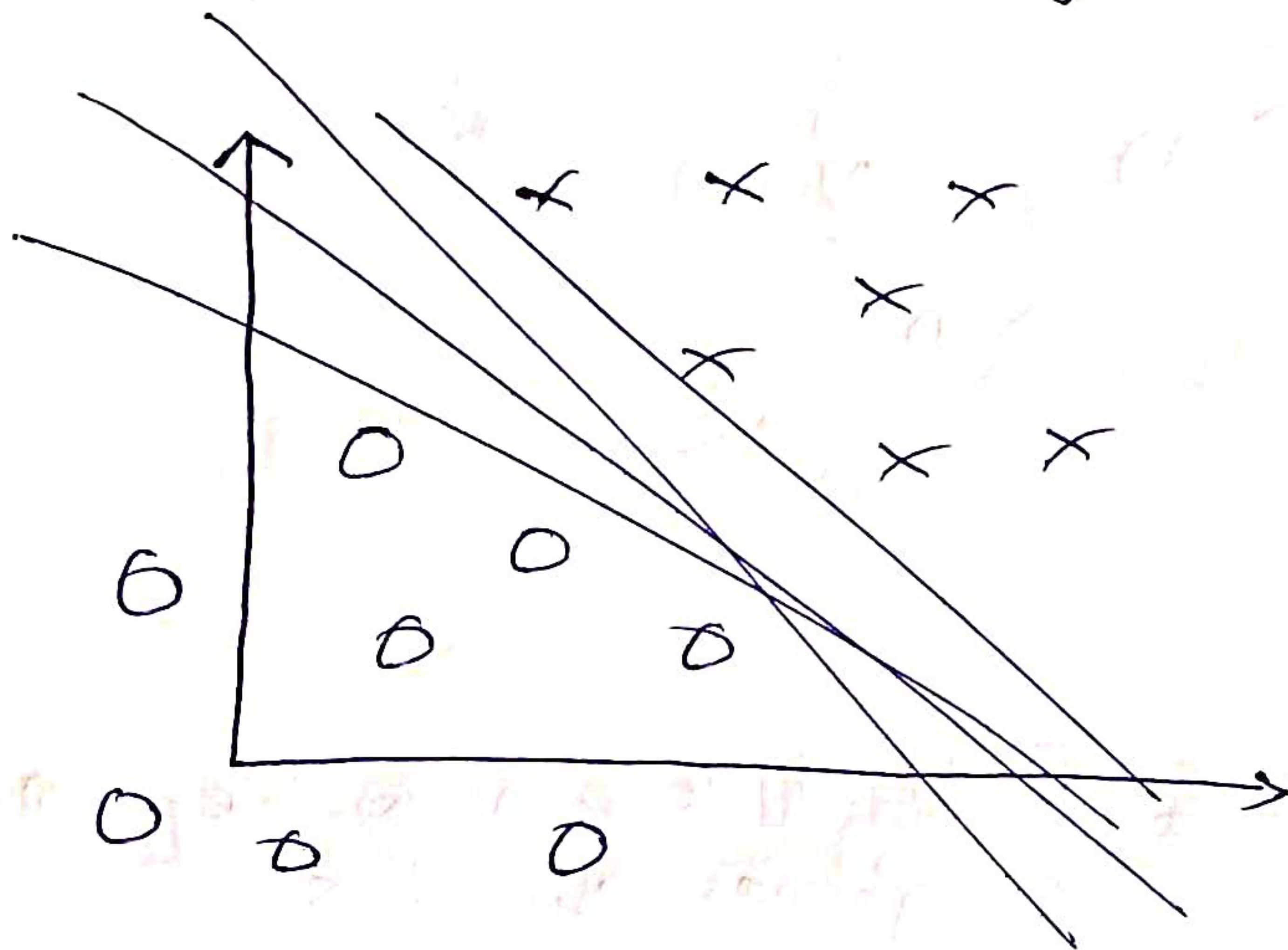


# SVM

(Support Vector Machine)



⇒ It is an algorithm for performing binary classification.

↳ We take featur. vector  $x$  map it to high dimension vect. ~~space~~.

