

$x_1, x_2, x_3 \in a, b, c$

$x_1 \quad x_2 \quad x_3 \quad Y$

$$I_G(x_1 == a) = \text{Entropy}() - [$$

$$P(x_1 == b)$$

$$P(x_1 == c)$$

$$P(x_2 == a)$$

$$P(x_2 == b)$$

$$P(x_2 == c)$$

$$P(x_3 == a)$$

$$P(x_3 == b)$$

$$P(x_3 == c)$$

Objective

$$\text{Min } \frac{1}{2} \|w\|^2 \quad \text{s.t.}$$

$$y(\vec{w} \cdot \vec{x} + b) \geq +1 \quad \text{for all points}$$

# Dual Problem

$$\text{Max} \quad \sum_{i=1}^m \alpha_i - \sum_{i=1}^m \sum_{j=1}^m \alpha_i y_i^i y_j^j \underbrace{(x^i \cdot x^j)}$$

$$\text{s.t} \quad \alpha_i \geq 0$$

$$\sum_{i=1}^m \alpha_i y_i^i = 0$$

$$\underline{x^i \cdot x^j}$$

$$\phi(x^i) \cdot \phi(x^j)$$

$$\underbrace{x^1, x^2, x^3, x^4, \dots, x^d}_{\text{dD}} \xrightarrow{\text{ID}} \dots$$

Kernel Function

①

$$k(x^i, x^j) = \langle \phi(x^i) \cdot \phi(x^j) \rangle$$

$$k(x, z) = (\langle x \cdot z \rangle)^2$$
$$= (x^T \cdot z)^2$$

$$x = [x_1 \quad x_2] \dots n$$

$$z = [z_1 \quad z_2] \quad O(n)$$

$$(x^T \cdot z)^2 = (x_1 z_1 + x_2 z_2)^2$$

$$x_1 z_1 x_1 z_1 + x_2 z_2 x_2 z_2 + 2 x_1 z_1 x_2 z_2$$

②

$$K(x, z) = (x^T \cdot z)^2$$

$$x = [x_1, x_2]$$

$$z = [z_1, z_2]$$

$$\phi(x) = [x_1 x_1 \quad x_1 x_2 \quad x_2 x_2 \quad x_2 x_1]$$

$$\phi(z) = [z_1 z_1 \quad z_1 z_2 \quad z_2 z_2 \quad z_2 z_1]$$

$$= \left( \underbrace{x_1 x_1 z_1 z_1}_{+ \cdot x_2 x_1 z_2 z_2} + x_1 x_2 z_1 z_2 + \underbrace{x_2 x_2 z_2 z_2} \right) O(n^2)$$

③

Quadratic kernel

$$k(X, Z) = (X^T \cdot Z + c)^{2=d}$$

$$X = [x_1, x_2] \quad Z = [z_1, z_2]$$

$$(x_1 z_1 + x_2 z_2 + c)^2 \quad O(n)$$

$$\left\{ \begin{aligned} &x_1 z_1 x_1 z_1 + x_2 z_2 x_2 z_2 + c^2 + \\ &2x_1 z_1 c + 2x_2 z_2 c + 2x_1 z_1 x_2 z_2 \end{aligned} \right\}$$

$$\begin{aligned} &(X^T \cdot Z) \\ X \cdot Z &= \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = x_1 z_1 + x_2 z_2 \end{aligned}$$

$$X^T = [x_1 \ x_2]$$

$$Z^T = [z_1 \ z_2]^{(4)}$$

$$\phi(X) = \begin{bmatrix} x_1 x_1 \\ \sqrt{2} x_1 x_2 \\ x_2 x_2 \\ \sqrt{2c} x_1 \\ \sqrt{2c} x_2 \\ c \end{bmatrix}$$

$$\phi(Z) = \begin{bmatrix} z_1 z_1 \\ \sqrt{2} z_1 z_2 \\ z_2 z_2 \\ \sqrt{2c} z_1 \\ \sqrt{2c} z_2 \\ c \end{bmatrix}$$

$$X^T = [x_1 \ x_2 \ \dots \ x_n]$$

$$\phi(X) = \left[ \begin{array}{l} \text{all } x_i^2 \\ \text{all } \sqrt{2c} x_i \end{array} \right], \quad \begin{array}{l} \text{all } \text{all } \sqrt{2} x_i x_j \\ i=1 \quad j=1 \end{array}, \quad d^{(n^2)}$$

