香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

COMP 5212
Machine Learning
Lecture 5

Support Vector Machine

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Recap: Kernel Trick

$$\theta = \sum_{i=1}^{n} \beta_i \phi(x^{(i)}) \qquad \beta_i \in R$$

Recap: Kernel Trick

parameter → feature map

$$\theta = \sum_{i=1}^{n} \beta_i \phi(x^{(i)}) \qquad \beta_i \in R$$

$$\beta_i := \beta_i + \alpha \left(y^{(i)} - \sum_{j=1}^{n} \beta_j \phi(x^{(j)})^T \phi(x^{(i)}) \right)$$

Recap: Kernel Trick

$$\theta = \sum_{i=1}^{n} \beta_i \phi(x^{(i)}) \qquad \beta_i \in R$$

$\langle \phi(x), \phi(z) \rangle$

$$\beta_i := \beta_i + \alpha \left(y^{(i)} - \sum_{j=1}^{n} \beta_j \phi(x^{(j)})^T \phi(x^{(i)}) \right)$$

Kernel $K(x, z) \quad \mathcal{X} \times \mathcal{X} \to \mathbb{R} \quad \mathcal{X}$ is the space of the input

$$K(x, z) \triangleq \langle \phi(x), \phi(z) \rangle$$

Recap: Kernel Trick

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- Compute $K(\phi(x^{(i)}), \phi(x^{(j)})) = < \phi(x^{(i)}), \phi(x^{(j)}) >$ for all i, j

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- Compute $K(\phi(x^{(i)}), \phi(x^{(j)})) = < \phi(x^{(i)}), \phi(x^{(j)}) >$ for all i, j
- Loop $$\beta_i := \beta_i + \alpha \left(y^{(i)} - \sum_{j=1}^{n} \beta_j K(x^{(i)}, x^{(j)}) \right) \quad \forall i \in \{1, \ldots, n\}$$

$\theta^T \phi(x)$

$O(p)$

Recap: Kernel Trick

- Compute $K(\phi(x^{(i)}), \phi(x^{(j)})) = < \phi(x^{(i)}), \phi(x^{(j)}) >$ for all i, j
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Recall that n is the number of data samples

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Recall that n is the number of data samples

- Inference: $$\theta^T \phi(x) = \sum_{i=1}^{n} \beta_i \phi(x^{(i)})^T \phi(x) = \sum_{i=1}^{n} \beta_i K(x^{(i)}, x)$$

Recap: Kernel Trick

- Compute $K(\phi(x^{(i)}), \phi(x^{(j)})) = < \phi(x^{(i)}), \phi(x^{(j)}) >$ for all i, j
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The Kernel function is all we need for training and inference!

Recap: Implicit Feature Map

- Explicit Feature Map: first define feature map $\phi(x)$, then compute the Kernel according to $\phi(x)$

- Implicit Feature Map: first define the Kernel Function K(), without knowing what the feature map is

Recap: Implicit Feature Map (Example)

$$K(x, z) = (x^T z)^2 \qquad x, z \in \mathbb{R}^d$$

Recap: Implicit Feature Map (Example)

$$K(x, z) = (x^T z)^2 \qquad x, z \in \mathbb{R}^d$$

What is the feature map to make K a valid kernel function?

Recap: Implicit Feature Map (Example)

$\phi(x)^T \phi(z)$

$$K(x, z) = (x^T z)^2 \qquad x, z \in \mathbb{R}^d$$

What is the feature map to make K a valid kernel function?

$$\begin{aligned} K(x,z) &= \left(\sum_{i=1}^{d} x_i z_i\right)\left(\sum_{j=1}^{d} x_j z_j\right) \\ &= \sum_{i=1}^{d}\sum_{j=1}^{d} x_i x_j z_i z_j \\ &= \sum_{i,j=1}^{d} (x_i x_j)(z_i z_j) \end{aligned}$$

Recap: Implicit Feature Map (Example)

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$$\phi(x) = \begin{bmatrix} x_1 x_1 \\ x_1 x_2 \\ x_1 x_3 \\ x_2 x_1 \\ x_2 x_2 \\ x_2 x_3 \\ x_3 x_1 \\ x_3 x_2 \\ x_3 x_3 \end{bmatrix}$$

Recap: Implicit Feature Map (Example)

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$$\phi(x) = \begin{bmatrix} x_1x_1 \\ x_1x_2 \\ x_1x_3 \\ x_2x_1 \\ x_2x_2 \\ x_2x_3 \\ x_3x_1 \\ x_3x_2 \\ x_3x_3 \end{bmatrix}$$

Requires O(d^2) compute for feature mapping

Recap: Implicit Feature Map (Example)

$$K(x, z) = (x^T z)^2 \qquad x, z \in \mathbb{R}^d$$

What is the feature map to make K a valid kernel function?

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$$\phi(x) = \begin{bmatrix} x_1x_1 \\ x_1x_2 \\ x_1x_3 \\ x_2x_1 \\ x_2x_2 \\ x_2x_3 \\ x_3x_1 \\ x_3x_2 \\ x_3x_3 \end{bmatrix}$$

Requires O(d^2) compute for feature mapping

Requires O(d) compute for Kernel function

What Makes a Valid Kernel Function: Necessary Condition

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- Kernel Matrix $K_{ij} = K(x^{(i)}, x^{(j)}) = \phi(x^{(i)})^T \phi(x^{(j)})$

What Makes a Valid Kernel Function: Necessary Condition

- Kernel Matrix $K_{ij} = K(x^{(i)}, x^{(j)}) = \phi(x^{(i)})^T \phi(x^{(j)})$

- K is symmetric

$$K(x, z) = K(z, x)$$

What Makes a Valid Kernel Function: Necessary Condition

- Kernel Matrix $K_{ij} = K(x^{(i)}, x^{(j)}) = \phi(x^{(i)})^T \phi(x^{(j)})$

- K is symmetric

$$
\begin{aligned}
z^T K z &= \sum_i \sum_j z_i K_{ij} z_j \\
&= \sum_i \sum_j z_i \phi(x^{(i)})^T \phi(x^{(j)}) z_j \\
&= \sum_i \sum_j z_i \sum_k \phi_k(x^{(i)}) \phi_k(x^{(j)}) z_j \\
&= \sum_k \sum_i \sum_j z_i \phi_k(x^{(i)}) \phi_k(x^{(j)}) z_j \\
&= \sum_k \left(\sum_i z_i \phi_k(x^{(i)}) \right)^2 \\
&\geq 0.
\end{aligned}
$$

What Makes a Valid Kernel Function: Necessary Condition

- Kernel Matrix $K_{ij} = K(x^{(i)}, x^{(j)}) = \phi(x^{(i)})^T \phi(x^{(j)})$

- K is symmetric

- K is positive semidefinite

$$
\begin{aligned}
z^T K z &= \sum_i \sum_j z_i K_{ij} z_j \\
&= \sum_i \sum_j z_i \phi(x^{(i)})^T \phi(x^{(j)}) z_j \\
&= \sum_i \sum_j z_i \sum_k \phi_k(x^{(i)}) \phi_k(x^{(j)}) z_j \\
&= \sum_k \sum_i \sum_j z_i \phi_k(x^{(i)}) \phi_k(x^{(j)}) z_j \\
&= \sum_k \left(\sum_i z_i \phi_k(x^{(i)}) \right)^2 \\
&\geq 0.
\end{aligned}
$$

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

$$z^T K z = \sum_i \sum_j z_i K_{ij} z_j$$

$$= \sum_i \sum_j z_i (x_i^T x_j)^2 z_j$$

$$\geq 0$$

What Makes a Valid Kernel Function: Necessary and Sufficient Condition

Theorem (Mercer). Let $K : \mathbb{R}^d \times \mathbb{R}^d \mapsto \mathbb{R}$ be given. Then for K to be a valid (Mercer) kernel, it is necessary and sufficient that for any $\{x^{(1)}, \ldots, x^{(n)}\}$, $(n < \infty)$, the corresponding kernel matrix is symmetric positive semi-definite.

$\langle x_i, x_j \rangle$

↑ replace

$K(x_i, x_j)$

Recap: Application of Kernel Methods

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- In generalized linear models (which we have shown)

Recap: Application of Kernel Methods

- In generalized linear models (which we have shown)
- In support vector machines (which we will show next)

Recap: Application of Kernel Methods

- In generalized linear models (which we have shown)
- In support vector machines (which we will show next)
- Any learning algorithm that you can write in terms of only $\langle x, z \rangle$

replace

$K(x, z)$

Recap: Application of Kernel Methods

- In generalized linear models (which we have shown)

- In support vector machines (which we will show next)

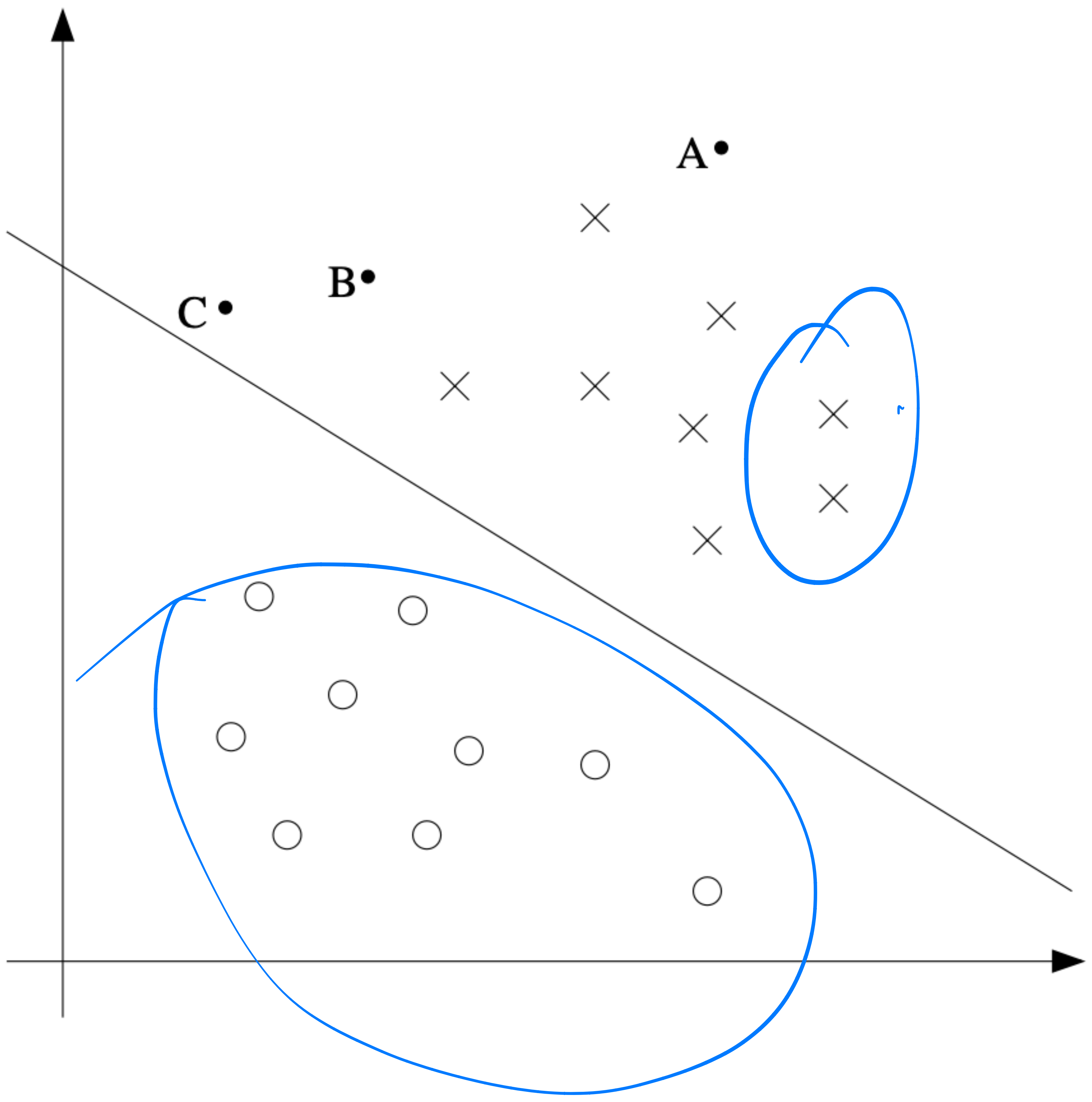
- Any learning algorithm that you can write in terms of only <x, z>

Just replace <x, z> with K(x, z), you magically transform the algorithm to work efficiently in the *implicit* high dimensional feature space

