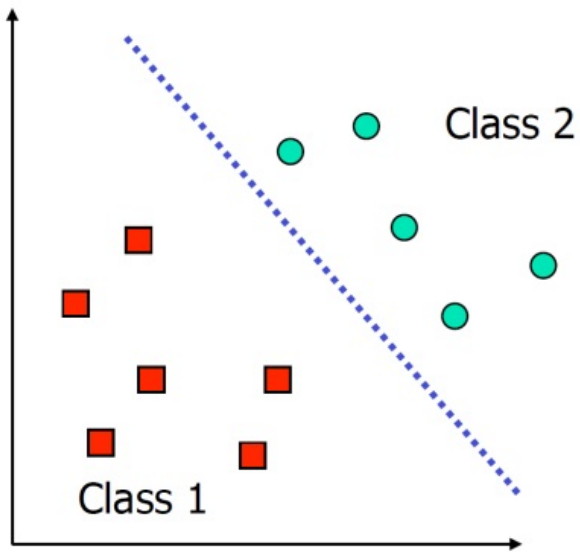
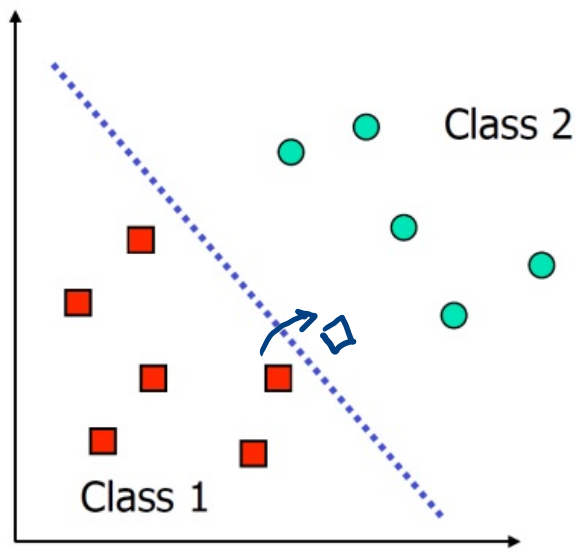


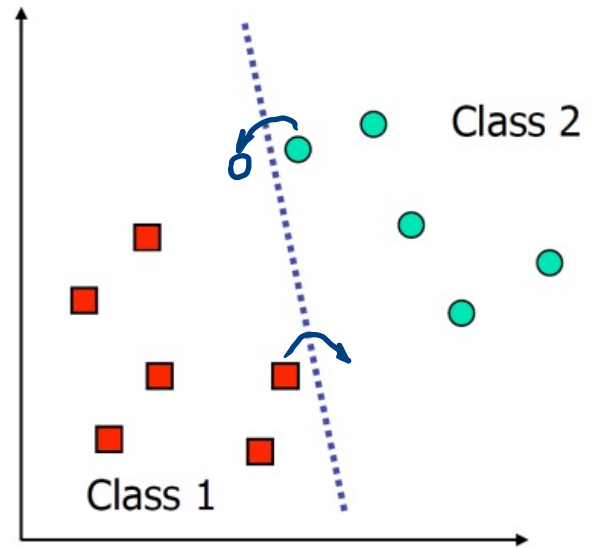
# Support vector machine (SVM)