$\hookrightarrow \binom{n+d}{d}$

$$k(x, z) = \exp\left(\frac{\|x - z\|^2}{2\sigma^2}\right)$$

$$k(x, z) = \langle \phi(x) \cdot \phi(z) \rangle$$

$k(x, z)$  - large if  $x$  &  $z$  are similar  
 small if dissimilar

Linear kernel

$$k(x, z) = (x^T z + \underline{c})$$



Valid kernels = Mercer kernel

$k(x, z)$  is valid if there exists  $\phi$  function s.t.

$$k(x, z) = \langle \phi(x) \cdot \phi(z) \rangle$$

Data set =  $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$

Kernel Matrix =  $K$

$x^{(1)} \cdot x^{(1)}$ 11	$x^{(1)} \cdot x^{(2)}$ 12	$x^{(1)} \cdot x^{(3)}$ 13	$\dots$	$x^{(1)} \cdot x^{(m)}$ 1m
$x^{(2)} \cdot x^{(1)}$ 21	$x^{(2)} \cdot x^{(2)}$ 22	$\dots$	$\dots$	$x^{(2)} \cdot x^{(m)}$ 2m
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$x^{(m)} \cdot x^{(1)}$ m1	$\dots$	$\dots$	$\dots$	$x^{(m)} \cdot x^{(m)}$ mm

$K$  = kernel Matrix  $m \times m$

Then for any vector  $Z \in \mathbb{R}^m$

$$\boxed{Z^T K Z} \geq 0 \quad K(x, z) = \phi(x)\phi(z)$$

~~$m \times m$~~   
 ~~$1 \times m$~~   
 ~~$m \times 1$~~   
 ~~$1 \times m$~~   
 ~~$m \times 1$~~   

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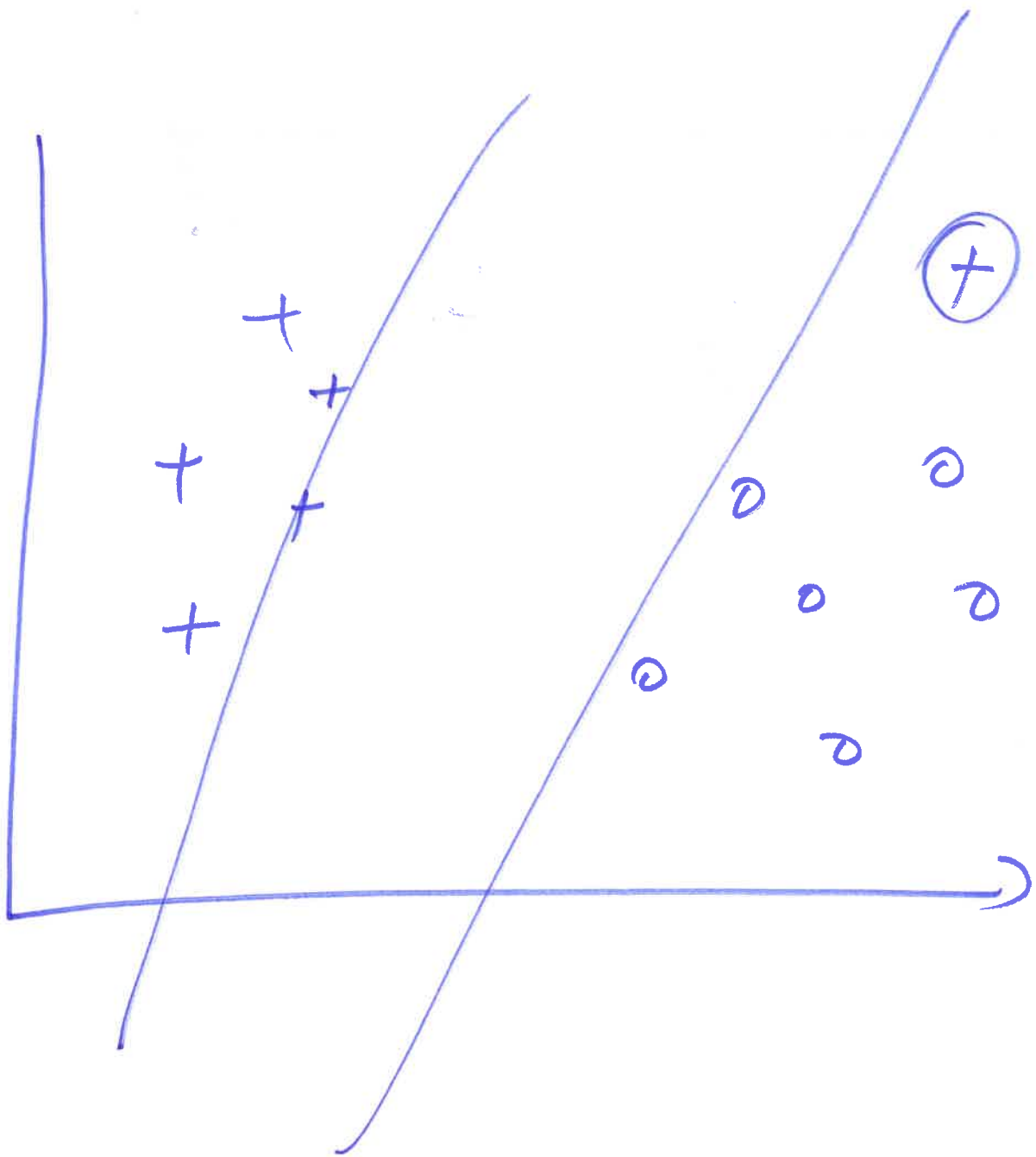
 $1 \times 1$