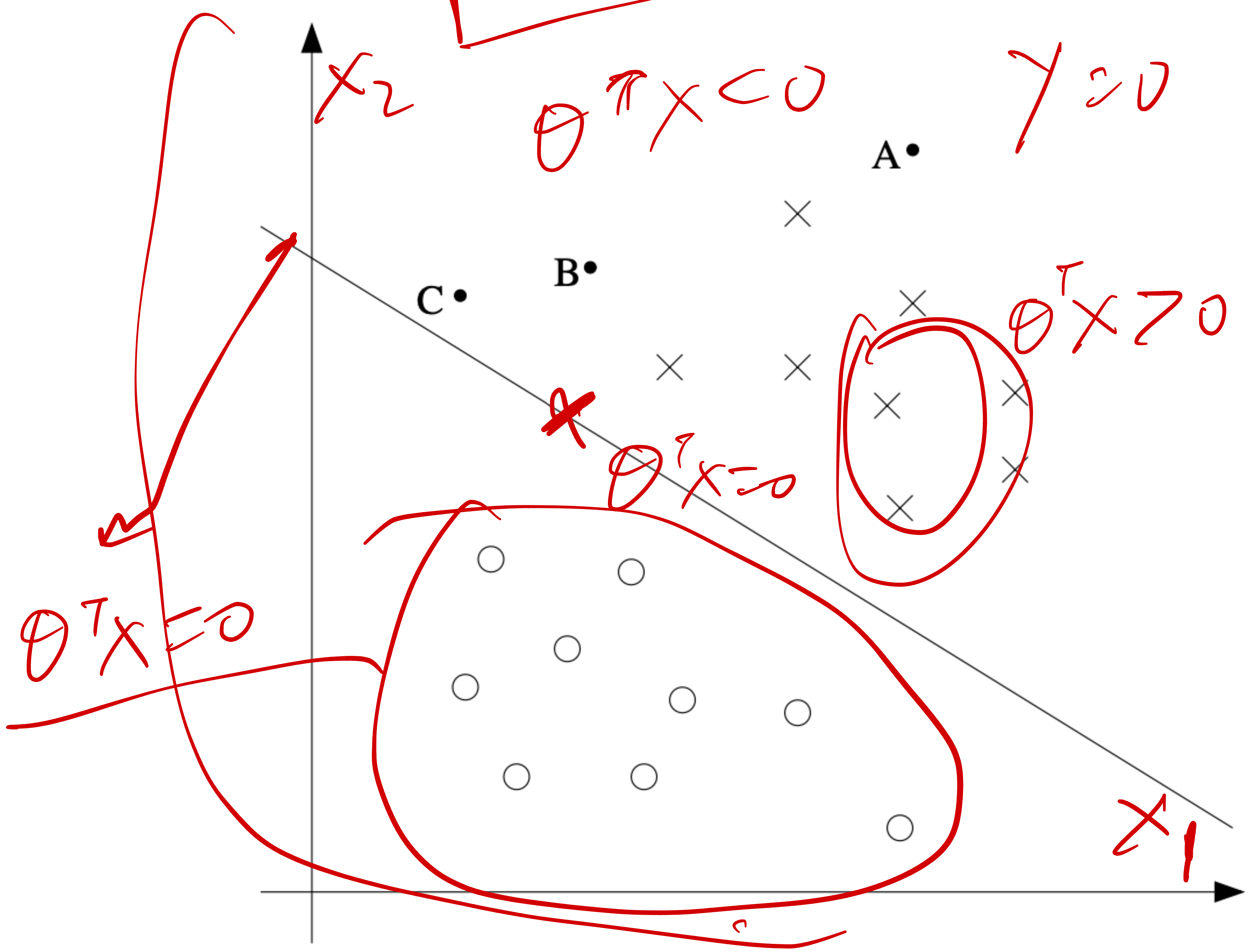
Support Vector Machines

Confidence in Logistic Regression

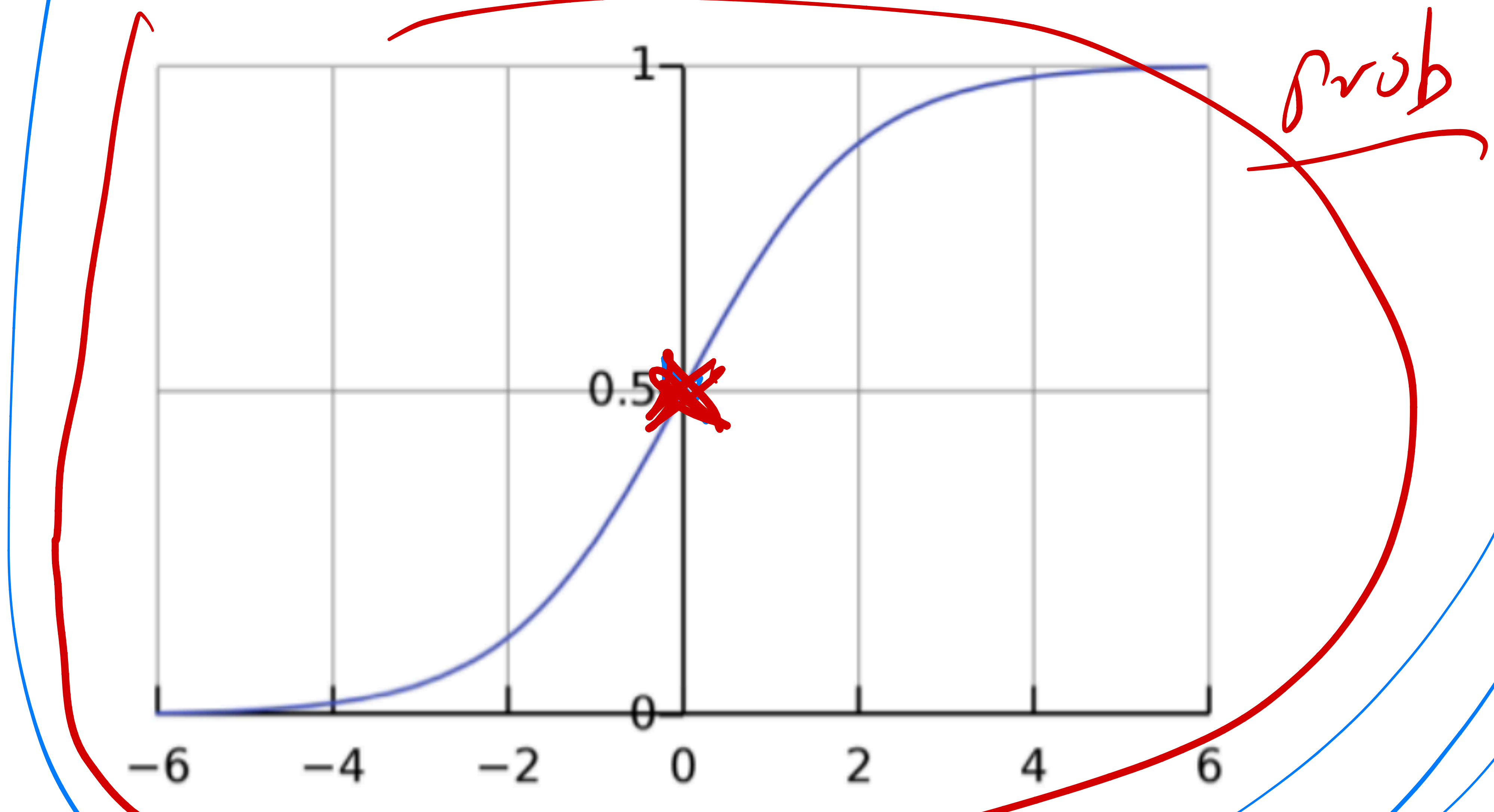
Confidence in Logistic Regression



Confidence in Logistic Regression

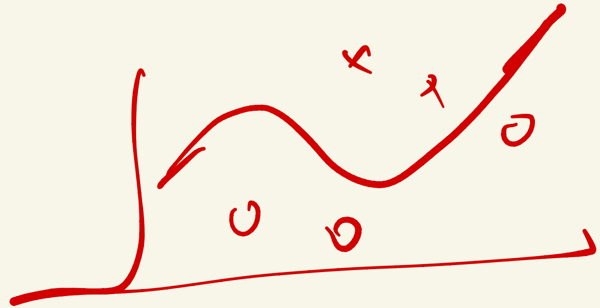


$$p(y) = \frac{1}{1 + e^{-\theta^T x}}$$



$\theta^T x \geq 0, \quad y=1$

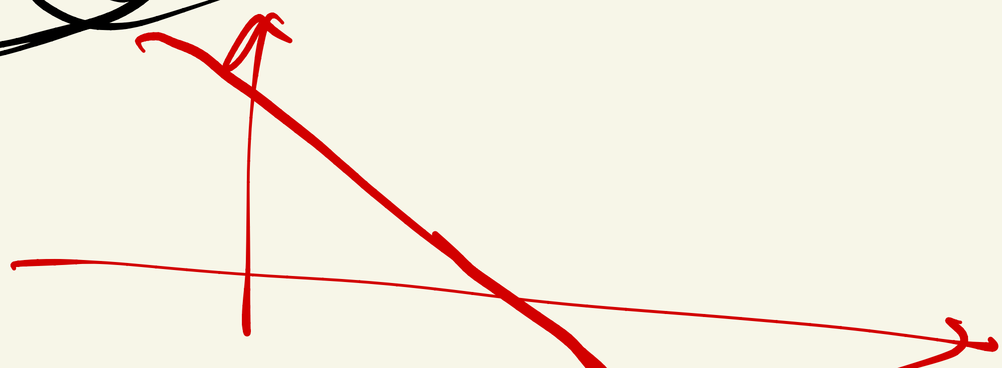
$\theta^T x < 0, \quad y=1$



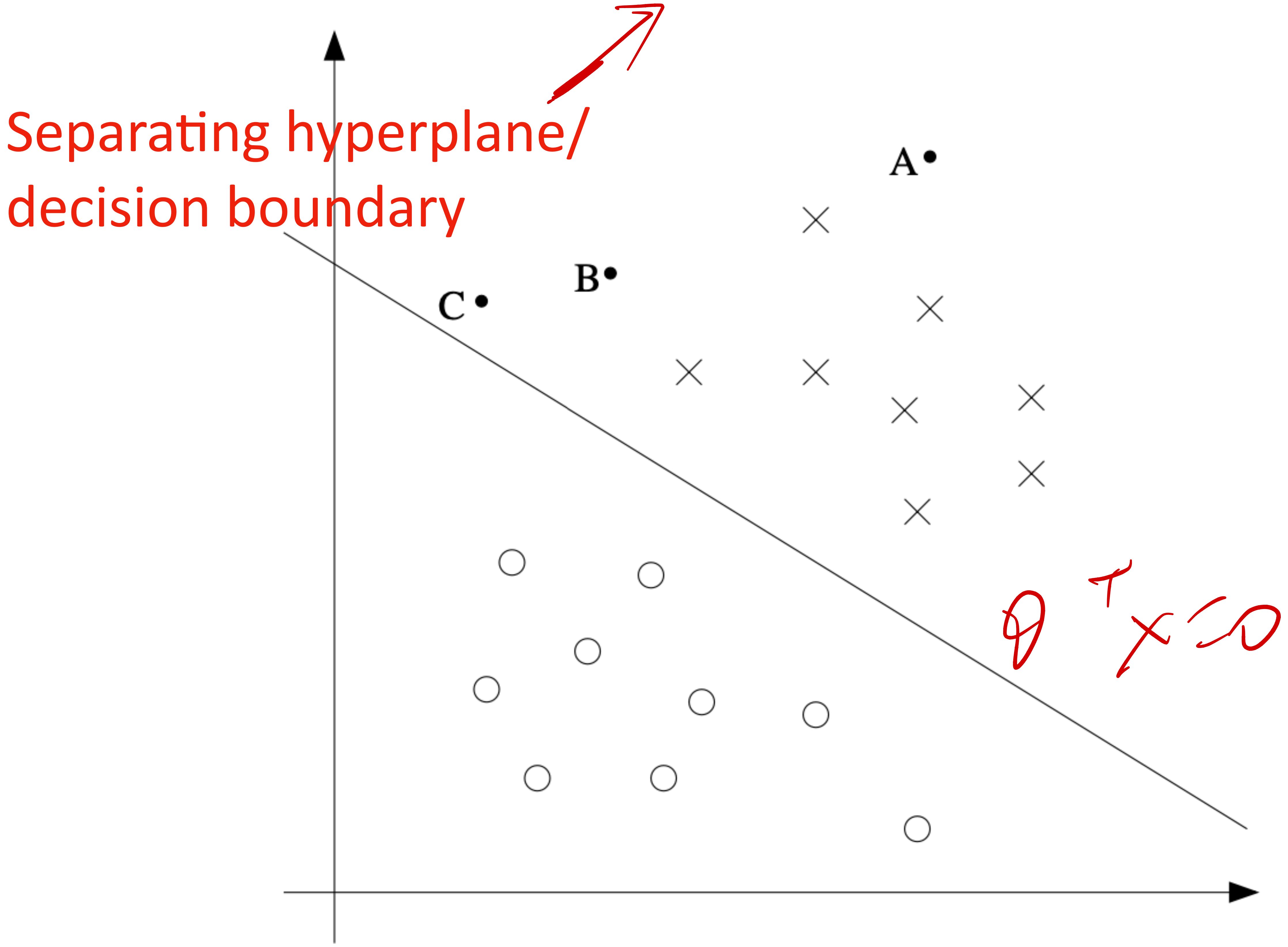
$x_0 = 1$

$\theta^T x = 0$ → linear