$$x \rightarrow x^*$$

## Optimal Margin Classifier

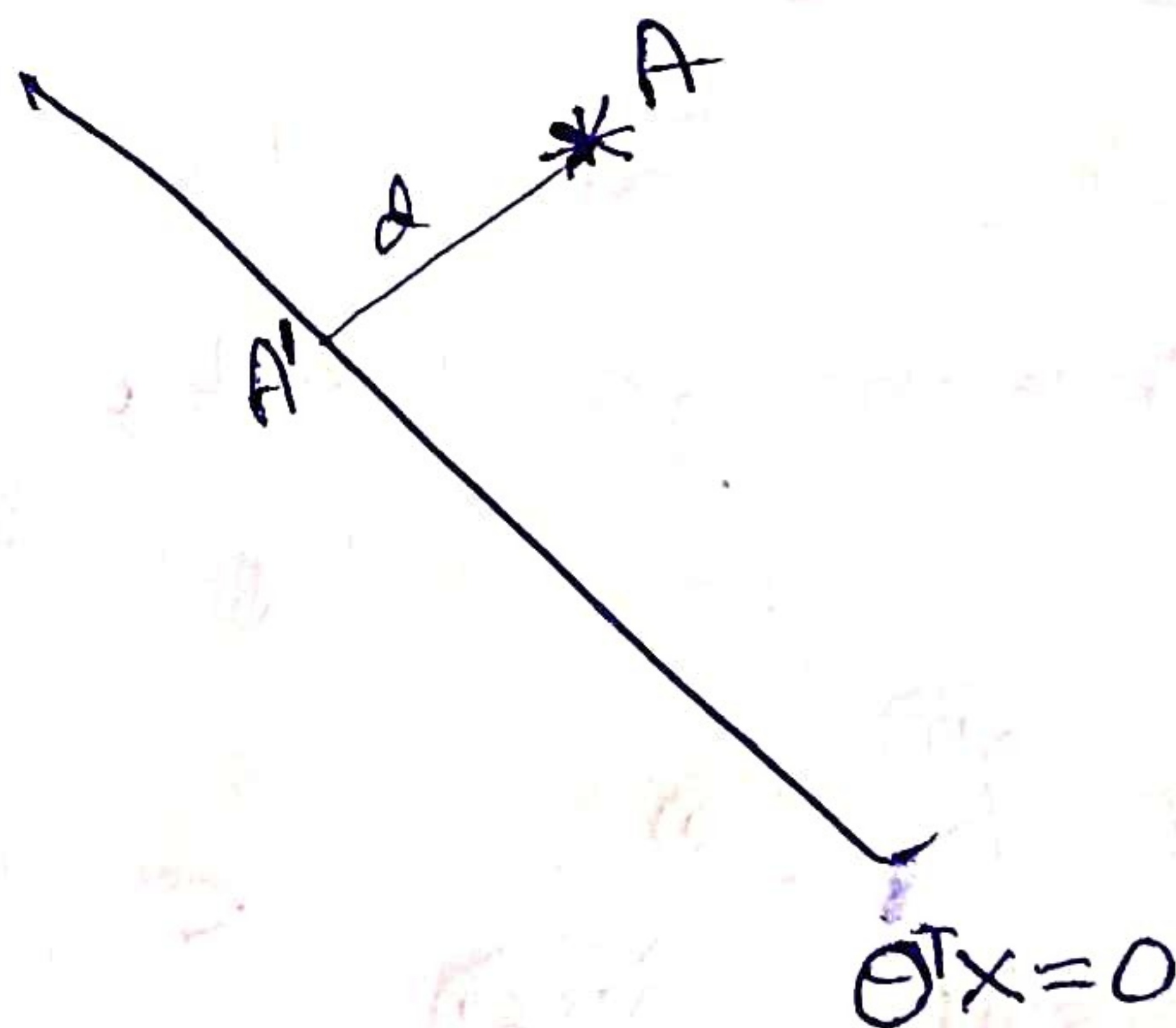
⇒ Assumption: Inputs can be separated <sup>into different classes</sup> by a linear decision boundary.

margin

→ Functional Margin  $\theta^T A$

→ Geometric Margin

$$\frac{\omega}{\|\omega\|}$$



~~scribble~~



⇒ Let  $\{ (x^{(i)}, y^{(i)}) \mid x^{(i)} \in \mathbb{R}^n, y^{(i)} \in \{-1, 1\}, i \in \{1, \dots, m\} \}$   
be the training set.

Objective: Find linear decision boundary ~~separating~~ separating  
the + and -ve examples.

Assumption: Inputs are Linearly Separable.

⇒ Let the separating hyperplane be parametrized as

$$\omega^T x + b = 0, \omega \in \mathbb{R}^n \text{ \& } b \in \mathbb{R}$$

Let us define

⇒ <sup>↑</sup> Margin for a data point  $(x^{(i)}, y^{(i)})$ :