$$= \sum_i \sum_j Z_i K_{ij} Z_j$$

$K_{ij} = \underbrace{\phi(x^i) \cdot \phi(x^j)}$

$$\geq 0$$

# Soft Margin SVM



Min

$$\frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \xi_i$$

s.t

$$\begin{aligned} & \left( y(w^T x + b) - 1 + \xi_i \right) \geq 0 \\ & \xi_i \geq 0 \end{aligned}$$

$$\mathcal{L}(w, b, \alpha, r) +$$

$$\begin{aligned} &= \frac{1}{2} w^2 + C \sum \xi_i - \sum_{i=1}^m \alpha_i (y(w^T x + b) + \xi_i) \\ &\quad - \sum_{i=1}^m r_i \xi_i \end{aligned}$$

$$\frac{\partial L}{\partial w} \Rightarrow w = \sum_{i=1}^m \alpha_i y^i x^i$$

$$\frac{\partial L}{\partial b} = \sum \alpha_i y^i = 0$$

$$\frac{\partial L}{\partial \eta_i} = C - \alpha_i - r_i = 0$$

$$\alpha_i = C - r_i$$

max

$$\sum \alpha_i - \frac{1}{2} \sum \sum \alpha_i \alpha_j y^i y^j (x^i \cdot x^j)$$