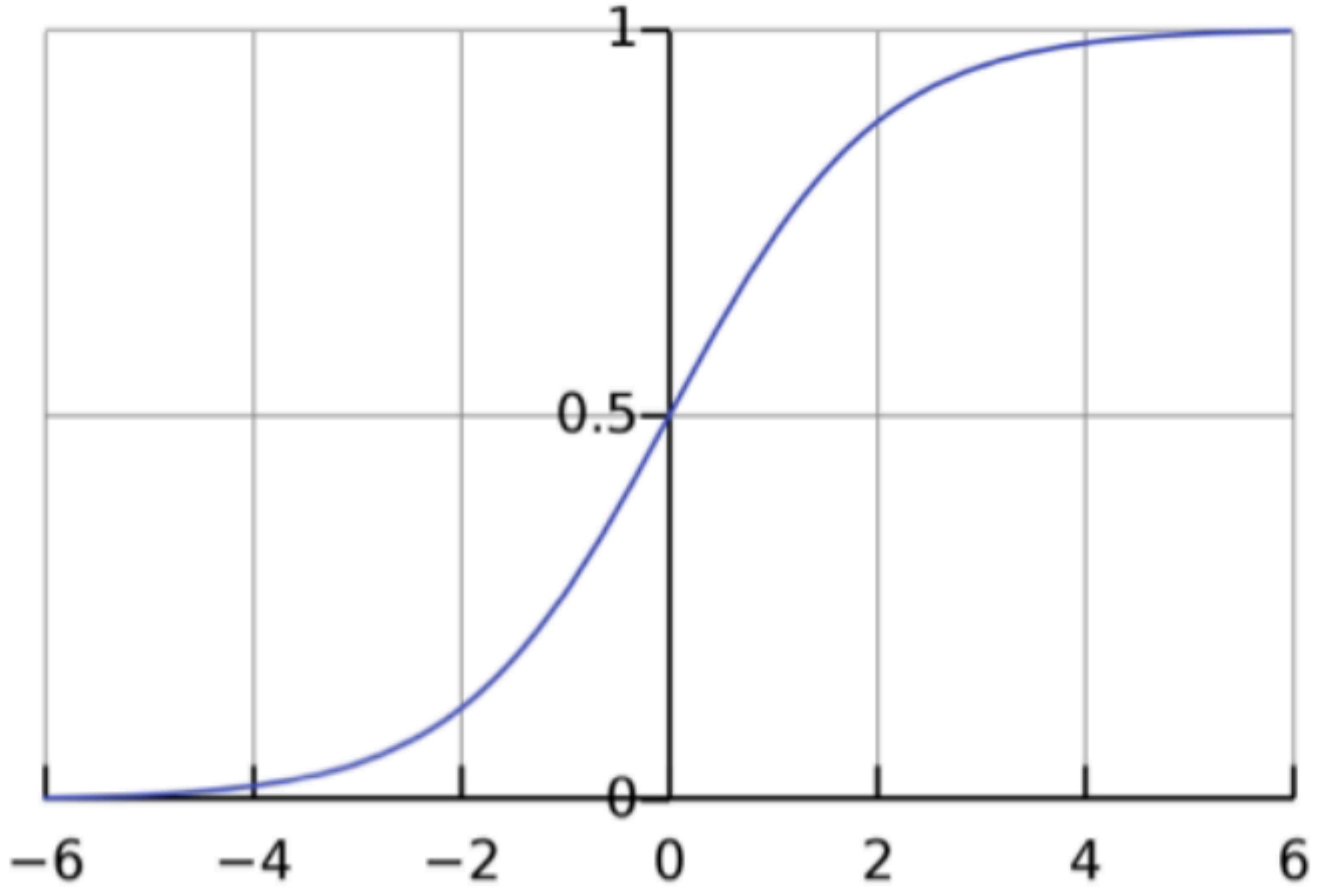
→ $\theta_1 x_1 + \theta_2 x_2 + \theta_0 = 0$



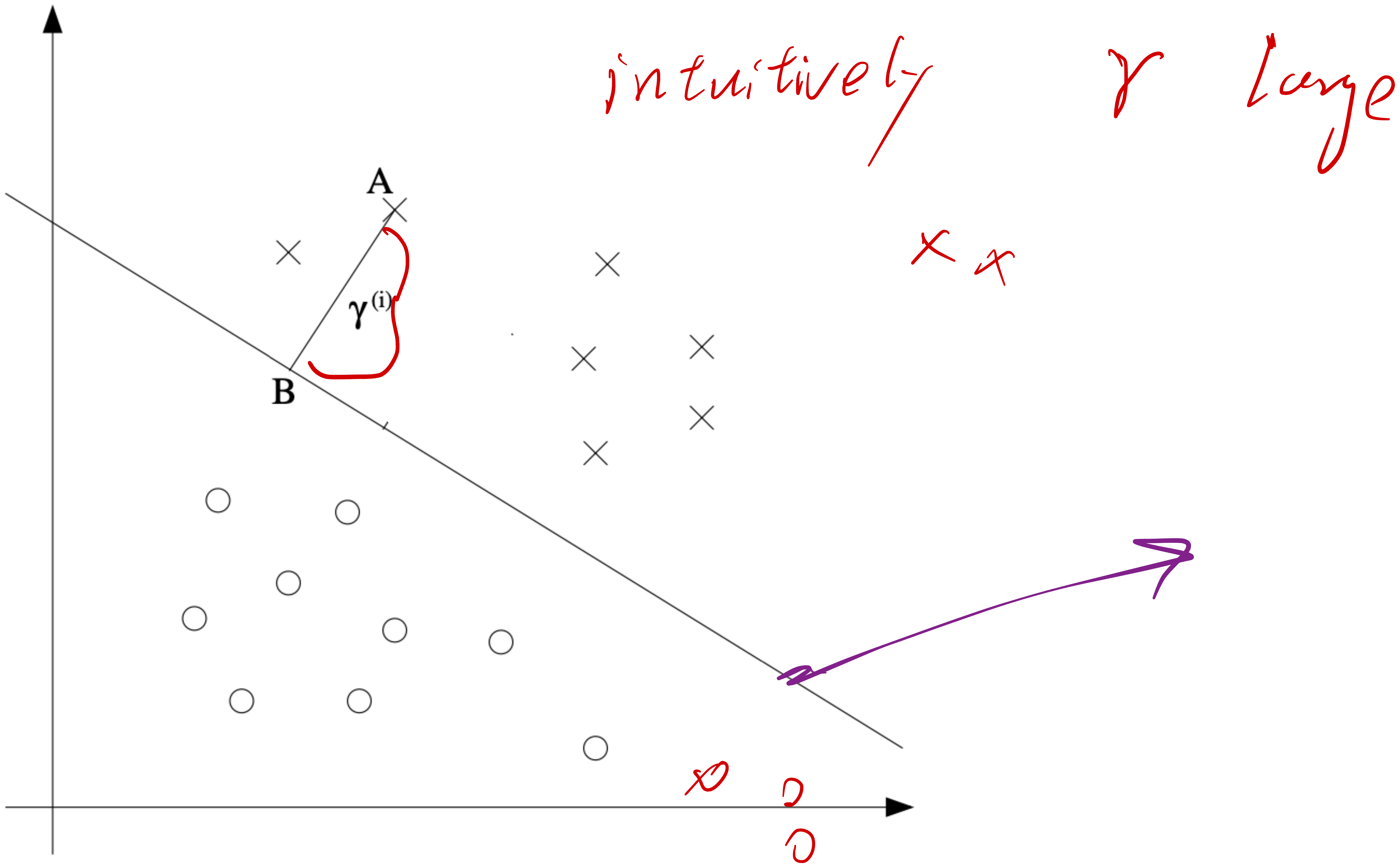
Confidence in Logistic Regression

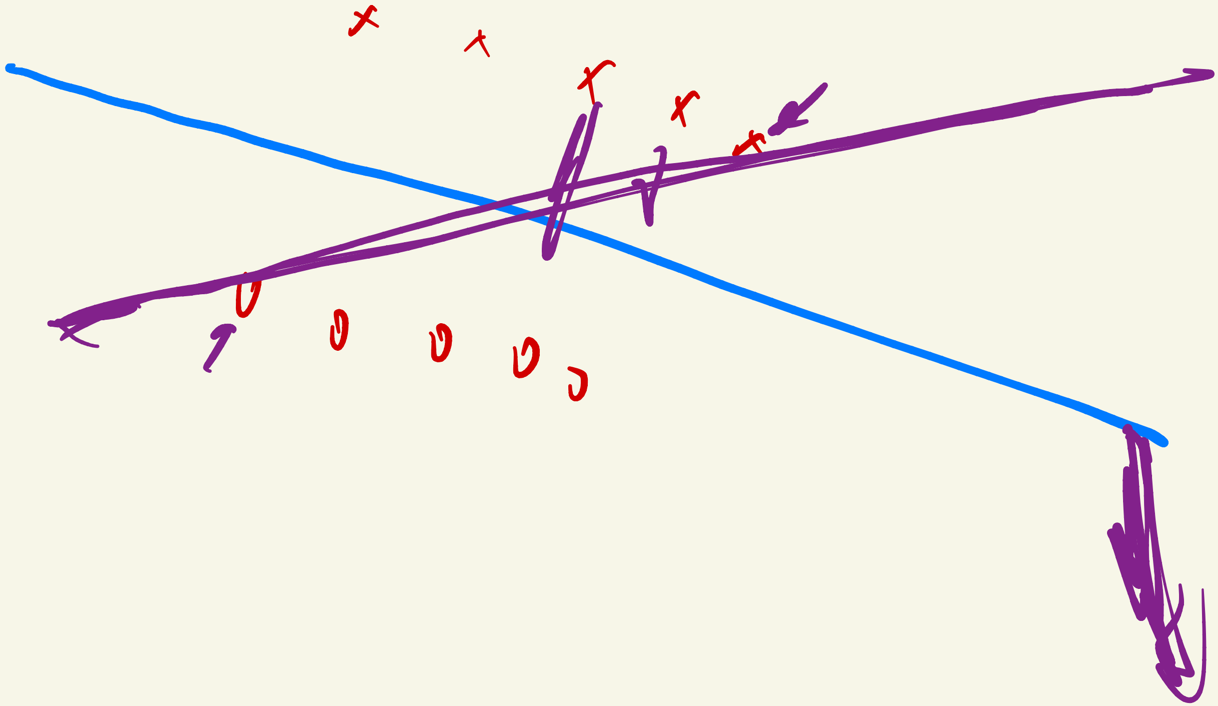


max $$p(y) = \frac{1}{1 + e^{-\theta^T x}}$$



Margin





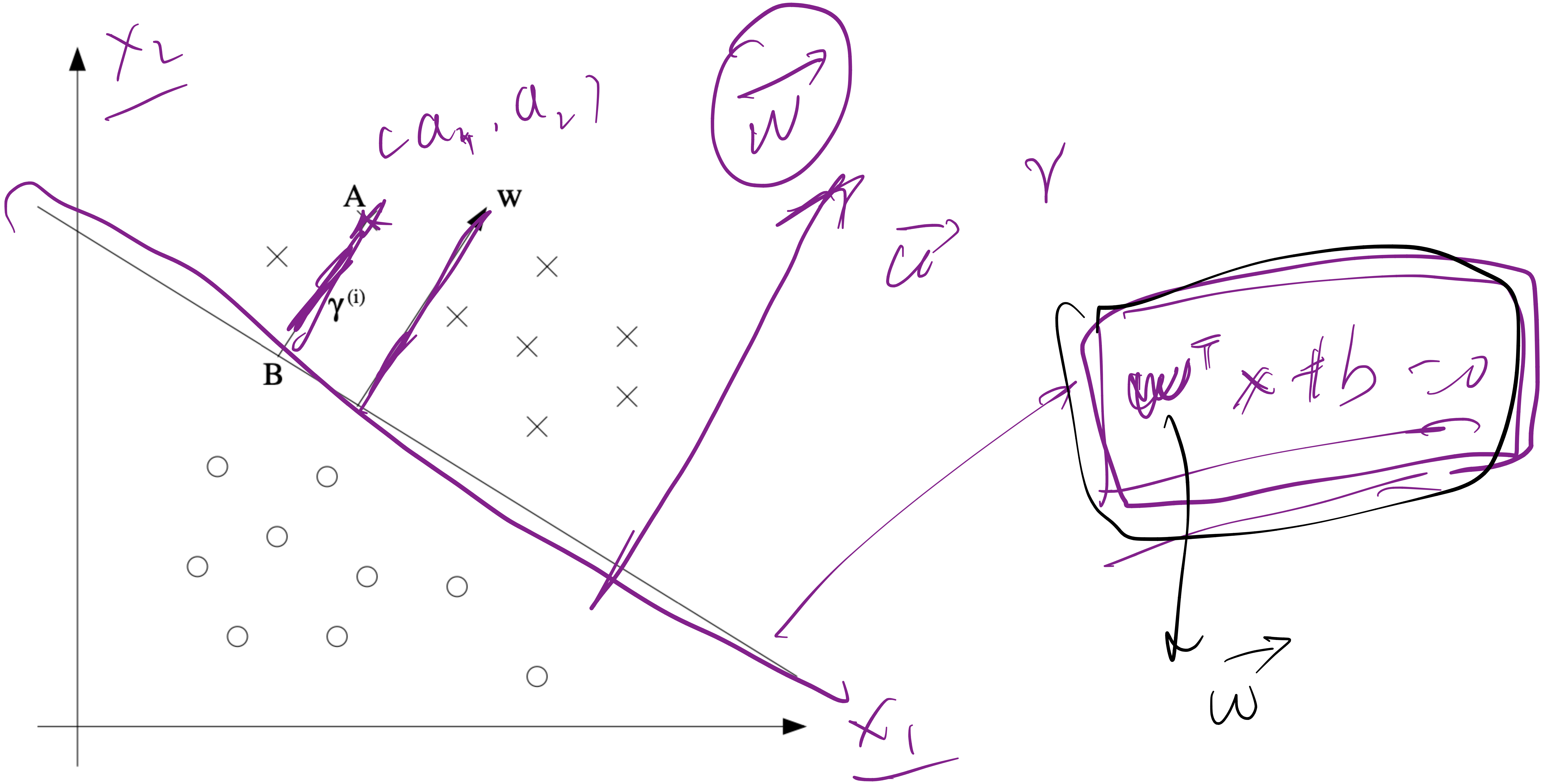
New Notations

Consider a binary classification problem, with the input feature x and $y \in \{-1, 1\}$ (instead of $\{0, 1\}$), the classifier is:

