

Assignment of chapter 5

Chengzhang Yang 16337272 Intelligent Science and Technology

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(a)

Denotes r as the distance between x_a and the hyperplane. Decompose x_a into two vectors x and $\frac{w}{||w||}r$ where x locates on the hyperplane and r is parallel to w .

Then

$$\begin{aligned}|g(x_a)| &= |w^t x_a + w_0| \\ &= |w^t x + r||w| + w_0| \\ &= r||w||\end{aligned}$$

Thus

$$r = \frac{|g(x_a)|}{||w||}$$

Suppose there is another point x' on the hyperplane.

Since $x - x'$ is an nonempty vector on hyperplane, we have

$$w^t(x - x') = w^t x + w_0 - (w^t x' + w_0) = 0$$

In other words, $x - x'$ is orthorgonal to w

Therefore

$$\begin{aligned}||x_a - x'||^2 &= ||x - x'||^2 + r^2 \\ ||x_a - x'||^2 &\geq ||x - x'||^2\end{aligned}$$

(b)

$$\begin{aligned}x_p = x &= \begin{cases} x_a - \frac{|g(x_a)|}{||w||}w, g(x_a) > 0 \\ x_a + \frac{|g(x_a)|}{||w||}w, g(x_a) < 0 \end{cases} \\ &= x_a - \frac{g(x_a)}{||w||^2}w\end{aligned}$$

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(a)

$$\frac{\partial J_s(a)}{\partial a_j} = 2 \sum_{i=1}^n (a^t y_i - b_i) y_{ij}$$

$$\frac{\partial J_s^2(a)}{\partial a_i a_j} = 2 \sum_{i=1}^n y_{ij}^2$$

$$H = \begin{bmatrix} 12 & -2 & 12 \\ -2 & 70 & 72 \\ 12 & 72 & 288 \end{bmatrix}$$

(b)

Recall

$$a_{k+1} \approx a_k - \eta(k) \nabla J(a_k)$$

Consider second order Taylor expansion

$$J(a) \approx J(a_k) + \nabla J^t(a - a_k) + \frac{1}{2}(a - a_k)^t H(a - a_k)$$

$$J(a_{k+1}) \approx J(a_k) - \eta(k) \|\nabla J\|^2 + \frac{1}{2} \eta^2(k) \nabla J^t H \nabla J$$

Compute the derivative of the equation above, we know that $J(a_{k+1})$ achieve its minimum when

$$\eta(k) = \frac{\|\nabla J\|^2}{\nabla J^t H \nabla J}$$

Since α is unknown, we could not explicitly give the value of η . Nevertheless, we can estimate the range of $\eta(k)$. With the help of eigenvalue, we know that

$$\frac{1}{\lambda_1} = \frac{v_1^2 + v_2^2 + \dots + v_n^2}{\lambda_1 v_1^2 + \lambda_1 v_2^2 + \dots + \lambda_1 v_n^2} \leq \frac{v_1^2 + v_2^2 + \dots + v_n^2}{\lambda_1 v_1^2 + \lambda_2 v_2^2 + \dots + \lambda_n v_n^2} \leq \frac{v_1^2 + v_2^2 + \dots + v_n^2}{\lambda_n v_1^2 + \lambda_n v_2^2 + \dots + \lambda_n v_n^2} = \frac{1}{\lambda_n}$$

where λ_1 and λ_n refer to the largest and smallest eigenvalue of H . Therefore, the range of η is [0.006452, 0.1846].

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Separate Y into four blocks.

$$Y = \begin{bmatrix} \mathbf{1}_1 & X_1 \\ -\mathbf{1}_2 & X_2 \end{bmatrix}$$

$$\therefore T^T Y a = Y^T b$$

$$\therefore \begin{bmatrix} \mathbf{1}_1^T & -\mathbf{1}_2^T \\ -X_1 & X_2^T \end{bmatrix} \begin{bmatrix} \mathbf{1}_1 & X_1 \\ -\mathbf{1}_2 & X_2 \end{bmatrix} a = \begin{bmatrix} \mathbf{1}_1 & X_1 \\ -\mathbf{1}_2 & X_2 \end{bmatrix} \begin{bmatrix} \frac{n}{n_1} \mathbf{1}_1 \\ \frac{n}{n_2} \mathbf{1}_2 \end{bmatrix}$$

$$\begin{bmatrix} n & (n_1 m_1 + n_2 m_2)^T \\ n_1 m_1 + n_2 m_2 & X_1^T X_1 + X_2^T X_2 \end{bmatrix} a = \begin{bmatrix} 0 \\ n(m_1 - m_2) \end{bmatrix} \quad (1)$$

