

# L24: Linear Classifiers

Classification, Loss functions

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FoDA

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# Classification

Input

$$(X, y) \in \mathbb{R}^d \times \{-1, +1\}$$

$$(x_i, y_i)$$

$x_i \in \mathbb{R}^d$   
stats

label

$$y \in \{-1, +1\}$$

win / lose

bug / not  
bug

Goal on new data  $x \in \mathbb{R}^d$

predict  $h(x) \rightarrow \{-1, +1\}$

$$h(x) = \text{sign}(g(x))$$

$$g(x) \in \mathbb{R}$$

$$-1 \quad \text{if} \quad g(x) \leq 0$$

$$+1 \quad \text{if} \quad g(x) > 0$$

Supervised Problem (data  $X$ , label  $y$ )

↳ cross-validation

# Linear Classifier

$$(x, y) \in \mathbb{R}^d \times \{-1, +1\}$$

$$g: \mathbb{R}^d \rightarrow \mathbb{R}$$

$$g(x) \Rightarrow \begin{cases} -1 & \text{if } g(x) < 0 \\ +1 & \text{if } g(x) > 0 \end{cases}$$

$$x = (x_1, x_2, \dots, x_d)$$

$\alpha = (\alpha_0, \alpha_1, \dots, \alpha_d)$   
↑ parameter

$$g_{\alpha}(x) = \alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_d x_d + \alpha_0$$

$$= \underbrace{\langle (\alpha_1, \alpha_2, \dots, \alpha_d) \rangle, x \rangle}_{w \in \mathbb{R}^d} + \underbrace{\alpha_0}_{b \in \mathbb{R}}$$