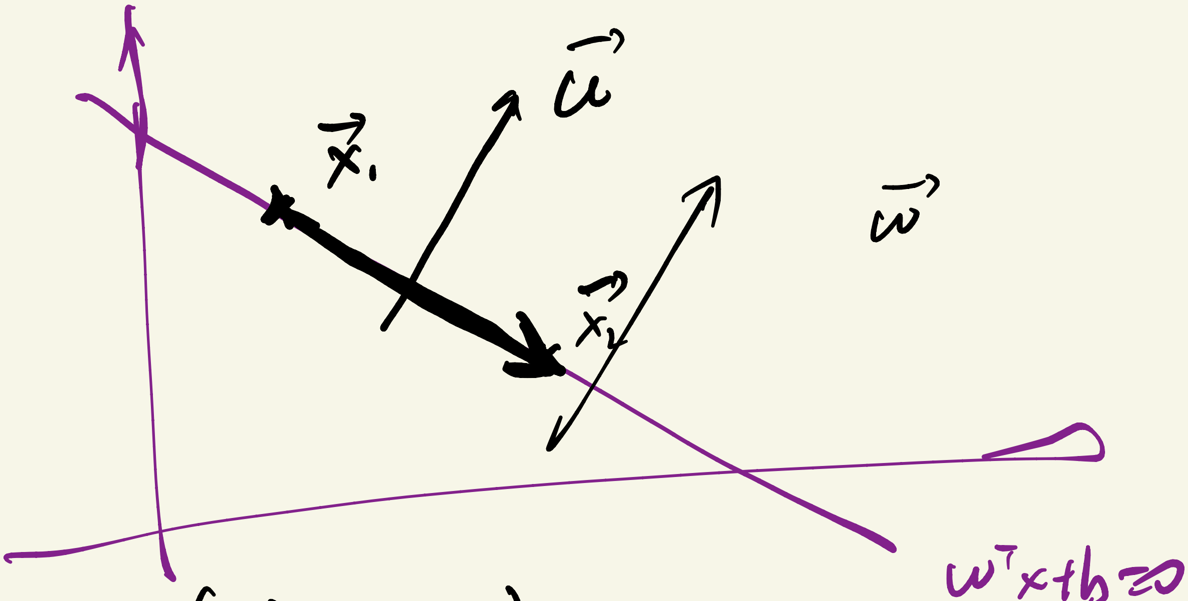
$$h_{w,b}(x) = g(w^T x + b).$$

$$g(z) = 1 \text{ if } z \geq 0, \text{ and } g(z) = -1$$

Geometric Margin



What is the geometric margin?

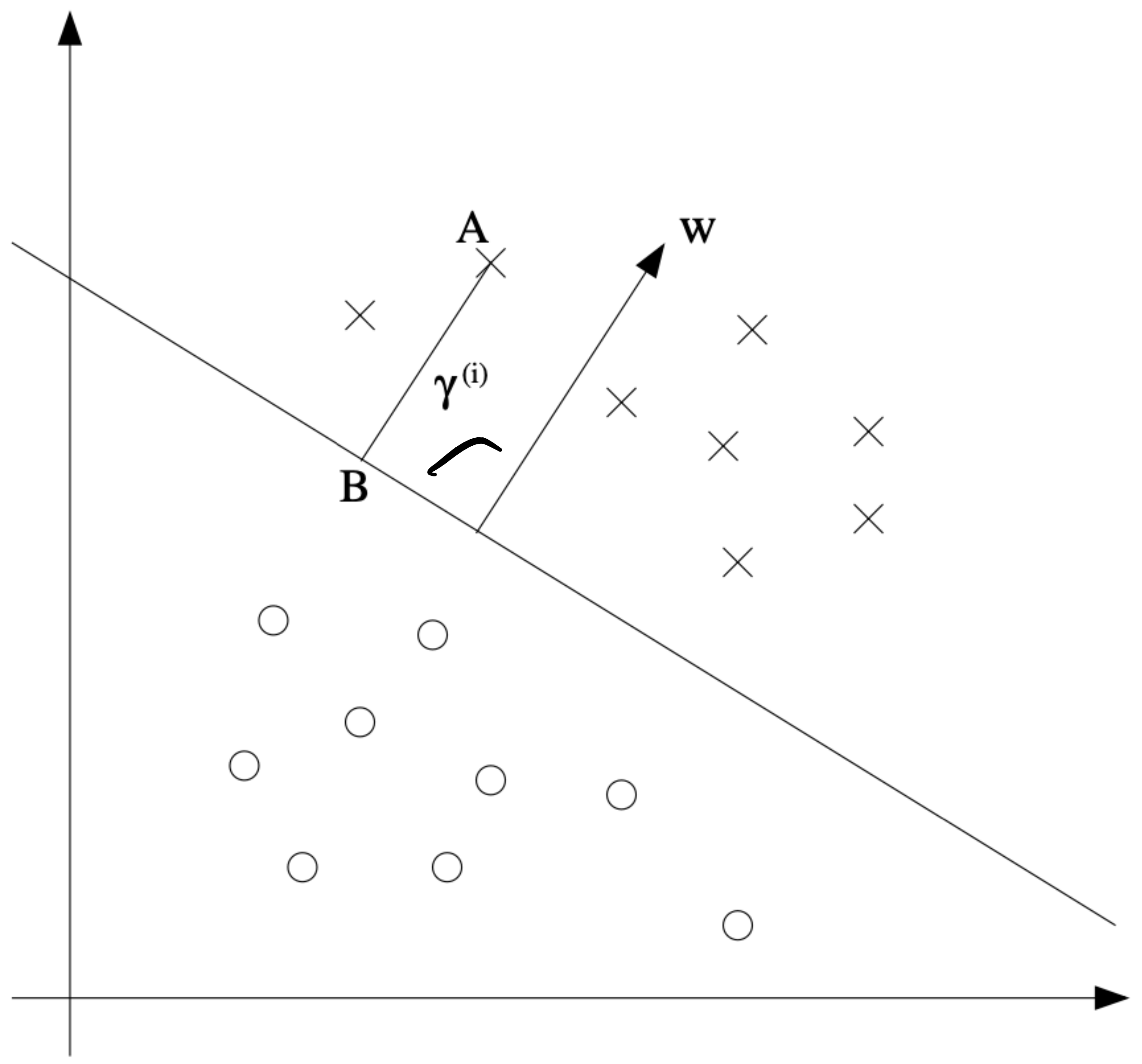


$$\vec{u} \cdot (\vec{x}_2 - \vec{x}_1) = 0$$

$$\left.\begin{array}{l} w^T \vec{x}_1 + b = 0 \\ w^T \vec{x}_2 + b = 0 \end{array}\right\} \Rightarrow w^T (\vec{x}_1 - \vec{x}_2) = 0$$

