

Question 1

(1)

Given that

1. The training data: $T = \{(x_1, y_1), \dots, (x_n, y_n)\}$, where $x_i \in \mathbb{R}^n$, $y_i \in \{-1, 1\}$, $i = 1, 2, \dots, N$
2. The hyperplane: $w \cdot x + b = 0$

The margin between a sample (x_i, y_i) and the hyperplane is defined accordingly,

$$\gamma_i = y_i \left(\frac{w}{\|w\|} \cdot x_i + \frac{b}{\|w\|} \right)$$

The minimal distance between the hyperplane and the training data is

$$\gamma = \min_{i=1,2,\dots,N} \gamma_i$$

The problem is equivalent to the below optimization problem

$$\begin{aligned} \underset{w,b}{\max} \quad & \gamma \quad \text{s.t.} \quad y_i \left(\frac{w}{\|w\|} \cdot x_i + \frac{b}{\|w\|} \right) \geq \gamma, \quad i=1,2,\dots,N \end{aligned}$$

Define $\gamma' = \frac{\gamma}{\|w\|}$, the equation (1) can be rewritten as

$$\begin{aligned} \underset{w,b}{\max} \quad & \gamma' \quad \text{s.t.} \quad y_i (w \cdot x_i + b) \geq \gamma', \quad i=1,2,\dots,N \end{aligned}$$

which is equivalent to the optimization problem (3)

$$\begin{aligned} \underset{w,b}{\min} \quad & \frac{1}{2} \|w\|^2 \quad \text{s.t.} \quad y_i (w \cdot x_i + b) - 1 \geq 0, \quad i=1,2,\dots,N \end{aligned}$$

Rewrite the equation (3) to the Lagrange multiplier format

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^N \alpha_i y_i (w \cdot x_i + b) + \sum_{i=1}^N \alpha_i$$

we have

$$\underset{w,b}{\min} \quad \underset{\alpha \geq 0}{\max} \quad L(w, b, \alpha) = \underset{\alpha \geq 0}{\max} \quad \underset{w,b}{\min} \quad L(w, b, \alpha)$$

$$\begin{aligned} \underset{w,b}{\min} \quad & L(w, b, \alpha) = \underset{w,b}{\min} \quad \frac{1}{2} \|w\|^2 - \sum_{i=1}^N \alpha_i y_i (w \cdot x_i + b) + \sum_{i=1}^N \alpha_i \end{aligned}$$

Let,

$$\begin{aligned} \frac{\partial L(w, b, \alpha)}{\partial w} &= w - \sum_{i=1}^N \alpha_i y_i x_i = 0 \\ \frac{\partial L(w, b, \alpha)}{\partial b} &= - \sum_{i=1}^N \alpha_i y_i = 0 \end{aligned}$$

we have

$$w = \sum_{i=1}^N \alpha_i y_i x_i, \quad \sum_{i=1}^N \alpha_i y_i = 0$$

Substituting equations (4) to $L(w, b, \alpha)$, we have

$$\begin{aligned} L(w, b, \alpha) &= \frac{1}{2} \left\| \sum_{i=1}^N \alpha_i y_i x_i \right\|^2 - \sum_{i=1}^N \alpha_i y_i \left(\sum_{i=1}^N \alpha_i y_i x_i \cdot x_i + b \right) + \\ &+ \sum_{i=1}^N \alpha_i \left(\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \right. \\ &\left. \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \right) - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) + \\ &+ \sum_{i=1}^N \alpha_i y_i \left(\sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \right) + \sum_{i=1}^N \alpha_i y_i \end{aligned}$$

Due to the weak dual theorem, the primal optimization problem

$$\min_{w, b} \frac{1}{2} \|w\|^2 \text{ s.t. } y_i(w \cdot x_i + b) - 1 \geq 0, i = 1, 2, \dots, N$$

is weak dual to the dual problem

$$\max_{\alpha} -\frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) + \sum_{i=1}^N \alpha_i y_i \text{ s.t. } \sum_{i=1}^N \alpha_i y_i = 0, i = 1, 2, \dots, N$$

If there is (w^*, b^*, α^*) and (w^*, b^*) is a feasible solution to the primal and (α^*) is feasible to the dual, then (w^*, b^*, α^*) is the optimal solution.

(2)

If we plot the 'support vectors', they are hyperplane. (In 2D, they are lines while they are planes in 3D)