Define

$$\begin{aligned}
m_i &= \frac{1}{n_i} \sum_{x \in D_i} x \\
S_W &= \sum_{i=1}^2 \sum_{x \in D_i} (x - m_i)(x - m_i)^T \\
&= \sum_{i=1}^2 \sum_{x \in D_i} [(x - m_i)x^T - (x - m_i)m_i^T] \\
&= \sum_{i=1}^2 \sum_{x \in D_i} [xx^T - 2\frac{1}{n_i} \sum_{y \in D_i} yx^T + m_i m_i^T] \\
&= \sum_{i=1}^2 [\sum_{j=1}^{n_i} x_j x_j^T - 2\frac{1}{n_i} \sum_{k=1}^{n_i} x_k \sum_{l=1}^{n_i} x_l^T + n_i m_i m_i^T] \\
&= \sum_{i=1}^2 [\sum_{j=1}^{n_i} x_j x_j^T - n_i m_i m_i^T] \\
&= X_1^T X_1 + X_2^T X_2 - n_1 m_1 m_1^T - n_2 m_2 m_2^T
\end{aligned}$$

Equation(1) can be written as

$$\begin{bmatrix} n & (n_1 m_1 + n_2 m_2)^T \\ n_1 m_1 + n_2 m_2 & S_W + n_1 m_1 m_1^T + n_2 m_2 m_2^T \end{bmatrix} a = \begin{bmatrix} 0 \\ n(m_1 - m_2) \end{bmatrix}$$

Solving equation set above, we have

$$\begin{aligned}
&(\frac{n_1 n_2 (m_1 m_1^T + m_2 m_2^T - 2m_1 m_2^T)}{n^2} + \frac{1}{n} S_W) w = m_1 - m_2 \\
&(\frac{n_1 n_2 (m_1 - m_2)(m_1 - m_2)^T}{n^2} + \frac{1}{n} S_W) w = m_1 - m_2
\end{aligned} \tag{2}$$

Since $(m_1 - m_2)(m_1 - m_2)^T w$ is just linear combination of $m_1 - m_2$ with different scalar, we can denote

$$(1 - \alpha)(m_1 - m_2) = \frac{n_1 n_2 (m_1 - m_2)(m_1 - m_2)^T}{n^2} w$$

Thus

$$w = \alpha n S_W^{-1} \tag{3}$$

Substitute w in equation(3) for equation(2) we have

$$\alpha = (1 + \frac{n_1 n_2}{n} (m_1 - m_2)^T S_W^{-1} (m_1 - m_2))^{-1}$$

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(1) When samples are linear separable

$$\exists a_0 \quad a_o^T y_k = b_k, 1 \leq k \leq n$$

$$0 \leq \min\{\tau : \tau \geq, a_i^T y_i + \tau \geq b_i\} = \min\{\tau : \tau \geq, a_k^T y_k + \tau \geq b_k\} = 0$$

$$\therefore J_\tau(a) \geq 0, J_\tau(a_0) = 0$$

$$\therefore \arg \max_{\alpha} J_\tau(a) = J_\tau(a_0)$$

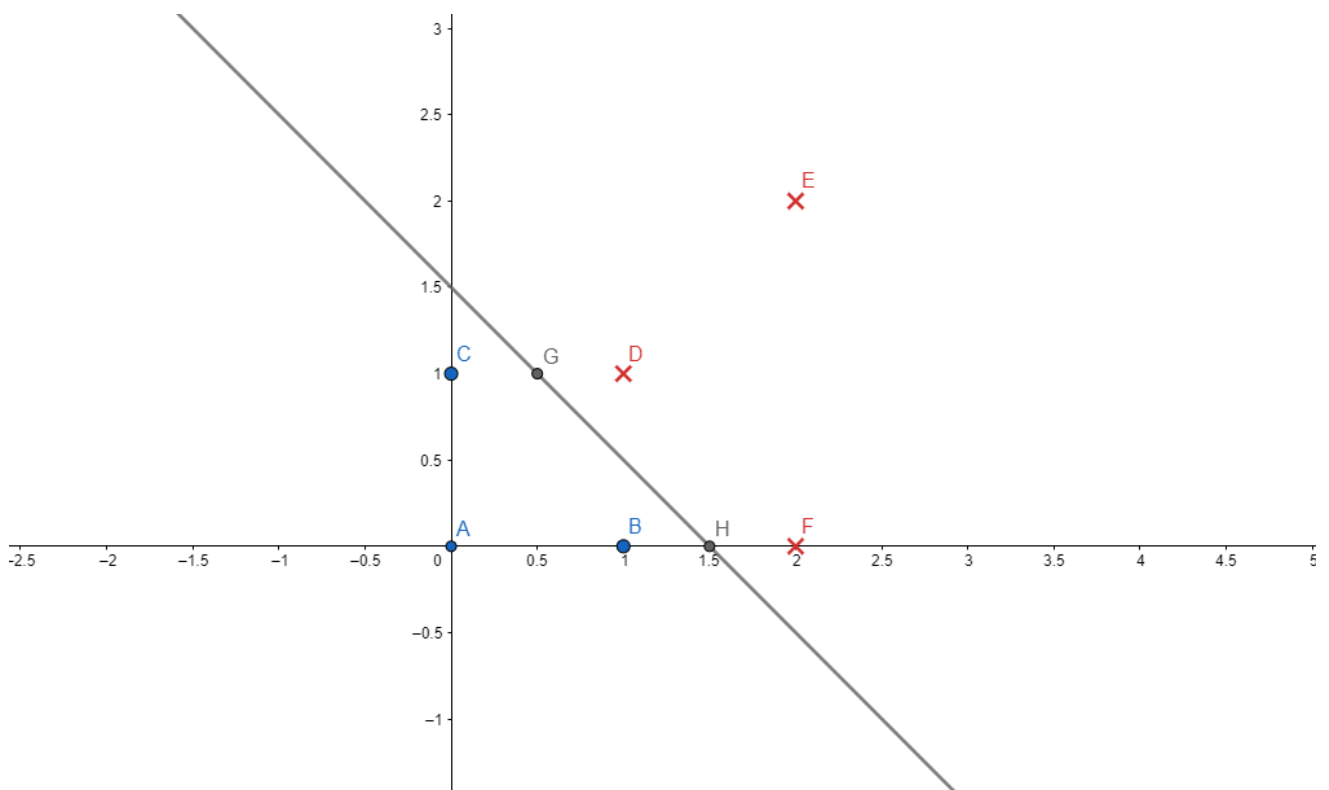
(2) When samples are not linear separable