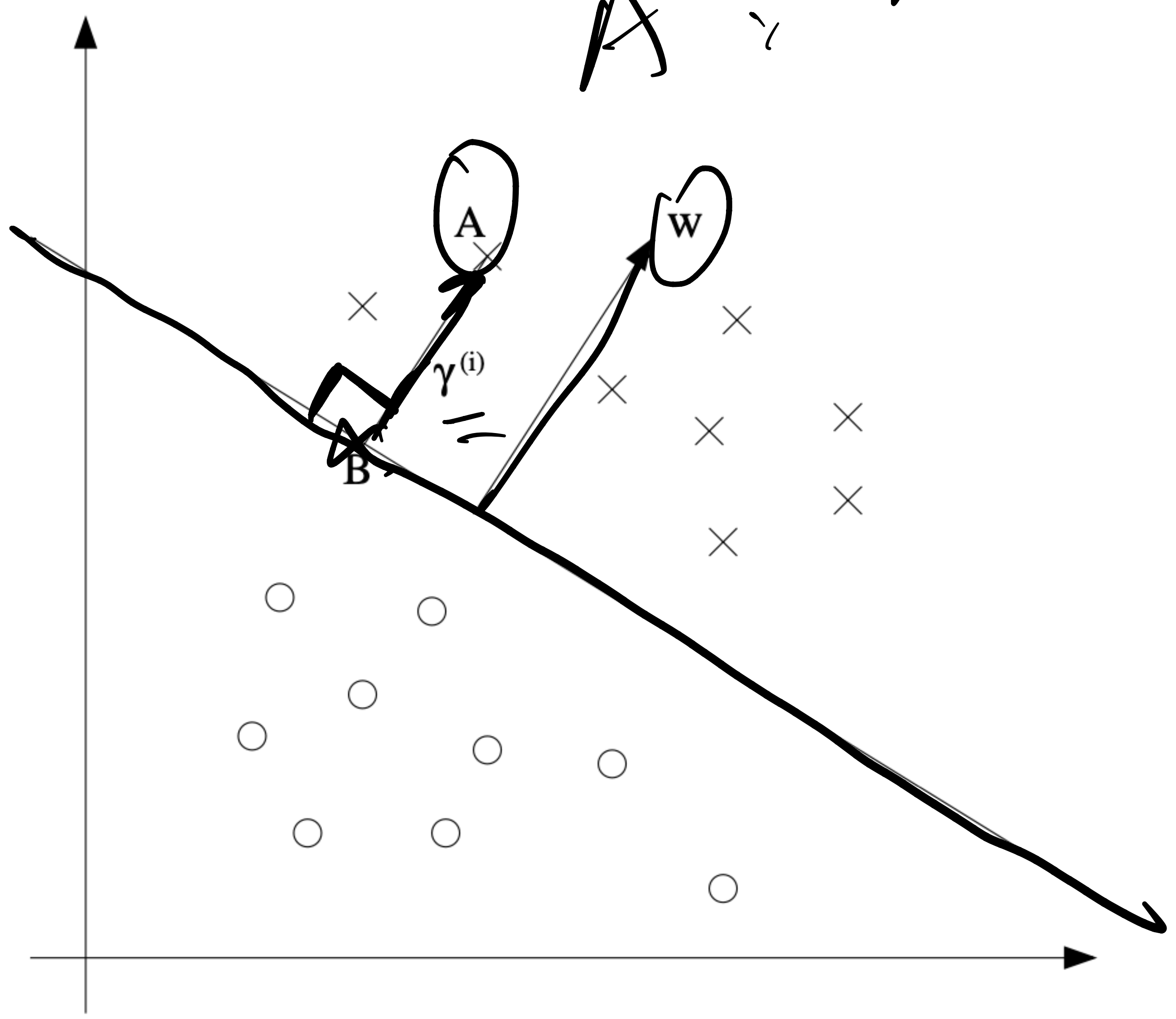
Geometric Margin

Geometric Margin



Geometric Margin

$\vec{A}$, $x^{(i)}$

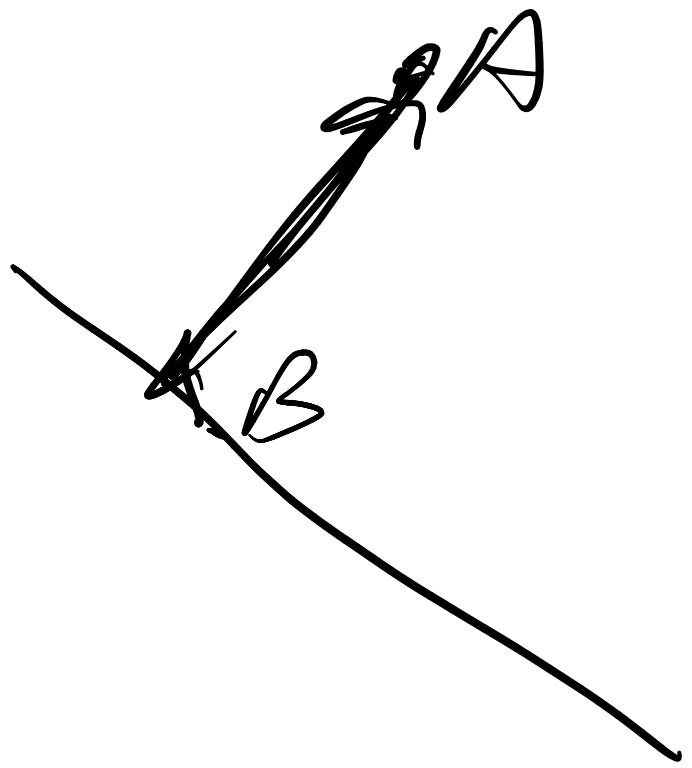


$||\vec{A} - \vec{B}||$

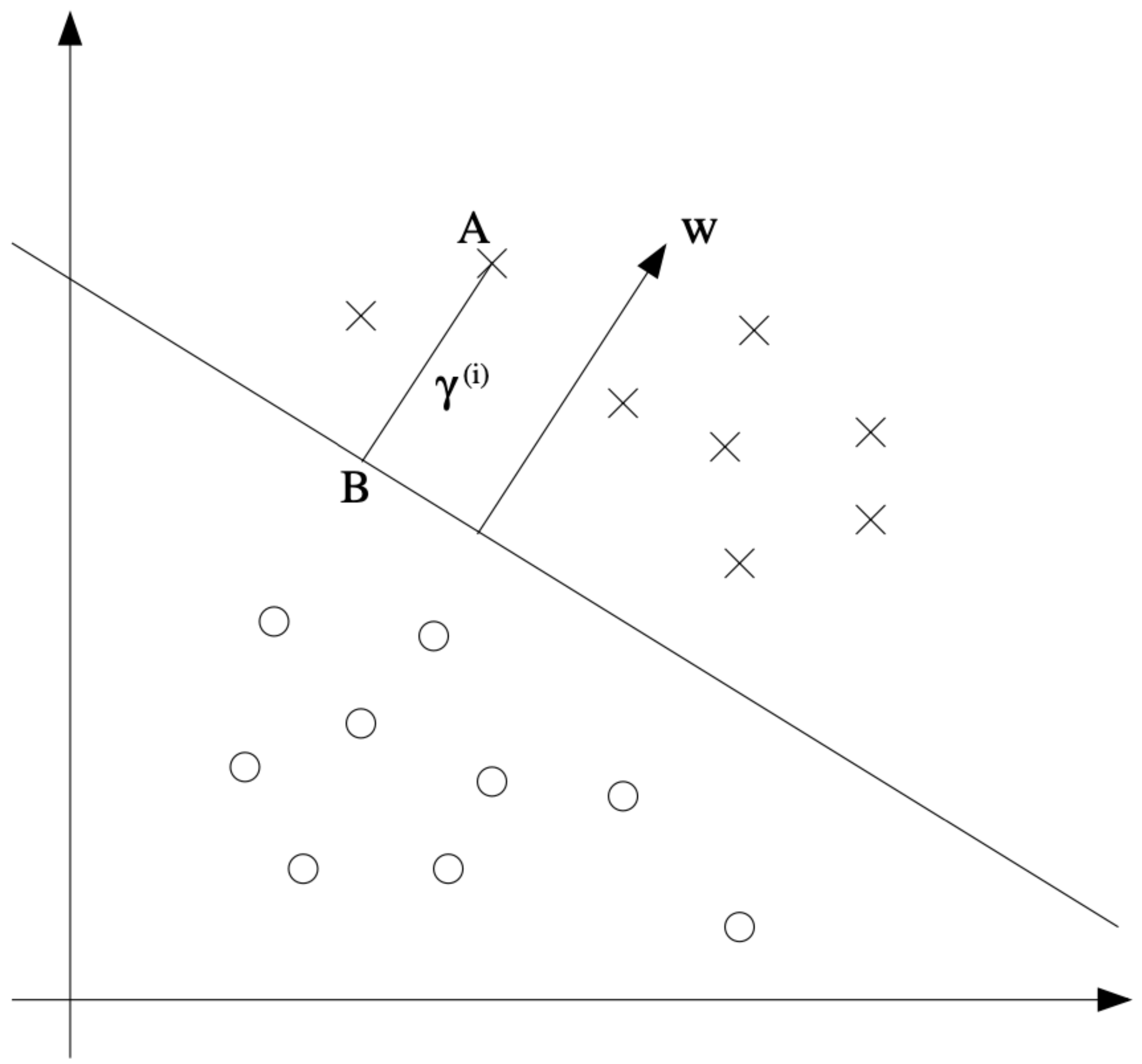
$$w^T \left(x^{(i)} - \gamma^{(i)} \frac{w}{||w||} \right) + b = 0.$$

$$\vec{B} = \vec{A} - \gamma \frac{\vec{w}}{||w||}$$

$$w^T \vec{B} + b = 0$$



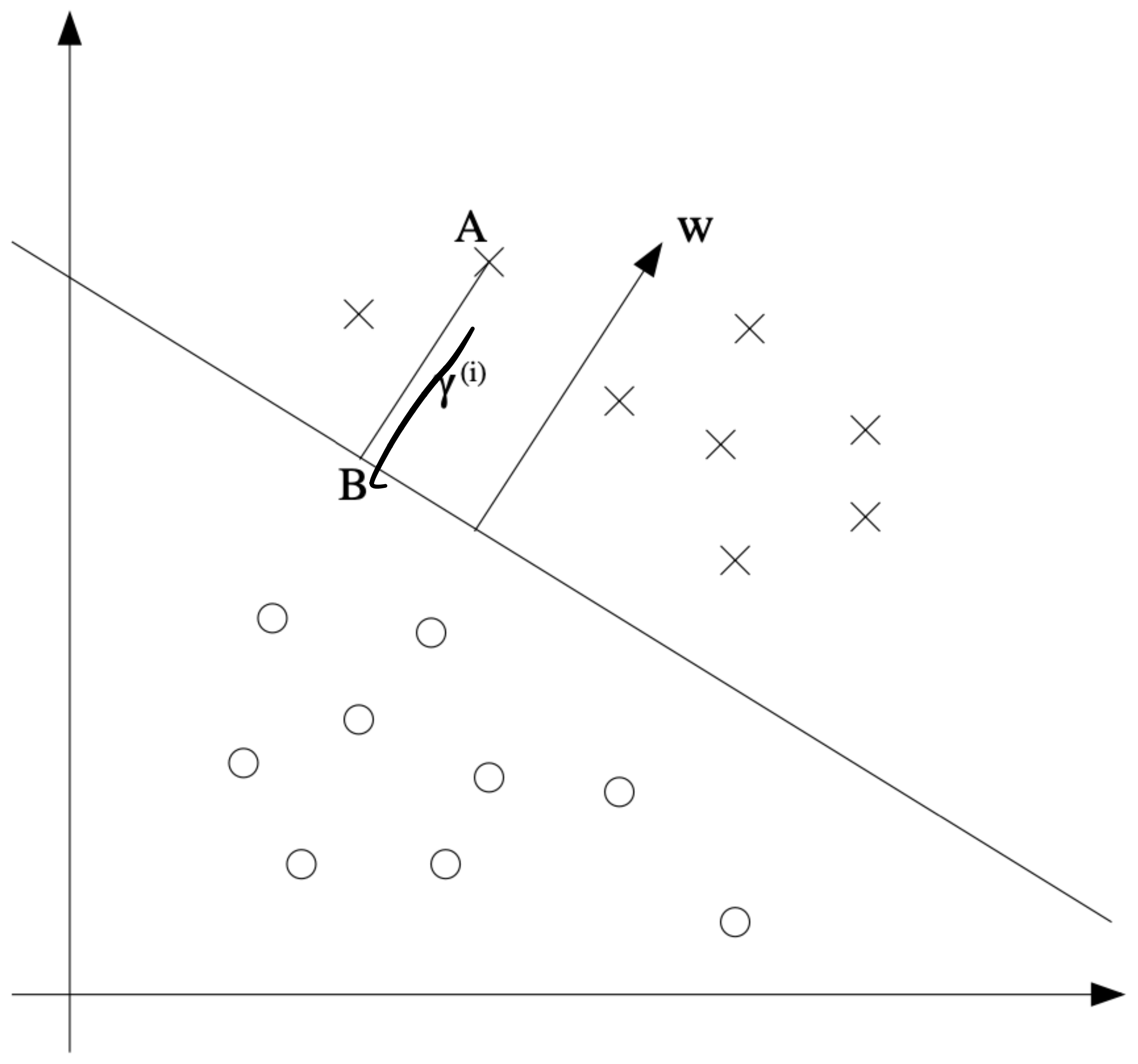
Geometric Margin



$$w^T \left(x^{(i)} - \gamma^{(i)} \frac{w}{||w||} \right) + b = 0.$$

$$\gamma^{(i)} = \frac{w^T x^{(i)} + b}{||w||} = \left(\frac{w}{||w||} \right)^T x^{(i)} + \frac{b}{||w||}$$

Geometric Margin



$$w^T \left(x^{(i)} - \gamma^{(i)} \frac{w}{||w||} \right) + b = 0.$$

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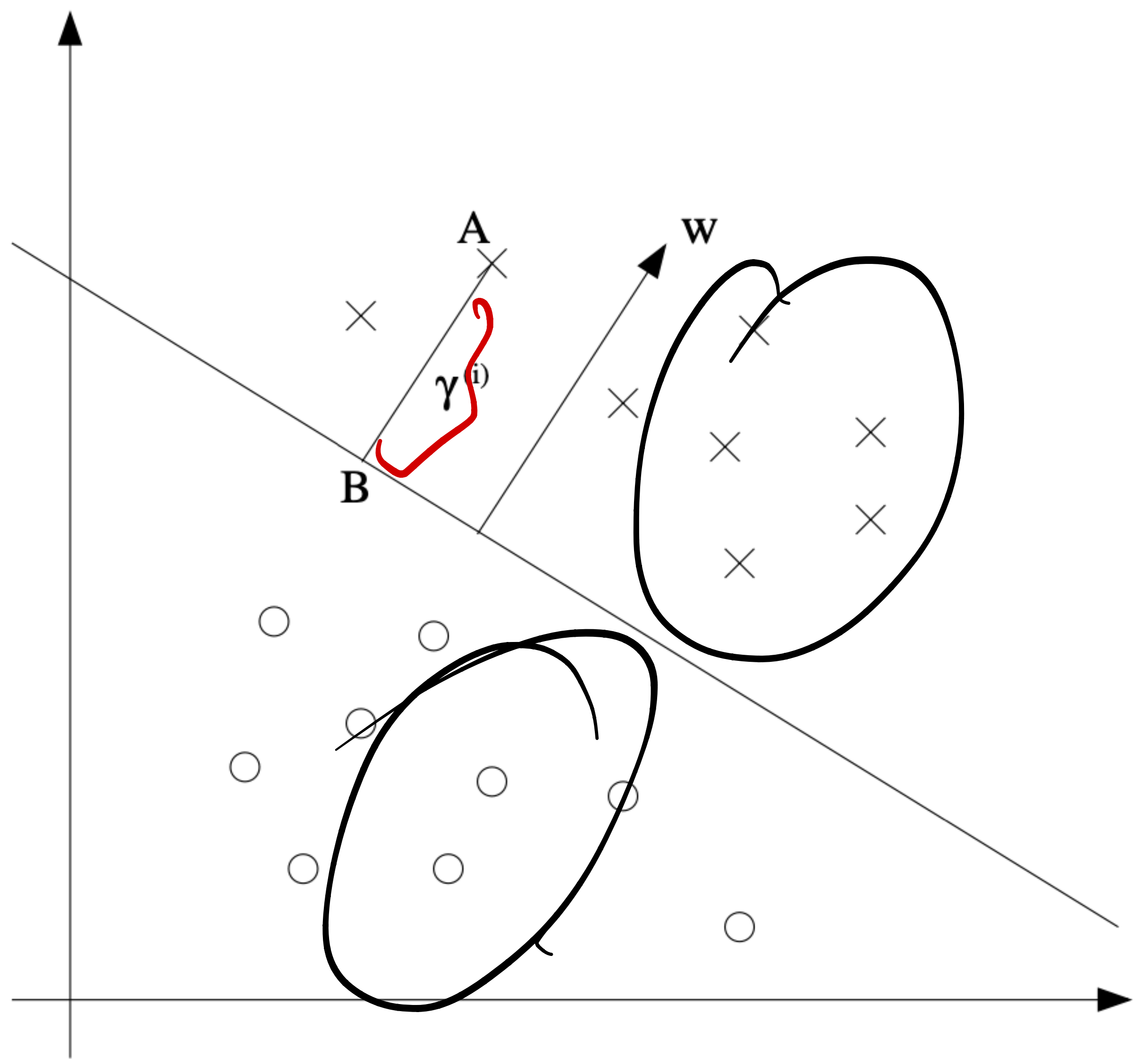
Generally

Geometric Margin



$$w^T\left(x^{(i)} - \gamma^{(i)}\frac{w}{||w||}\right) + b = 0.$$

$$\gamma^{(i)} = \frac{w^T x^{(i)} + b}{||w||} = \left(\frac{w}{||w||}\right)^T x^{(i)} + \frac{b}{||w||}$$