①

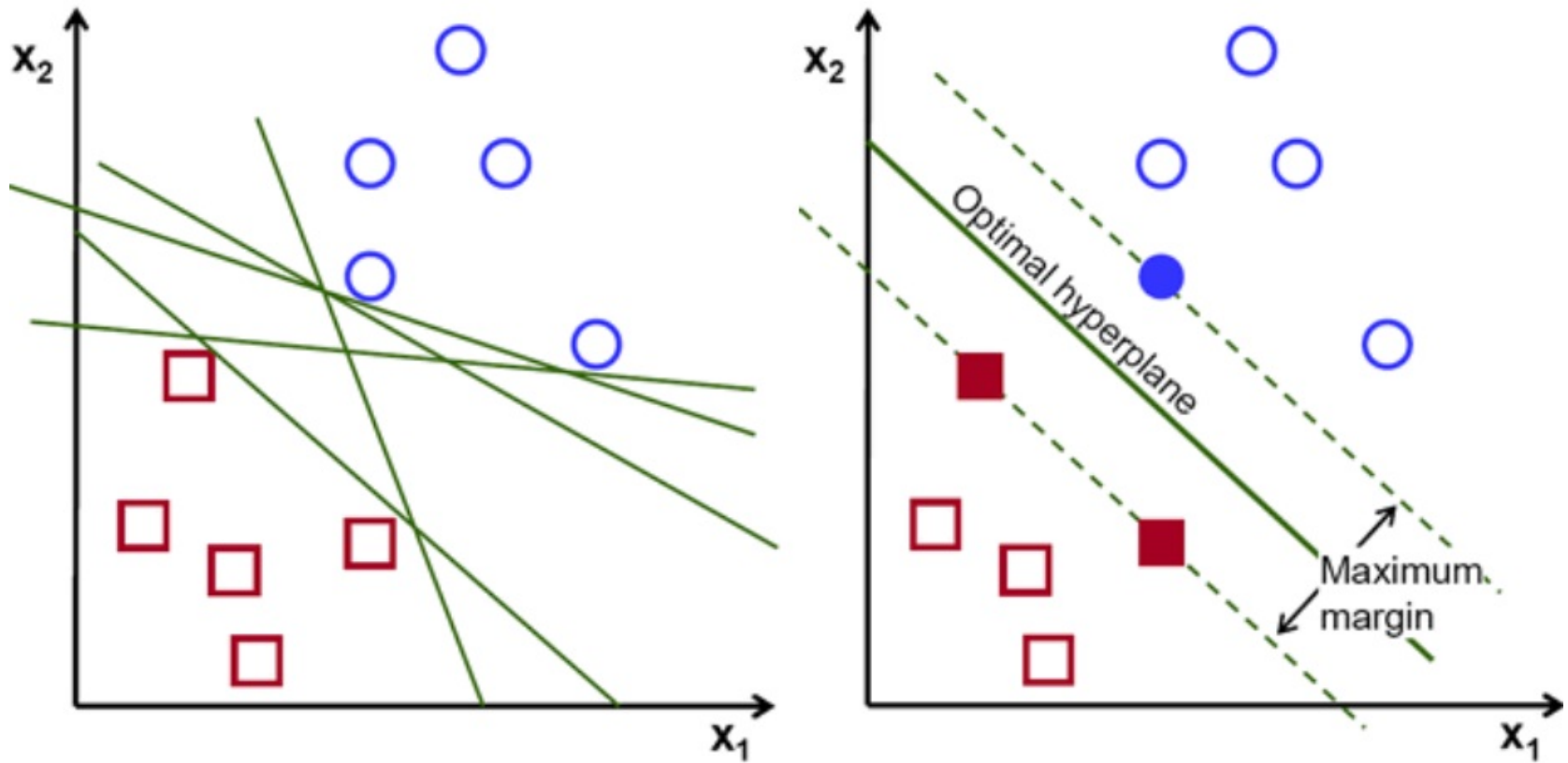


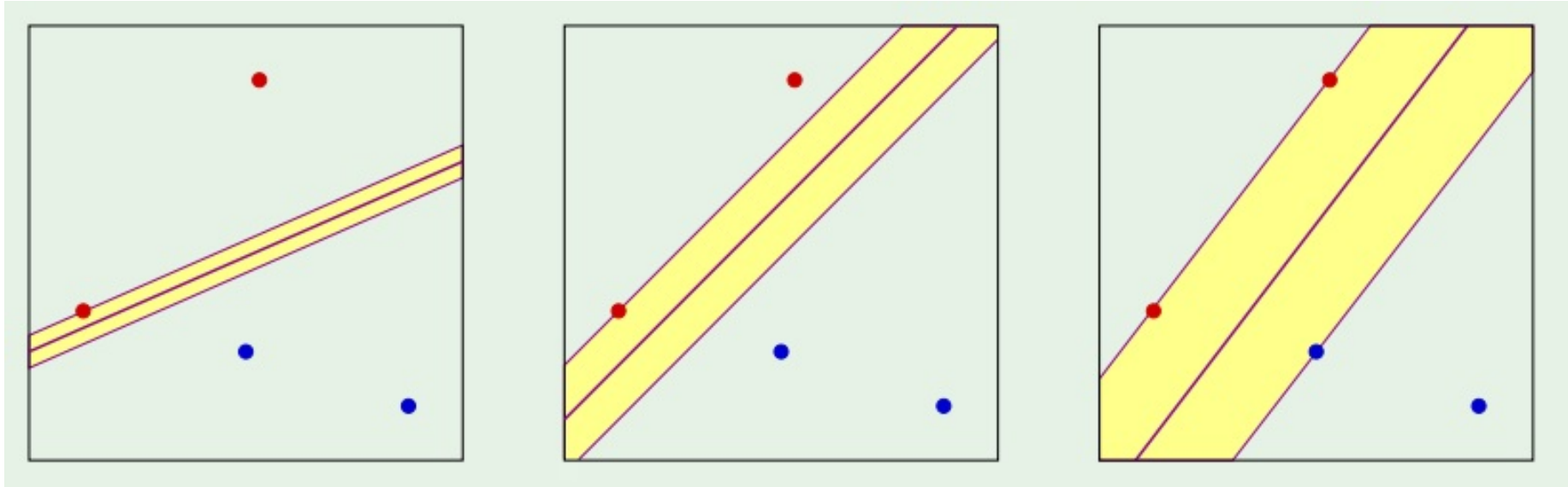
②

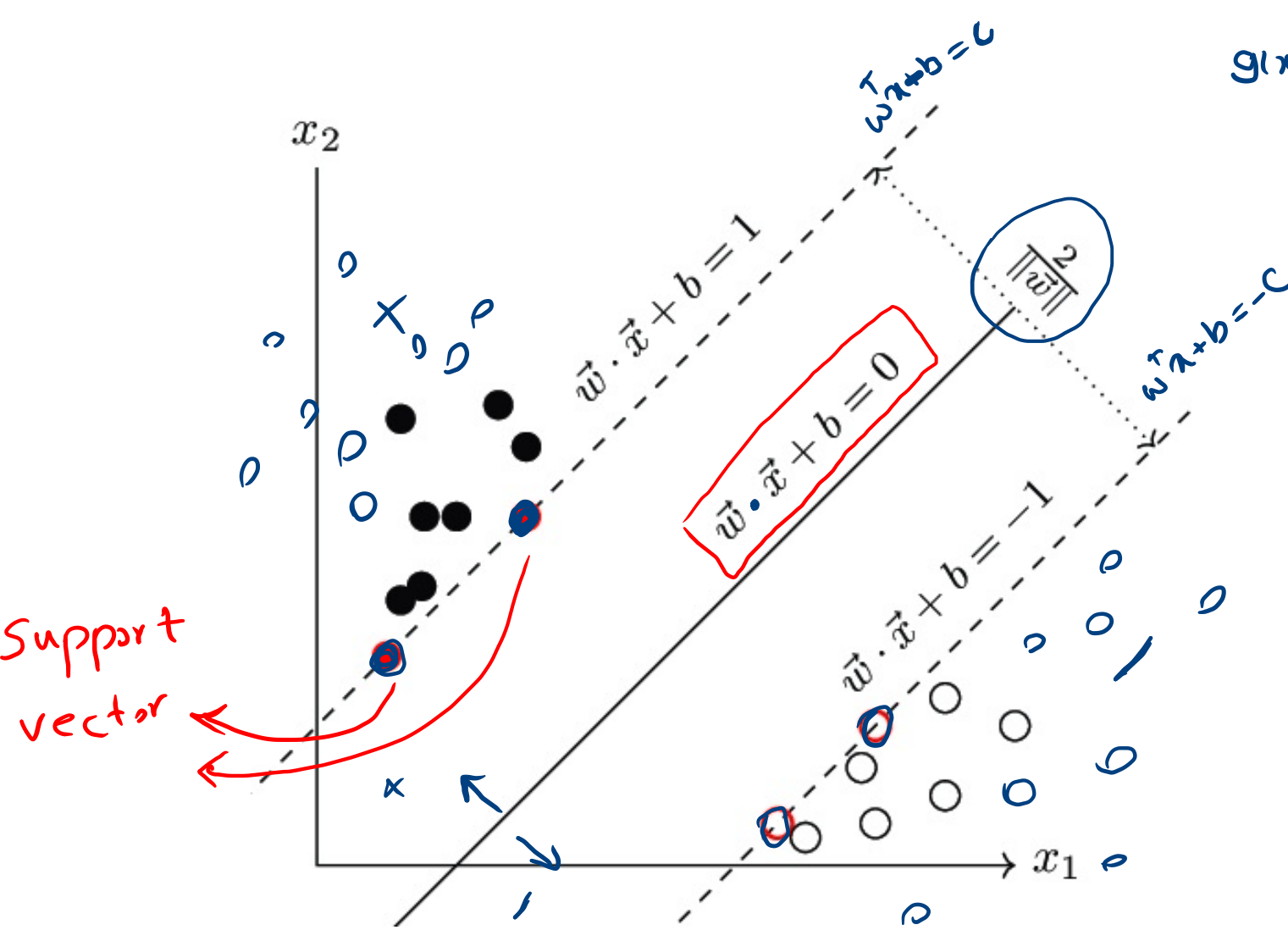


③

# Support Vector Machine (SVM)







$$g(x) = \underline{\underline{\omega}}^T \underline{\underline{x}} + \underline{\underline{b}} = 0$$

$$g(x) \begin{matrix} + \\ - \end{matrix} > < 0$$

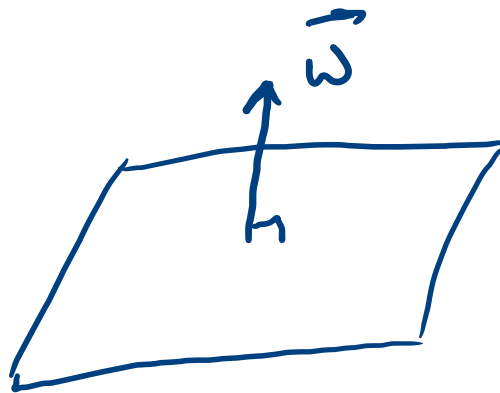
$$\omega \cdot x = \omega^T x$$

$$\langle \omega, x \rangle$$

$$\omega^T x + b = c$$

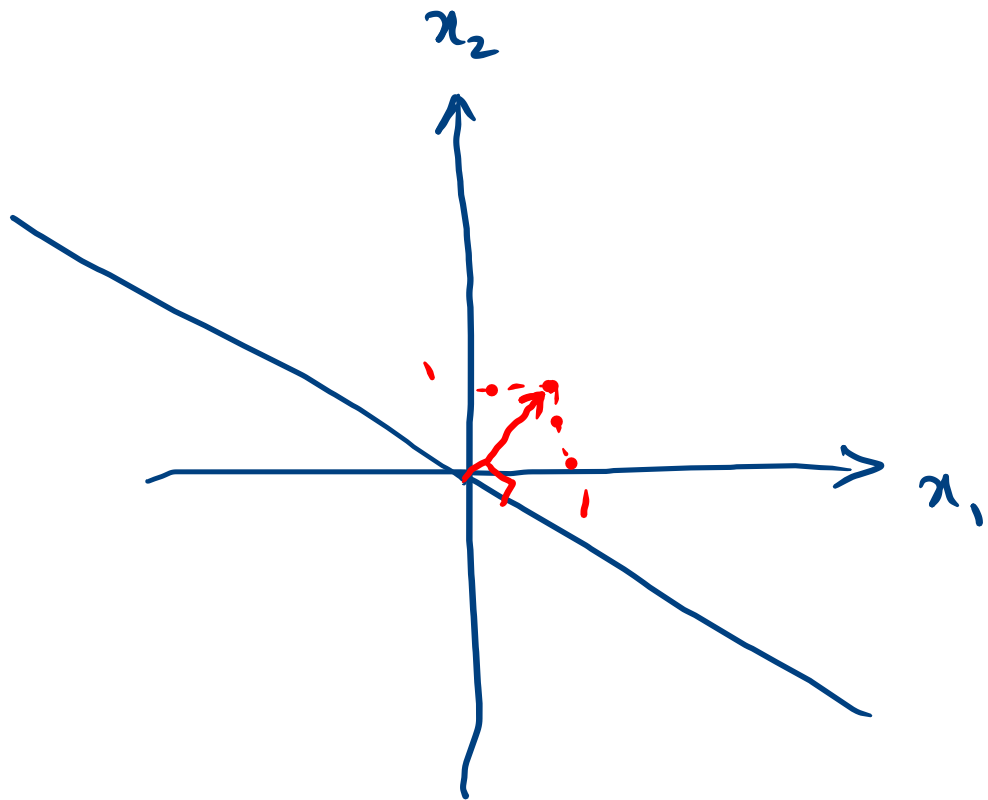
$$\underbrace{\frac{c}{\|\omega\|}}_{\omega} x + \underbrace{\frac{b}{\|\omega\|}}_b = 1$$