$$\forall a, \quad a_0^T y_i < b_i, 1 \leq i \leq n$$

$$\begin{aligned} \min_{\tau, a} \{ \tau : \tau \geq 0, a^T y_i + \tau \geq b_i \} &= \min_{\tau, a} \{ \tau : \tau \geq 0, \tau \geq b_i - a^T y_i \} \\ &= \min_{\tau, a} \{ \tau : \tau \geq 0, \tau \geq \max_a \{ b_i - a^T y_i \} \} \\ &= \min_a \{ \max_{a^T y_i \leq b_i} \{ b_i - a^T y_i \} \} \\ &= \min_a J_\tau(a) \end{aligned}$$

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(a)



$$w = [3, -2, -2]^T$$

(b)

point B, C, D, F

(c)

The dual problem is

$$\begin{aligned} \text{maximize } L_D(w, b, a) &= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j x_i^T x_j \\ \text{s.t. } \alpha_i &\geq 0 \text{ and } \sum_{i=1}^n \alpha_i y_i = 0 \end{aligned}$$

Then

$$\begin{aligned}
L_D &= 2(a_1 + a_2 + a_3) - \frac{1}{2} \sum_{i=1}^5 \sum_{j=1}^5 \alpha_i \alpha_j y_i y_j x_i^T x_j \\
&+ \sum_{i=1}^5 \alpha_i (a_1 + a_2 + a_3 - a_4 - a_5 - a_6) y_i x_6^T x_i \\
&- \frac{1}{2} (a_1 + a_2 + a_3 - a_4 - a_5)^2 x_6^T x_6
\end{aligned}$$

Compute partial derivative of $a_1, a_2, a_3, \dots, a_5$, we get

$$\begin{bmatrix} 1 & 2 & 2 & 0 & -1 \\ 2 & 5 & 3 & 1 & -1 \\ 2 & 3 & 5 & -1 & -3 \\ 0 & -1 & 1 & -1 & -1 \\ 1 & 1 & 3 & -1 & -2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ 2 \\ 0 \\ 0 \end{bmatrix}$$

Simplify matrix of the right side

$$\begin{bmatrix} 1 & 2 & 2 & 0 & -1 \\ 0 & 1 & -1 & 1 & 1 \\ 0 & 1 & -1 & 1 & 1 \\ 0 & 1 & -1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} a' = \begin{bmatrix} 2 \\ -2 \\ 2 \\ 0 \\ 0 \end{bmatrix}$$

Obviously, this matrix is unsolvable. The optimal solution is on the boundary of the domain.

We can merely satisfy only one condition among equation (2)~(4).

(i) Assume that equation (2) holds

We can conclude that $a'_3 > 0$ if all element of a' is greater or equal to zero.

However, in the condition above, we could not find a solution.

(ii) Assume that equation (3) holds

We can get

$$\begin{cases} a = [4 & 0 & 0 & 0 & 2 & 2]^T, & L(a) = 4 \\ a = [2 & 0 & 0 & 2 & 0 & 0]^T, & L(a) = 2 \end{cases}$$

(iii) Assume that equation (4) holds

We can get

$$a = [2 \quad 0 \quad 0 \quad 0 \quad 0 \quad 2]^T, \quad L(a) = 2$$

In summary, $a = [4 \quad 0 \quad 0 \quad 0 \quad 2 \quad 2]^T$

$$w = \sum_{i=1}^6 \alpha_i y_i x_i = [2 \quad 2]^T$$

Using point A , we have

$$b = \frac{1}{y_1} - w^T x_i = -3$$

Therefore, $w = [3, -2, -2]^T$, which is the identical solution of **(a)**