Generally

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

Geometric Margin

Given a training set $S = \{(x^{(i)}, y^{(i)}); i = 1,\ldots,n\}$

$$\gamma = \min_{i=1,\ldots,n} \gamma^{(i)}$$

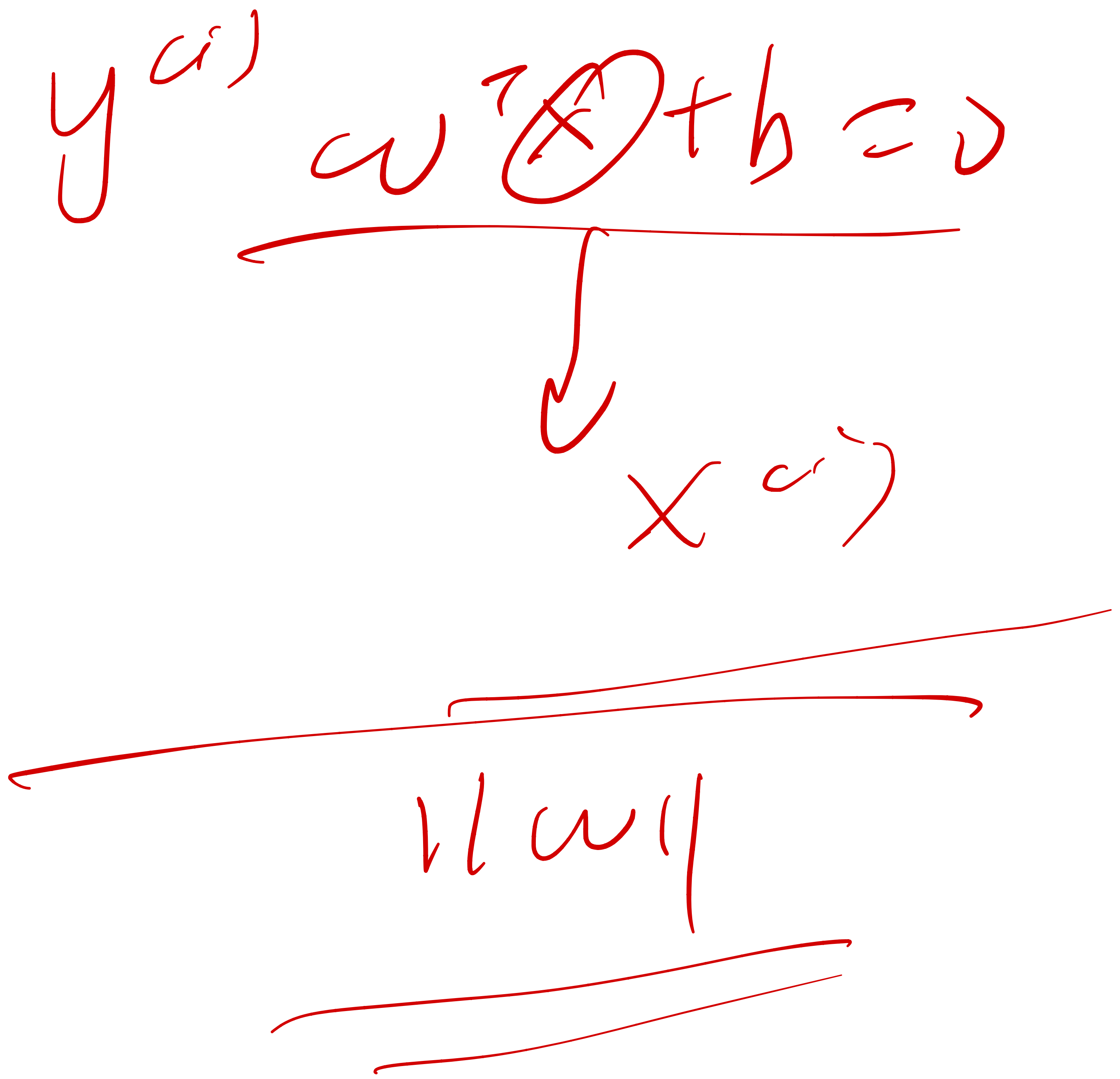
max γ

$$\max \min_{i=1,\ldots,n} \gamma^{(i)}$$

Functional Margin

Given a training example $(x^{(i)}, y^{(i)})$

$$\hat{\gamma}^{(i)} = y^{(i)}(w^T x^{(i)} + b).$$



Functional Margin

Given a training example $(x^{(i)}, y^{(i)})$

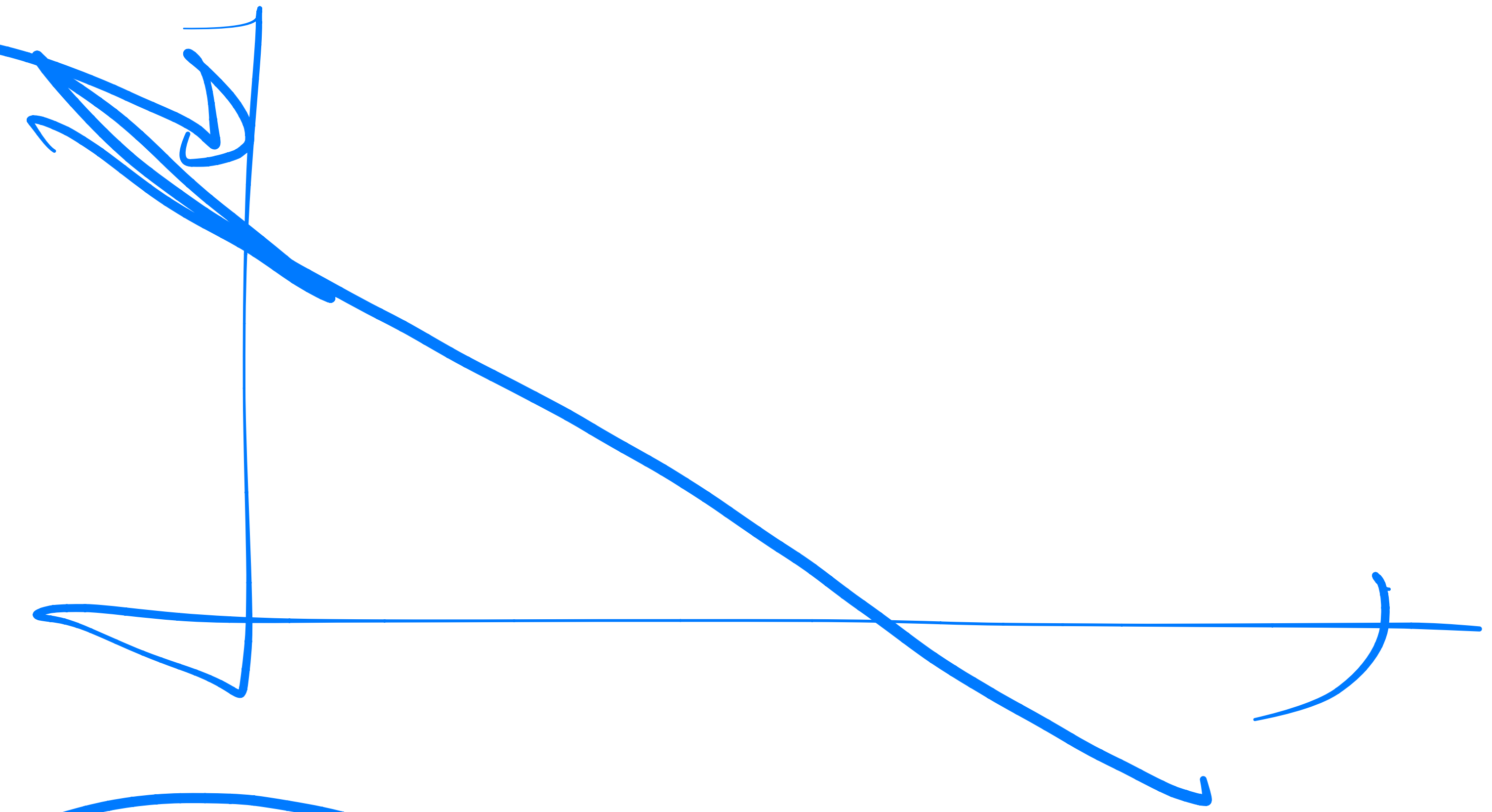
$$\hat{\gamma}^{(i)} = y^{(i)}(w^T x^{(i)} + b).$$

$$\gamma = \frac{\hat{\gamma}}{\|w\|}$$

Given a training set $S = \{(x^{(i)}, y^{(i)}); i = 1,\ldots,n\}$

$$\hat{\gamma} = \min_{i=1,\ldots,n} \hat{\gamma}^{(i)}$$

Functional Margin



Given a training example $(x^{(i)}, y^{(i)})$

$$\hat{\gamma}^{(i)} = y^{(i)}(w^T x^{(i)} + b).$$

Given a training set $S = \{(x^{(i)}, y^{(i)}); i = 1,\ldots,n\}$

$$\hat{\gamma} = \min_{i=1,\ldots,n} \hat{\gamma}^{(i)}$$

Functional margin changes when rescaling parameters, making it a bad objective, e.g. when w->2w, b->2b, the functional margin changes while the separating plane does not really change

The Optimization Problem

geometric

$$\max_{w,b} \min_{i=1,\dots,n} \gamma^{(i)}$$

The Optimization Problem

$$\max_{w,b} \min_{i=1,\ldots,n} \gamma^{(i)}$$

$$\max_{\hat{\gamma},w,b} \frac{\hat{\gamma}}{||w||}$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

$$\frac{y^{(i)}(w^T x^{(i)} + b)}{||w||} \geq \frac{\hat{\gamma}}{||w||}$$

The Optimization Problem

$$\max_{w,b} \min_{i=1,\ldots,n} \gamma^{(i)}$$

$w \to 2w$

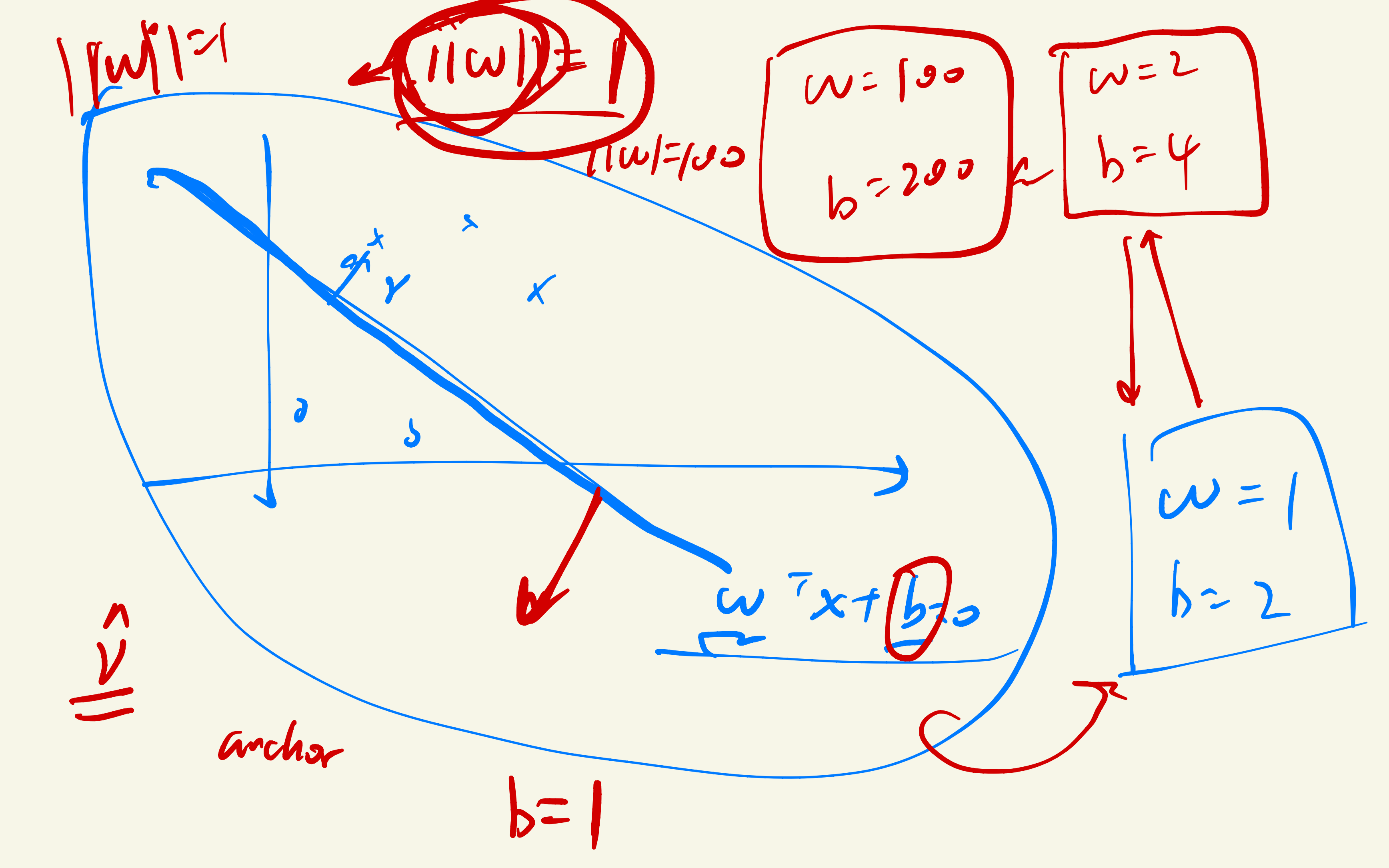
$b \to 2b$

$\hat{\gamma} \to 2\hat{\gamma}$

$$\max_{\hat{\gamma},w,b} \frac{\hat{\gamma}}{||w||}$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

Infinite solutions, as $\hat{\gamma}$ can be at any scale without changing the classifier


||w||=1
||w|| = 1
||w||=100
w=100
b=200
w=2
b=4
w=1
b=2
wᵀx+b=0
anchor
b=1

The Optimization Problem

$$\max_{w,b} \quad \min_{i=1,\ldots,n} \gamma^{(i)}$$

⇩

$$\max_{\hat{\gamma},w,b} \quad \frac{\hat{\gamma}}{||w||}$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

Infinite solutions, as $\hat{\gamma}$ can be at any scale without changing the classifier

||w|| is not easy to deal with, non-convex objective

The Optimization Problem

$$\max_{\hat{\gamma},w,b} \quad \frac{\hat{\gamma}}{||w||}$$
$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

The Optimization Problem

$$\max_{\hat{\gamma},w,b} \quad \frac{\hat{\gamma}}{||w||}$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

Add constraint $\hat{\gamma} = 1$

The Optimization Problem

$$\max_{\hat{\gamma},w,b} \quad \frac{\hat{\gamma}}{||w||}$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

