Solution: The Lagrangian is given by,

$$L_p(\mathbf{w}, \boldsymbol{\alpha}, d) = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{2} \alpha_i \left\{ y_i \left(\mathbf{x}_i^T \mathbf{w} + d \right) - 1 \right\} \tag{4.3}$$

which can be simplified to obtain (4.1)

4.2 Show that the stationarity condtion with respect to $\mathbf{w}$ yields

$$\begin{pmatrix} \mathbf{I} & -\begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{w} \\ \boldsymbol{\alpha} \\ d \end{pmatrix} = 0 \tag{4.4}$$

Solution: From the stationarity condition

$$\nabla_{\mathbf{w}} L_p(\mathbf{w}, \boldsymbol{\alpha}, d) = 0 \tag{4.5}$$

$$\text{or,} \quad \mathbf{w} - \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix} \boldsymbol{\alpha} = 0 \tag{4.6}$$

resulting in (4.4).

4.3 Show that the stationarity condition with respect to $\boldsymbol{\alpha}$ yields

$$\begin{pmatrix} \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix}^T & \mathbf{0} & \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \end{pmatrix} \begin{pmatrix} \mathbf{w} \\ \boldsymbol{\alpha} \\ d \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \tag{4.7}$$

Solution:

$$\nabla_{\boldsymbol{\alpha}} L_p(\mathbf{w}, \boldsymbol{\alpha}, d) = 0 \quad (4.8)$$

$$\implies \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix}^T \mathbf{w} + d\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \end{pmatrix} = 0 \quad (4.9)$$

after simplification resulting in (4.7)

4.4 Find the stationarity condition with respect to d.
Solution:

$$\nabla_d L_p(\mathbf{w}, \boldsymbol{\alpha}, d) = 0 \qquad (4.10)$$

$$\implies \begin{pmatrix} y_1 & y_2 \end{pmatrix} \boldsymbol{\alpha} = 0 \qquad (4.11)$$

$$\text{or,} \quad \begin{pmatrix} \mathbf{0} & \begin{pmatrix} y_1 & y_2 \end{pmatrix} & 0 \end{pmatrix} \begin{pmatrix} \mathbf{w} \\ \boldsymbol{\alpha} \\ d \end{pmatrix} = 0 \qquad (4.12)$$

4.5 Obtain a matrix equation for $\mathbf{w}$ and d.
Solution: (4.4) (4.7) and (4.12) can be stacked into a single matrix equation as

$$\begin{pmatrix} \mathbf{I} & -\begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix} & \mathbf{0} \\ \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix}^T & \mathbf{0} & \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} \\ \mathbf{0} & \begin{pmatrix} y_1 & y_2 \end{pmatrix} & 0 \end{pmatrix} \begin{pmatrix} \mathbf{w} \\ \boldsymbol{\alpha} \\ d \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 0 \end{pmatrix} \qquad (4.13)$$

4.6 Find the optimal values of $\mathbf{w}$ and d by solving (4.13) using python.

5 Duality

5.1 Substitute (4.4) and (4.12) in the primal function to obtain the Lagrangian (Wolfe) dual objective function L_D.
Solution: From (4.4)

$$\mathbf{w} = \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix} \boldsymbol{\alpha} \qquad (5.1)$$

$$\implies \mathbf{w}^T\mathbf{w} = \boldsymbol{\alpha}^T \begin{pmatrix} y_1\mathbf{x}_1^T \\ y_2\mathbf{x}_2^T \end{pmatrix} \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix} \boldsymbol{\alpha} \quad (5.2)$$

$$\text{and } \boldsymbol{\alpha}^T \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix}^T \mathbf{w} = \mathbf{w}^T\mathbf{w} \qquad (5.3)$$

From (4.12),

$$\begin{pmatrix} y_1 & y_2 \end{pmatrix} \boldsymbol{\alpha} = 0 \qquad (5.4)$$

$$\implies \boldsymbol{\alpha}^T d \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = 0 \qquad (5.5)$$

Substituting from the above in (4.1),

$$L_D(\boldsymbol{\alpha}) = -\frac{1}{2}\boldsymbol{\alpha}^T \begin{pmatrix} y_1\mathbf{x}_1^T \\ y_2\mathbf{x}_2^T \end{pmatrix} \begin{pmatrix} y_1\mathbf{x}_1 & y_2\mathbf{x}_2 \end{pmatrix} \boldsymbol{\alpha} + \boldsymbol{\alpha}^T \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad (5.6)$$

5.2 Formulate the equivalent optimization problem for (2.8) using (5.6).