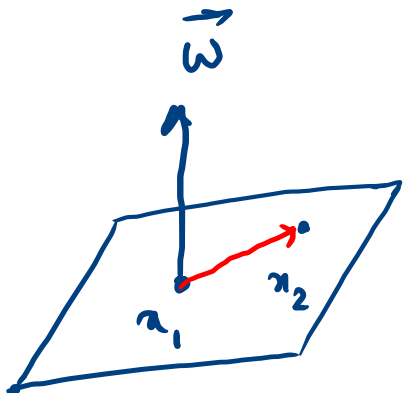
$$\underline{\omega^T x + b}$$



$$x_1 + x_2 = 0$$

$$\omega = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$





$$\omega^T x + b = 0$$



$$\langle \vec{w}, \vec{x_1 x_2} \rangle = 0$$

$$\begin{aligned} \omega^T (x_2 - x_1) &= \omega^T x_2 - \omega^T x_1 \\ &= \underbrace{\omega^T x_2 + b}_0 - \underbrace{\omega^T x_1 - b}_0 = 0 \end{aligned}$$

$$w^*, b^* = \arg \max_{w, b} \text{margin}(w, b)$$

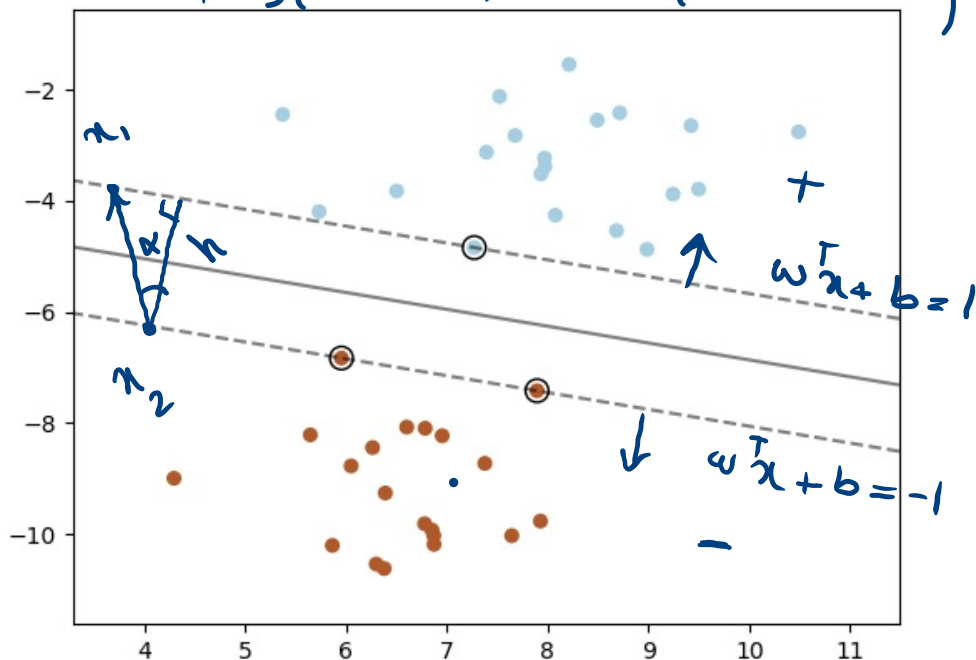
$$D = \{ (x_1, y_1), \dots, (x_n, y_n) \}$$

$$\text{s.t. } \left. \begin{array}{l} \text{if } y_i = +1 \Rightarrow w^T x_i + b \geq 1 \\ \text{else if } y_i = -1 \Rightarrow w^T x_i + b \leq -1 \end{array} \right\}$$