Add constraint $\hat{\gamma} = 1$

$$\min_{w,b} \quad \frac{1}{2}||w||^2$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, n$$

The Optimization Problem

$$\max_{\hat{\gamma},w,b} \quad \frac{\hat{\gamma}}{||w||}$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \hat{\gamma}, \quad i = 1, \ldots, n$$

Add constraint $\hat{\gamma} = 1$

$$\min_{w,b} \quad \frac{1}{2}||w||^2$$

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, n$$

Assumption: the training dataset is linearly separable

Lagrange Duality — Lagrange Multiplier

Lagrange Duality — Lagrange Multiplier

$$\min_w \quad f(w)$$
$$\text{s.t.} \quad h_i(w) = 0, \quad i = 1, \ldots, l.$$

Lagrange Duality — Lagrange Multiplier

$$\min_w \quad f(w)$$
$$\text{s.t.} \quad h_i(w) = 0, \quad i = 1, \ldots, l.$$

$$\mathcal{L}(w, \beta) = f(w) + \sum_{i=1}^{l} \beta_i h_i(w)$$

Lagrange Duality — Lagrange Multiplier

$$\begin{aligned} \min_w \quad & f(w) \\ \text{s.t.} \quad & h_i(w) = 0, \quad i = 1, \ldots, l. \end{aligned}$$

min $$\mathcal{L}(w, \beta) = f(w) + \sum_{i=1}^{l} \beta_i h_i(w)$$

Solve w, β

$$\frac{\partial \mathcal{L}}{\partial w_i} = 0; \quad \frac{\partial \mathcal{L}}{\partial \beta_i} = 0,$$

Lagrange Multiplier: Example

$$\min_{x,y} 5x - 3y$$

$$\text{s.t.} \quad x^2 + y^2 = 136$$

$\min_{x,y,\beta} L(x, y, \beta)$

$L(x, y, \beta) = 5x - 3y + \beta(x^2 + y^2 - 136)$

$\frac{\partial L}{\partial x} = 5 + 2\beta x = 0$

$\frac{\partial L}{\partial y} = -3 + 2\beta y = 0$

$\frac{\partial L}{\partial \beta} = x^2 + y^2 - 136 = 0$

Generalized Lagrangian

Generalized Lagrangian

Primal optimization problem

$$\begin{aligned} \min_w \quad & f(w) \\ \text{s.t.} \quad & g_i(w) \leq 0, \quad i = 1, \ldots, k \\ & h_i(w) = 0, \quad i = 1, \ldots, l. \end{aligned}$$

$y(w^T x + b) \geq 1$

$1 - y(w^T x + b) \leq 0$

Generalized Lagrangian

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Generalized Lagrangian

$$\mathcal{L}(w, \alpha, \beta) = f(w) + \sum_{i=1}^{k} \alpha_i g_i(w) + \sum_{i=1}^{l} \beta_i h_i(w)$$

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$$\min_{w,\beta} L(w, \beta)$$

Generalized Lagrangian

$$\mathcal{L}(w,\alpha,\beta) = f(w) + \sum_{i=1}^{k} \alpha_i g_i(w) + \sum_{i=1}^{l} \beta_i h_i(w)$$

$$\theta_{\mathcal{P}}(w) = \max_{\alpha,\beta\,:\,\alpha_i \geq 0} f(w) + \sum_{i=1}^{k} \alpha_i g_i(w) + \sum_{i=1}^{l} \beta_i h_i(w)$$

$\min \theta_p(w)$

$h_i(w) = 0$

$\max_{\beta} f(w) + \sum_{i=1}^{l} \beta_i h_i(w)$

Generalized Lagrangian

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$$\theta_{\mathcal{P}}(w) = \begin{cases} f(w) & \text{if } w \text{ satisfies primal constraints} \\ \infty & \text{otherwise.} \end{cases}$$

Generalized Lagrangian

Consider this optimization problem

$$\min_w \theta_{\mathcal{P}}(w) = \min_w \max_{\alpha,\beta\,:\,\alpha_i \geq 0} \mathcal{L}(w, \alpha, \beta)$$

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It has exactly the same solution as our original problem

$$p^* = \min_w \theta_{\mathcal{P}}(w)$$

$$\max_{\alpha,\beta:\alpha_i \geq 0} \min_w L(w,\alpha,\beta)$$

The Dual Problem in Optimization

In optimization, sometimes the primal optimization is hard to solve, then we may find a related alternative optimization problem that can be solved more easily, to solve the orignal problem in an indirect way

The Dual Problem

$$\theta_{\mathcal{D}}(\alpha, \beta) = \min_{w} \mathcal{L}(w, \alpha, \beta)$$

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The primal optimization problem

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KKT Conditions

KKT Conditions

Denote the solution to the primal problem as $w*$, the solution to the dual problem as $\alpha*, \beta*$, then zero duality gap is sufficient and necessary (i.e. equivalent) to satisfy KKT Conditions:

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$$\begin{aligned}
\frac{\partial}{\partial w_i}\mathcal{L}(w^*, \alpha^*, \beta^*) &= 0, \quad i = 1, \ldots, d \\
\frac{\partial}{\partial \beta_i}\mathcal{L}(w^*, \alpha^*, \beta^*) &= 0, \quad i = 1, \ldots, l \\
\alpha_i^* g_i(w^*) &= 0, \quad i = 1, \ldots, k \\
g_i(w^*) &\leq 0, \quad i = 1, \ldots, k \\
\alpha^* &\geq 0, \quad i = 1, \ldots, k
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Normal Lagrange multiplier equations

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Normal Lagrange multiplier equations (first two conditions)

The original constraints (last two conditions)

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\end{aligned}$$

If $\alpha_i^* > 0$, then $g_i(w^*) = 0$, the inequality is actually equality

Supporting Vectors

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$$\alpha_i^* g_i(w^*) \quad = \quad 0, \quad i = 1, \ldots, k$$

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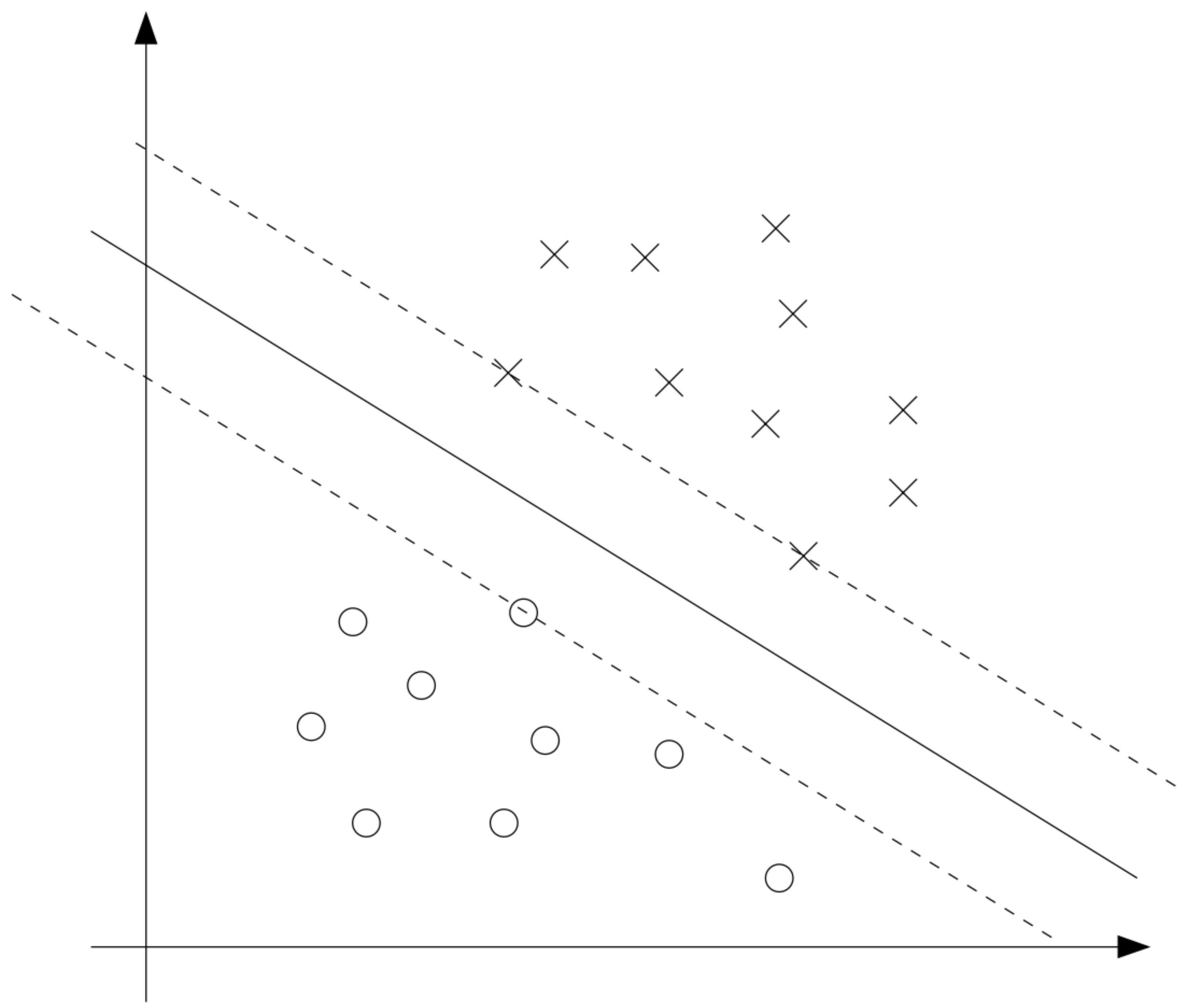

Supporting Vectors

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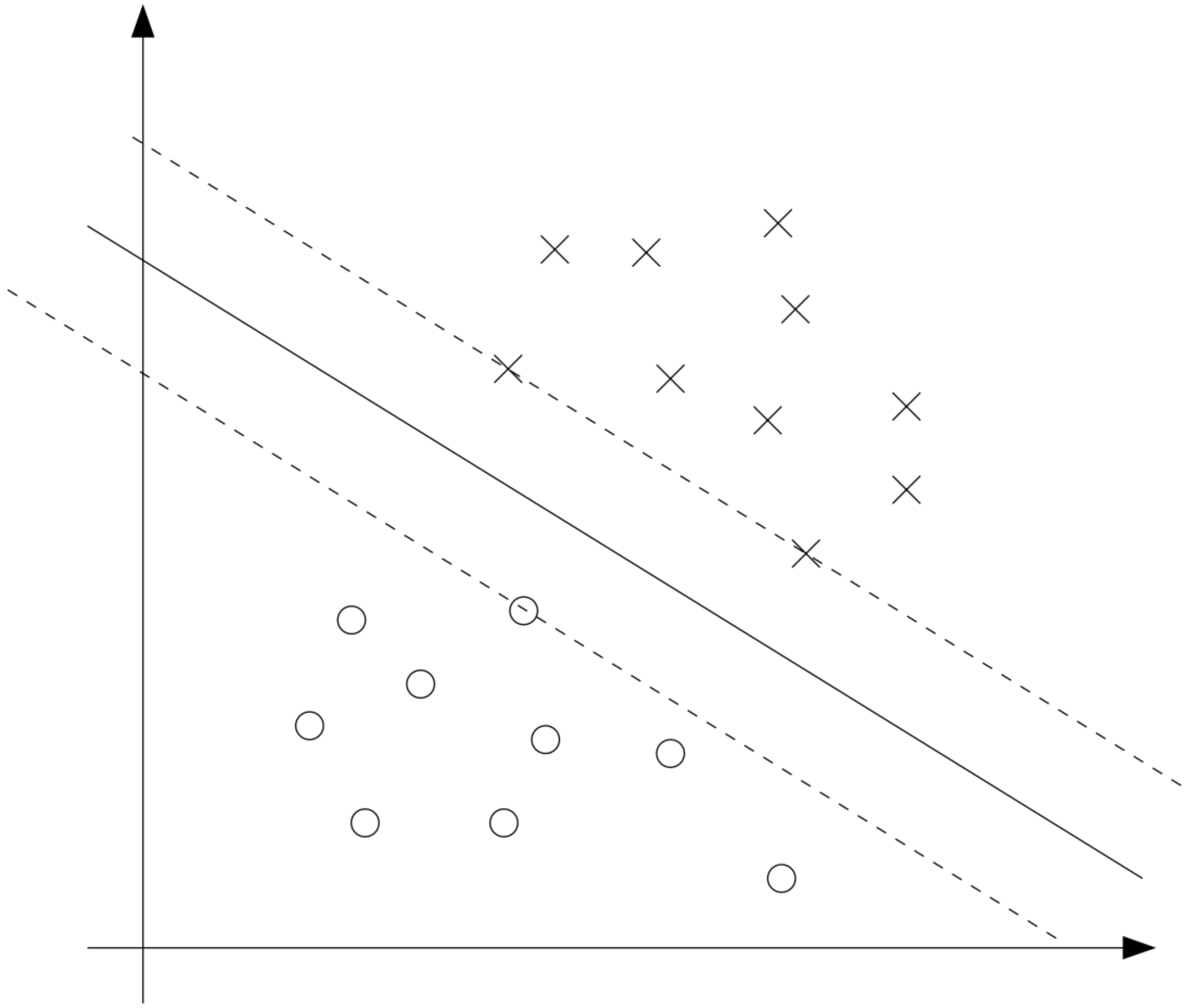

Only the 3 points have non-zero α_i, and they are called supporting vectors

Lagrangian for SVM

Lagrangian for SVM

$$\mathcal{L}(w, b, \alpha) = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} \alpha_i \left[y^{(i)}(w^T x^{(i)} + b) - 1 \right]$$

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$$\theta(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y^{(i)} y^{(j)} \alpha_i \alpha_j (x^{(i)})^T x^{(j)}$$

The Dual Problem of SVM

The Dual Problem of SVM

$$
\begin{aligned}
\max_{\alpha} \quad & W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} y^{(i)} y^{(j)} \alpha_i \alpha_j \langle x^{(i)}, x^{(j)} \rangle \\
\text{s.t.} \quad & \alpha_i \geq 0, \quad i = 1, \ldots, n \\
& \sum_{i=1}^{n} \alpha_i y^{(i)} = 0,
\end{aligned}
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Kernel is all we need!