$$s.t. C \leq \alpha_i \leq 0, \quad \sum \alpha_i y^i = 0$$

$$\alpha = 0 \Rightarrow y(w^T x + b) \geq 1$$

$$0 < \alpha < c \Rightarrow y(w^T x + b) = 1$$

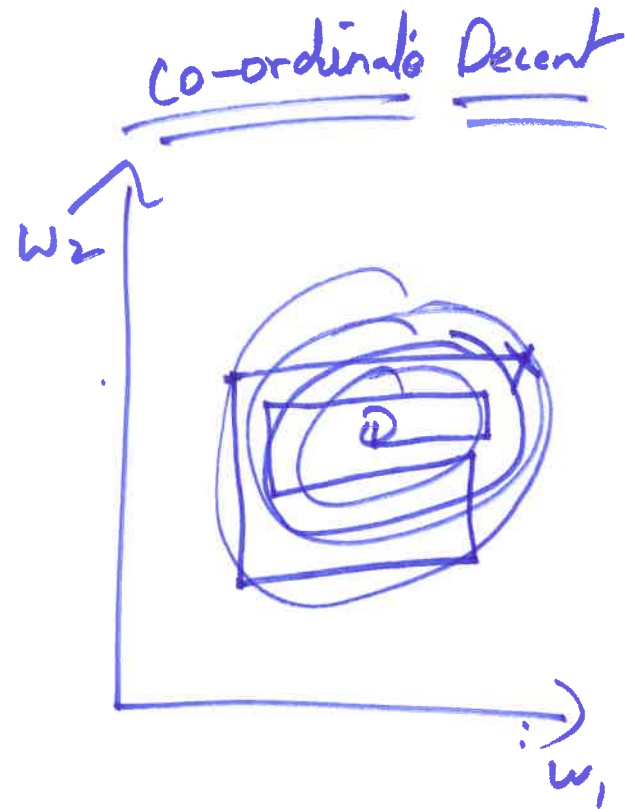
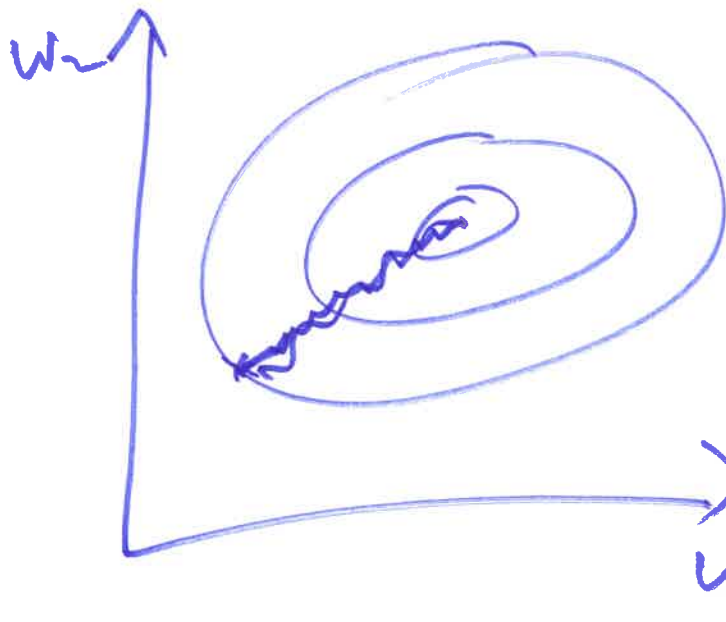
$$\alpha = c \Rightarrow y^i(w^T x + b) \leq 1$$

\_\_\_\_\_ X \_\_\_\_\_ X

SMO  $\rightarrow$  Sequential Minimum  
Optimization

Co-ordinate Ascent

Gradient Descent



max  $W(\alpha_1, \alpha_2, \dots, \alpha_m)$   
 no constraints on  $\alpha_i$ 's

Repeat { For  $i = 1$  to  $m$   
 $\alpha_i = \underset{\alpha_i}{\operatorname{argmax}} W(\alpha_i, \underbrace{\alpha_1, \dots, \alpha_{i-1}, \alpha_{i+1}, \dots, \alpha_m}_{\substack{\text{const}}})$

3

SVM

We have constrain  $\sum \alpha_i y^i = 0$

$\alpha_1, \alpha_2$

$$\sum \alpha_i y^i = 0$$

$$\alpha_1 y^1 + \alpha_2 y^2 + \alpha_3 y^3 + \dots + \alpha_m y^m = 0$$

$$\alpha_1 y^1 + \alpha_2 y^2 = -(\alpha_3 y^3 + \dots + \alpha_m y^m)$$

$$= -\xi$$

$$\alpha_1 y^1 = +y^1 \left( -\xi - \alpha_2 y^2 \right)$$

$$\textcircled{a} \alpha_2^2 + \textcircled{b} \alpha_2 + \textcircled{c} = 0$$



$$ax^2 + by + c = 0 \quad \text{A}$$

$$x = \frac{-b \pm \dots}{\dots}$$

$$= \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$\angle \alpha > 0$$