$$g_{\alpha=(w,b)}(x) = \langle w, x \rangle + b$$

$$\|w\| = 1$$

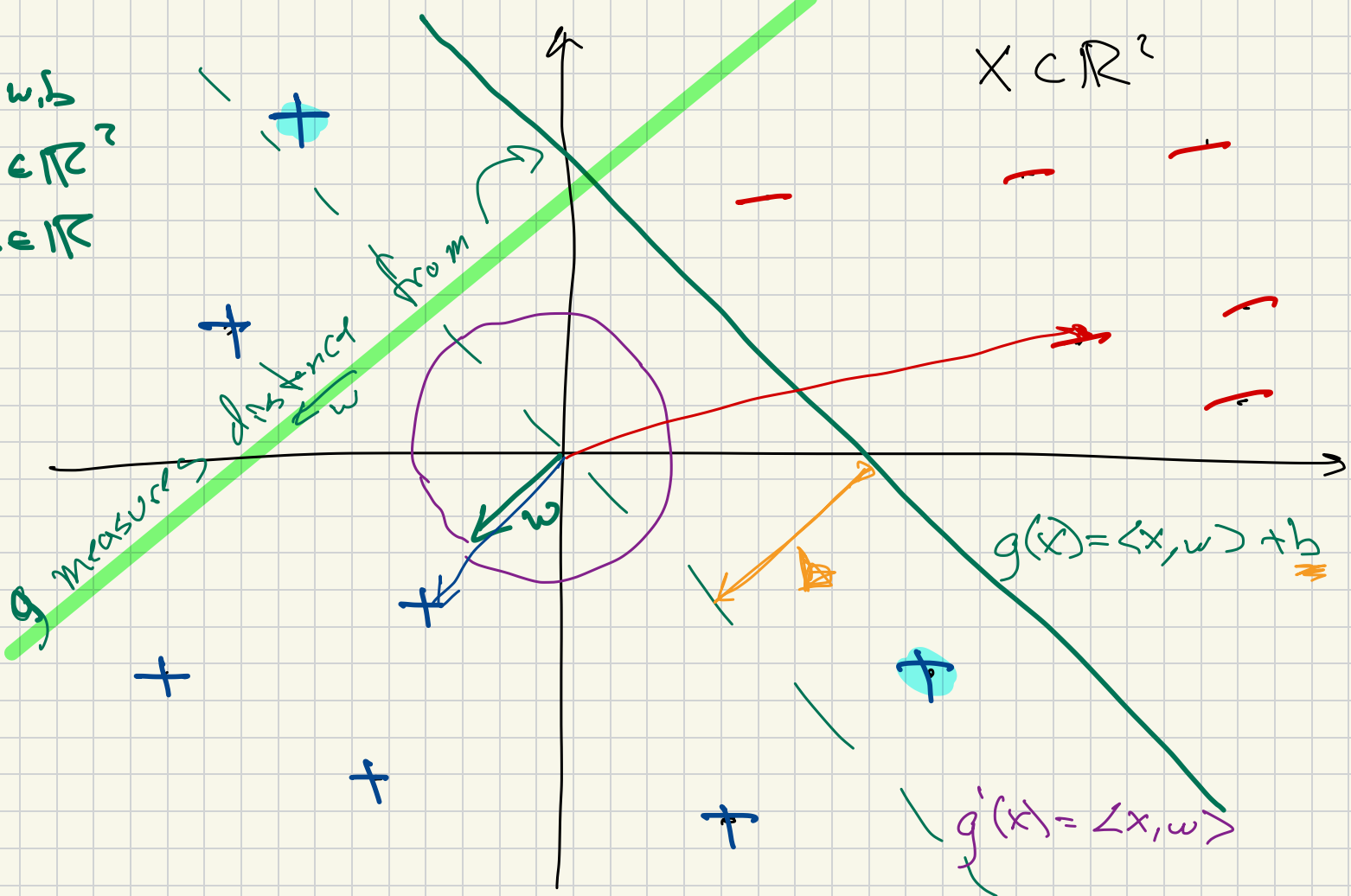
$$b \in \mathbb{R}$$

$$\Rightarrow \langle \alpha, (1; x) \rangle$$

$$\alpha, (1; x) \in \mathbb{R}^{d+1}$$

$g, w, b$   
 $w \in \mathbb{R}^2$   
 $b \in \mathbb{R}$

$X \subset \mathbb{R}^2$



distance from

$g$  measuring

$$g(x) = \langle x, w \rangle + b$$

$$g'(x) = \langle x, w \rangle$$

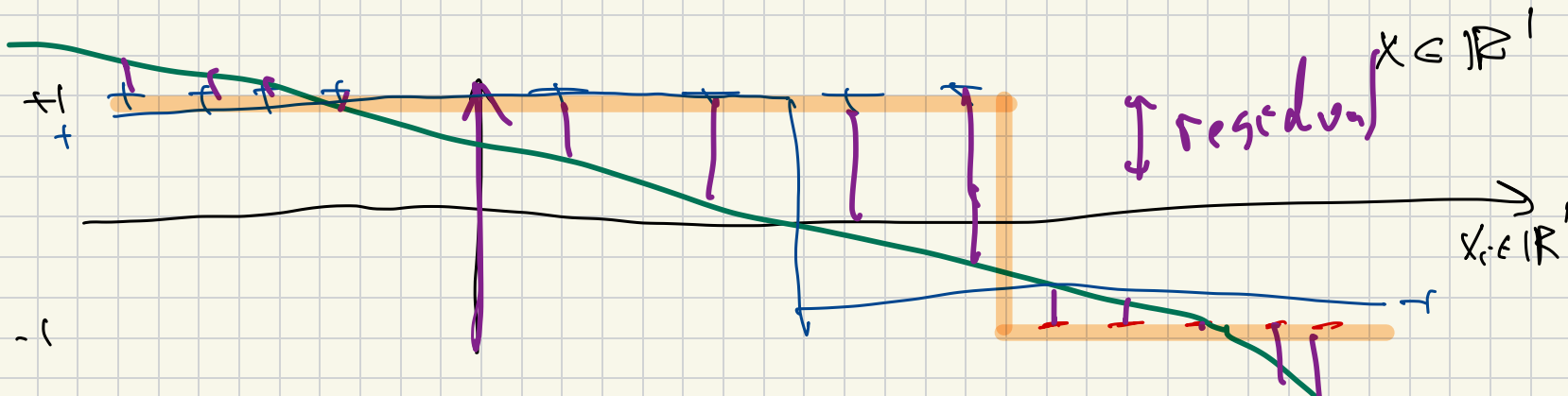
How do we formulate "best"  $g_{w,b}$

? sum of squared errors?

$$f_{X,Y}(x) = \sum_{x_i \in X} (g_x(x_i) - y_i)^2$$

not right  
option

$$h(x) = \text{sign}(g(x))$$



Goal: Minimize # misclassified points.

$$\Delta(g_{\alpha}, (x, y)) = \sum_{i=1}^n \left( 1 - \mathbb{1}(\text{sign}(y_i) = \text{sign}(g(x_i))) \right)$$

Run GD of  $\Delta(\alpha)$

$\mathbb{1}$  indicator

- compute gradient  $\nabla \Delta(\alpha)$   
↳ always 0, undefined

$\mathbb{1}$ : True  $\Rightarrow$  1  
False  $\Rightarrow$  0

- convex? No

Loss Function : convex approximation of  $\Delta$

$$f(\alpha) = \mathcal{L}(g_\alpha, (x, y)) = \sum_{i=1}^n \ell(\underbrace{g_\alpha, (x_i, y_i)}_{z_i})$$

$$z_i = y_i g_\alpha(x_i) \in \mathbb{R}$$

$$= \sum_{i=1}^n \ell_\alpha(z_i)$$

$$\text{if } z_i > 0 \Rightarrow y_i = \text{sign}(g_\alpha(x_i))$$

$$z_i < 0 \Rightarrow y_i \neq \text{sign}(g_\alpha(x_i))$$

$$= \sum_{i=1}^n \rho_i(\alpha)$$