① → Functional Margin

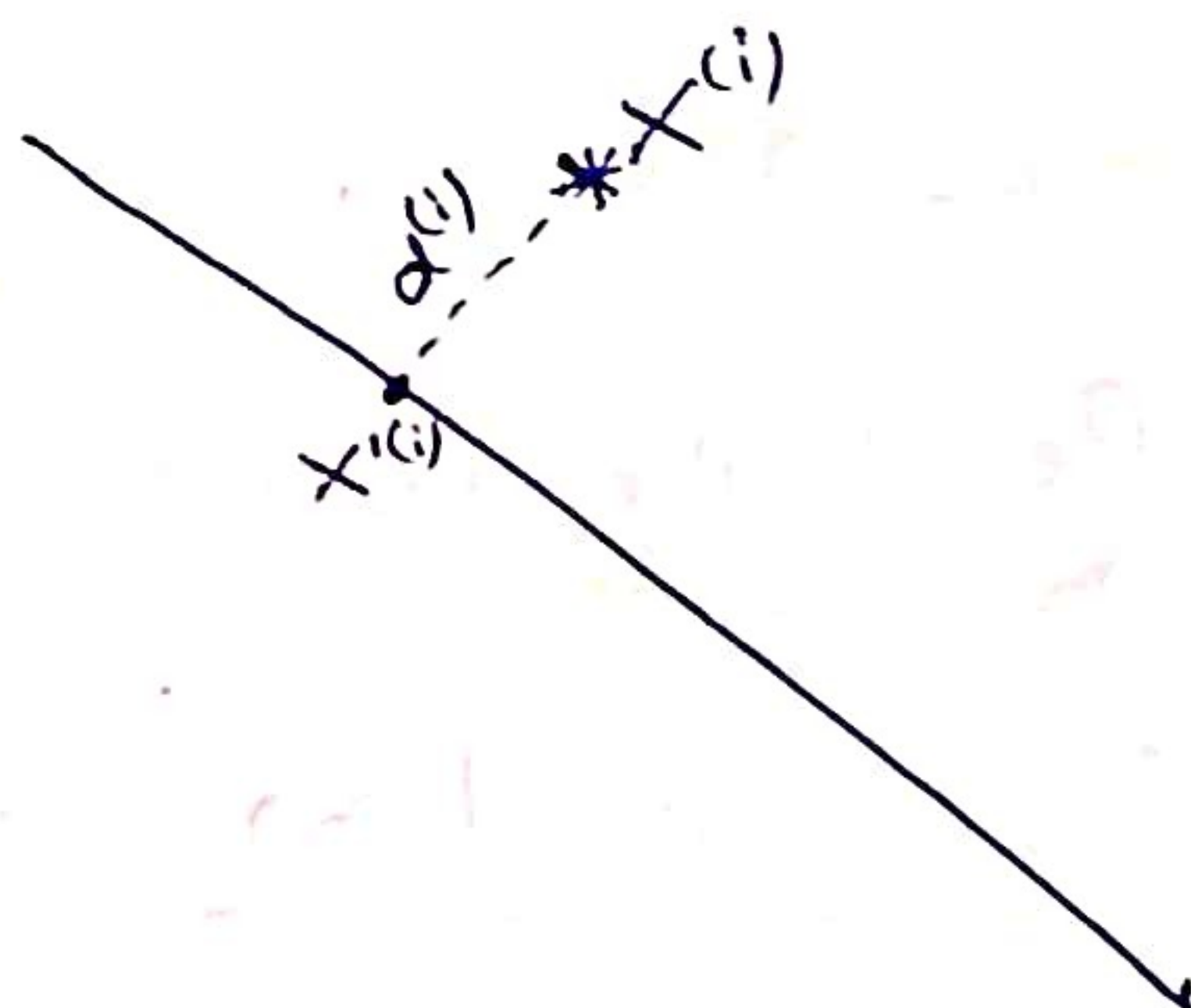
$$y^{(i)} \theta^T x^{(i)}$$

or

$$\theta = \begin{bmatrix} b \\ \omega \end{bmatrix}$$

$$y^{(i)} [\omega^T x^{(i)} + b]$$

② → Geometric Margin



Margin

→ Gives a sense of how  
far a point is from  
Separating line.  
(decision boundary)  
(No direction)

$$x'^{(i)} = x^{(i)} - d^{(i)} y^{(i)} \frac{\omega}{\|\omega\|_2}$$

$$\omega^T x'^{(i)} + b = 0$$

$$\omega^T x^{(i)} - d^{(i)} y^{(i)} \frac{\omega^T \omega}{\|\omega\|_2} + b = 0$$

$\xrightarrow{\|\omega\|_2^2}$   
 $\xrightarrow{\|\omega\|_2}$



$$d^{(i)} y^{(i)} \|w\|_2 = w^T x^{(i)} + b$$

$$\Rightarrow d^{(i)} = y^{(i)} \left( \left( \frac{w}{\|w\|_2} \right)^T x^{(i)} + \frac{b}{\|w\|_2} \right)$$

(Euclidean)

$\Rightarrow$  Geometric margin is the absolute distance<sup>↑</sup> of a data point from the decision boundary.

\* Geometric Margin of training Set

$$\min_i d^{(i)}$$

or

$$\min_i y^{(i)} \left( \left( \frac{w}{\|w\|_2} \right)^T x^{(i)} + \frac{b}{\|w\|_2} \right)$$

$\Rightarrow$  Optimal margin Classifier, finds <sup>the</sup> ~~a~~ decision boundary that maximizes the geometric margin.

$\Rightarrow$  The above can be formulated as the <sup>following</sup> ~~an~~ optimization Problem: -

$$\max_{w, b} \min_i y^{(i)} \left( \frac{w^T x^{(i)} + b}{\|w\|_2} \right) \quad \forall i = \{1, \dots, m\}$$

$$\begin{array}{ll} \max & \gamma \\ w, b, \gamma & \\ \text{st} & \frac{y^{(i)} (w^T x^{(i)} + b)}{\|w\|_2} \geq \gamma \quad \forall i = \{1, \dots, m\} \end{array}$$