$$y_i \in \{ \pm 1 \}$$

$$\boxed{y_i (w^T x_i + b) \geq 1}$$

$$i = 1, \dots, n$$



$$h = \left| \|x_1, x_2\|_2 \cos \alpha \right|$$

$$= \left| \frac{\|w\|_2}{\|w\|_2} \|x_1, x_2\| \cos \alpha \right|$$

$$= \frac{1}{\|w\|_2} \left| \langle w, \vec{x_1 x_2} \rangle \right|$$

$$\Rightarrow h = \frac{1}{\|w\|_2} \left| w^T (x_1 - x_2) \right| = \frac{1}{\|w\|_2} \left| \underbrace{w^T x_1 + b}_1 - \underbrace{w^T x_2 + b}_1 \right| = \frac{2}{\|w\|_2}$$

$$\max_{w, b} \frac{2}{\|w\|_2}$$

$$\text{s.t. } y_i (w^T x_i + b) \geq 1$$

$$w^T x + b$$

$$(2w^T x + b)$$

✓

≡

$$\min_{w, b} \|w\|_2^2$$

$$\text{s.t. } y_i (x_i^T w + b) \geq 1$$



hard margin SVM



$$\min_{\underline{x}} f(\underline{x})$$

s.t.

$$g_i(\underline{x}) \leq 0 \quad i=1, \dots, m$$

$$h_i(\underline{x}) = 0 \quad i=1, \dots, p$$

KKT conditions

$$\text{Lagrangian: } L(\underline{x}, \underline{\lambda}, \underline{\mu}) = f(\underline{x}) + \sum_{i=1}^m \lambda_i g_i(\underline{x}) + \sum_{i=1}^p \mu_i h_i(\underline{x})$$

$$\lambda_i \geq 0 \quad i=1, \dots, m$$

KKT:

$$\textcircled{1} \quad \nabla_{\underline{x}} L(\underline{x}, \underline{\lambda}, \underline{\mu}) = 0$$

$$\underline{x}^*, \underline{\lambda}^*, \underline{\mu}^*$$

$$\textcircled{2} \quad h_i(\underline{x}) = 0$$

$$\underline{g_i(\underline{x}) \leq 0}$$

$$\textcircled{3} \quad \lambda_i \geq 0$$

$$\textcircled{4} \quad \underline{\lambda_i g_i(\underline{x}) = 0} \rightarrow \text{Complementary Slackness}$$

$$\begin{array}{ll}
 \min_x & f(x) \\
 \text{s.t.} & g_i(x) \leq 0 \quad i=1, \dots, m \\
 & h_i(x) = 0 \quad i=1, \dots, p
 \end{array}
 \quad \left. \vphantom{\begin{array}{l} \min_x \\ \text{s.t.} \end{array}} \right\} \Rightarrow x^*$$

$$L(x, \mu, \lambda) = f(x) + \sum_{i=1}^m \lambda_i g_i(x) + \sum_{i=1}^p \mu_i h_i(x)$$

$$\underline{g(\mu, \lambda)} = \min_x \underline{L(x, \mu, \lambda)}$$

$$g(\mu, \lambda) \leq f(x^*)$$

$$\begin{aligned}
 \underline{g(\mu, \lambda)} &= \min_x L(x, \mu, \lambda) \leq L(x^*, \mu, \lambda) \\
 &= f(x^*) + \underbrace{\sum_{i=1}^m \lambda_i g_i(x^*)}_{\substack{\geq 0 \quad \leq 0 \\ \leq 0}} + \underbrace{\sum_{i=1}^p \mu_i h_i(x^*)}_0
 \end{aligned}$$

$$\leq f(x^*)$$

$$g(\lambda, \mu) \leq \underline{f(x^*)}$$

$$\forall \lambda_i \geq 0, \mu$$

primal problem

$$\begin{aligned} \max_{\lambda, \mu} \quad & g(\lambda, \mu) \\ & \lambda_i \geq 0 \end{aligned}$$

→ Dual problem

Dual var.

Lagrange

multipliers

KKT ~

Dual solution  $\leq$  Primal solution

$$g(\lambda^*, \mu^*) \leq f(x^*)$$

weak  
duality

Strong Duality:

$$g(\lambda^*, \mu^*) = f(x^*)$$

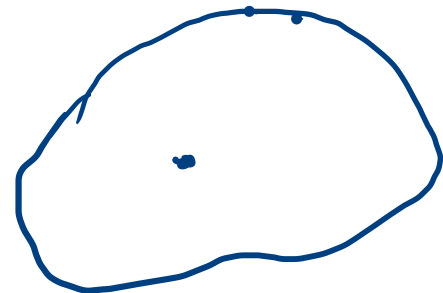
①

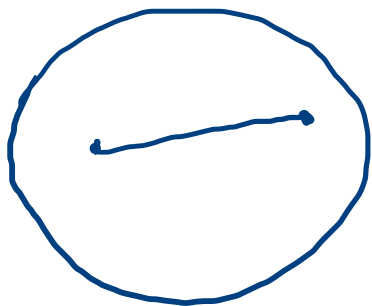
convex

②

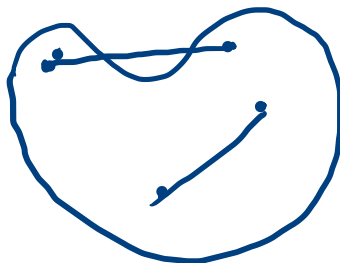
$$\exists x \quad g_i(x) < 0$$

Slater's  
Condition  $\leftarrow$



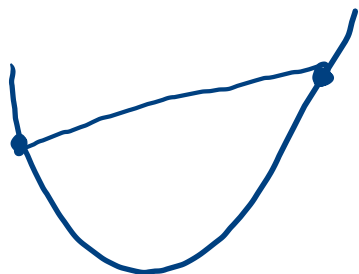


convex



non-convex

$f(x)$



$$\underline{w^T x} + z < 0$$

$$\left\{ \begin{array}{l} f(x) \rightarrow \text{convex} \\ g_i(x) \rightarrow \text{=} \\ h_i(x) \rightarrow \text{خطی} \end{array} \right.$$

$$\min_{\omega, b} \frac{1}{2} \|\omega\|_2^2$$

$$1 - y_i(\omega^T x_i + b) \leq 0$$

$$\text{s.t. } y_i(\omega^T x_i + b) \geq 1 \quad i=1, \dots, n$$

$$L(\omega, b, \lambda) = \frac{1}{2} \|\omega\|_2^2 + \sum_{i=1}^n \lambda_i (1 - y_i(\omega^T x_i + b))$$

$$\frac{\partial L}{\partial \omega} = \omega + \sum_{i=1}^n -\lambda_i y_i x_i = 0 \Rightarrow \omega = \sum_{i=1}^n \lambda_i y_i x_i$$

$$\frac{\partial L}{\partial b} = -\sum_{i=1}^n \lambda_i y_i = 0 \Rightarrow \sum_{i=1}^n \lambda_i y_i = 0$$

$$g(\lambda) = \frac{1}{2} \left( \sum_i \lambda_i y_i x_i \right)^T \left( \sum_i \lambda_i y_i x_i \right) + \sum_{i=1}^n \lambda_i - \sum_i \lambda_i y_i \left( \sum_j \lambda_j y_j x_j \right)^T x_i - \underbrace{\sum_i \lambda_i y_i b}_0$$

$$= \frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j x_i^T x_j - \sum_i \sum_j \lambda_i \lambda_j y_i y_j x_i^T x_j + \sum_i \lambda_i$$

$$\Rightarrow g(\lambda) = -\frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j x_i^T x_j + \sum_i \lambda_i \quad \lambda_i \geq 0$$

$$\begin{array}{ll} \max_{\lambda} & g(\lambda) \\ \text{s.t.} & \lambda_i \geq 0 \end{array}$$

$$\Rightarrow \lambda^* = \begin{bmatrix} \lambda_1^* \\ \vdots \\ \lambda_n^* \end{bmatrix}$$

$$\omega^* = \sum_{i=1}^n \lambda_i^* y_i x_i$$

Complementary Slackness:

$$\lambda_i^* g_i(x^*) = 0$$

$$\underbrace{\lambda_k^*}_{\neq 0} (y_k(\omega^{*T} x_k + b)) = 0$$