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After solving α (with standard quadratic optimization algorithms)

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From KKT Conditions

The Dual Problem of SVM

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$$w = \sum_{i=1}^{n} \alpha_i y^{(i)} x^{(i)} \qquad b^* = -\frac{\max_{i:y^{(i)}=-1} {w^*}^T x^{(i)} + \min_{i:y^{(i)}=1} {w^*}^T x^{(i)}}{2}$$

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From the original constraints

Inference

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\begin{aligned}
w^T x + b &= \left(\sum_{i=1}^{n} \alpha_i y^{(i)} x^{(i)} \right)^T x + b \\
&= \sum_{i=1}^{n} \alpha_i y^{(i)} \langle x^{(i)}, x \rangle + b.
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We never need to really compute w

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Most α_i are 0, only the supporting examples will influence the final prediction

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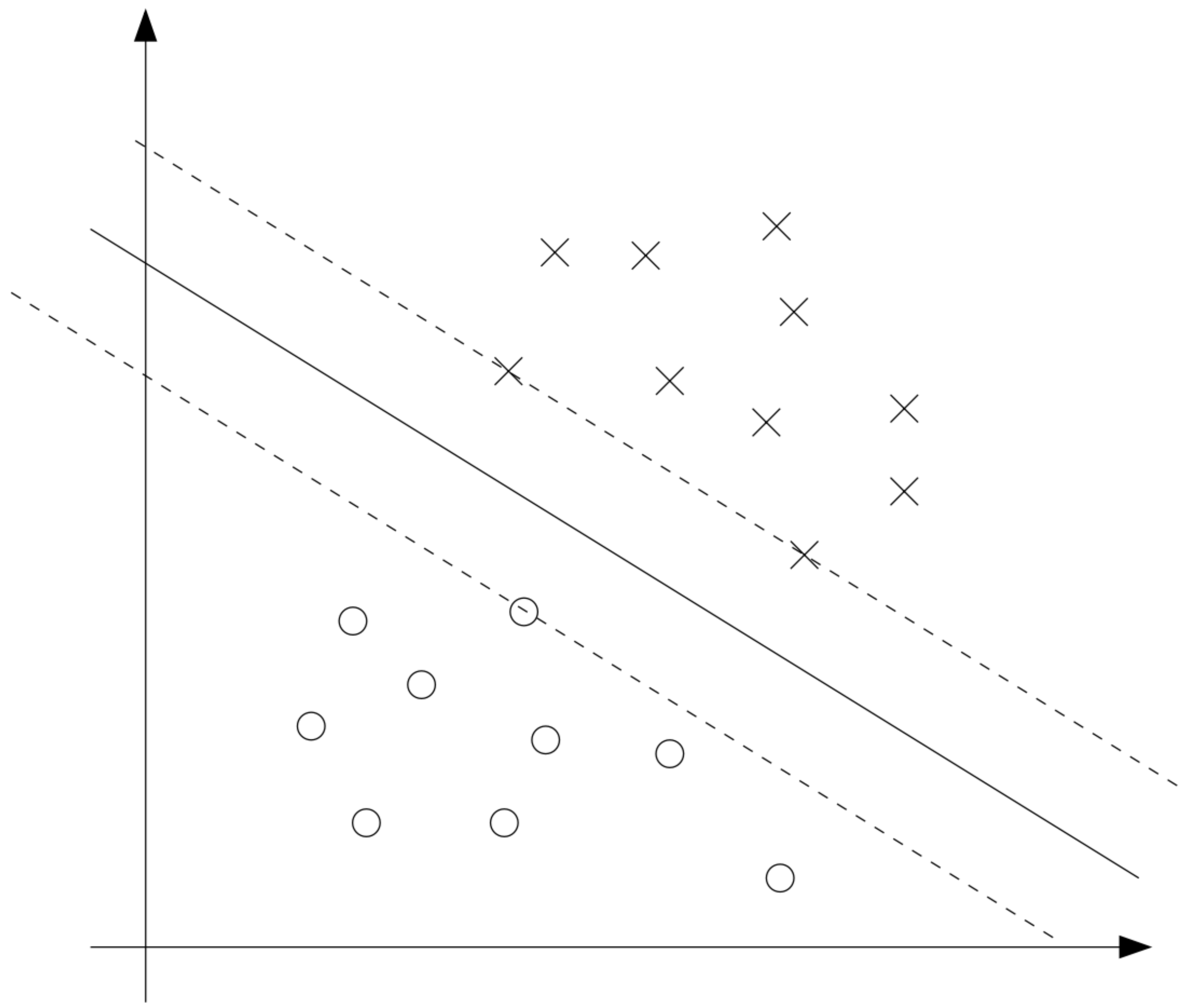

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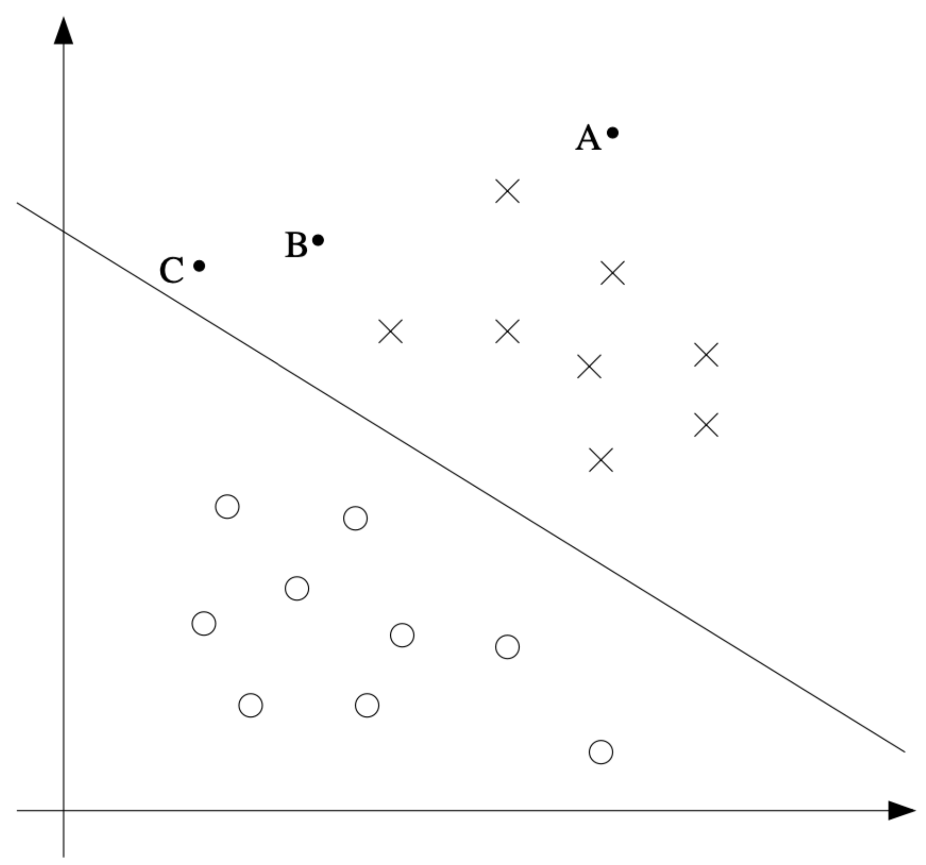
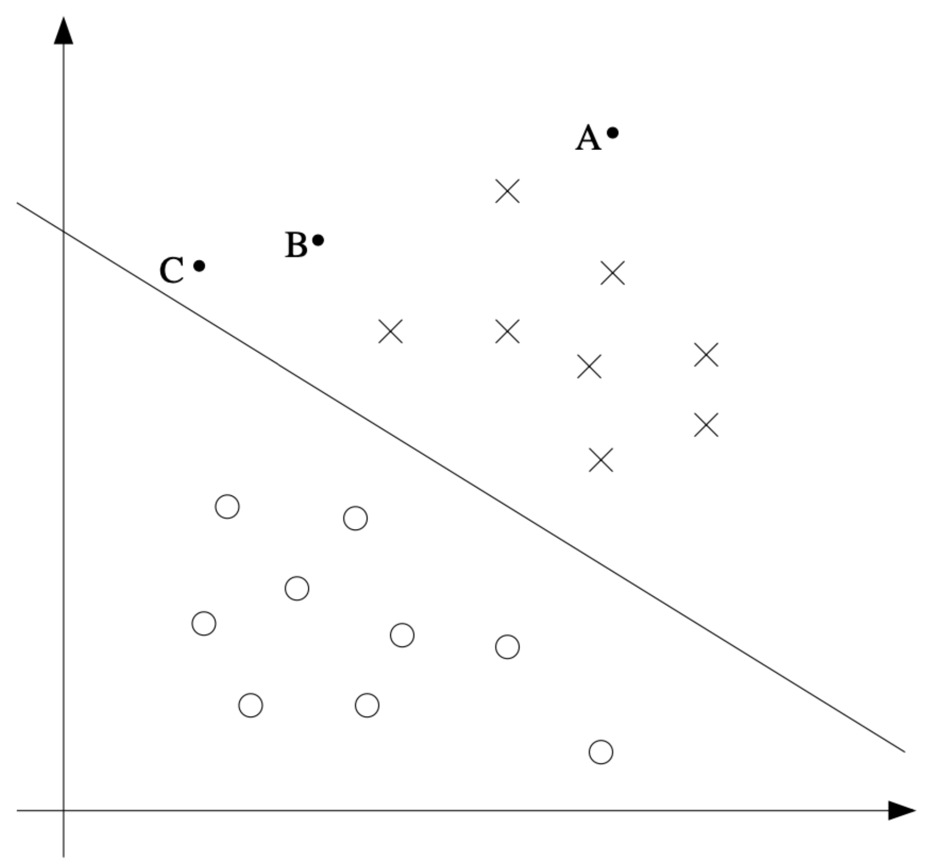
Review of the High-Level Logic

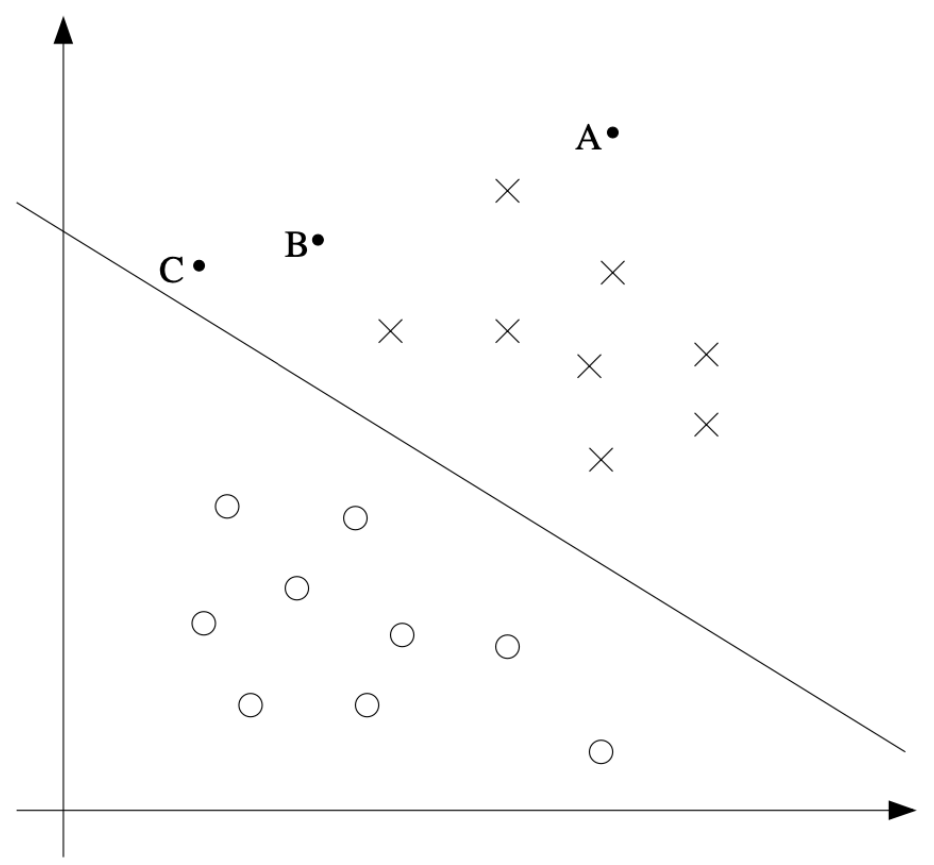


Review of the High-Level Logic



Review of the High-Level Logic

$$h_{w,b}(x) = g(w^T x + b).$$



Review of the High-Level Logic

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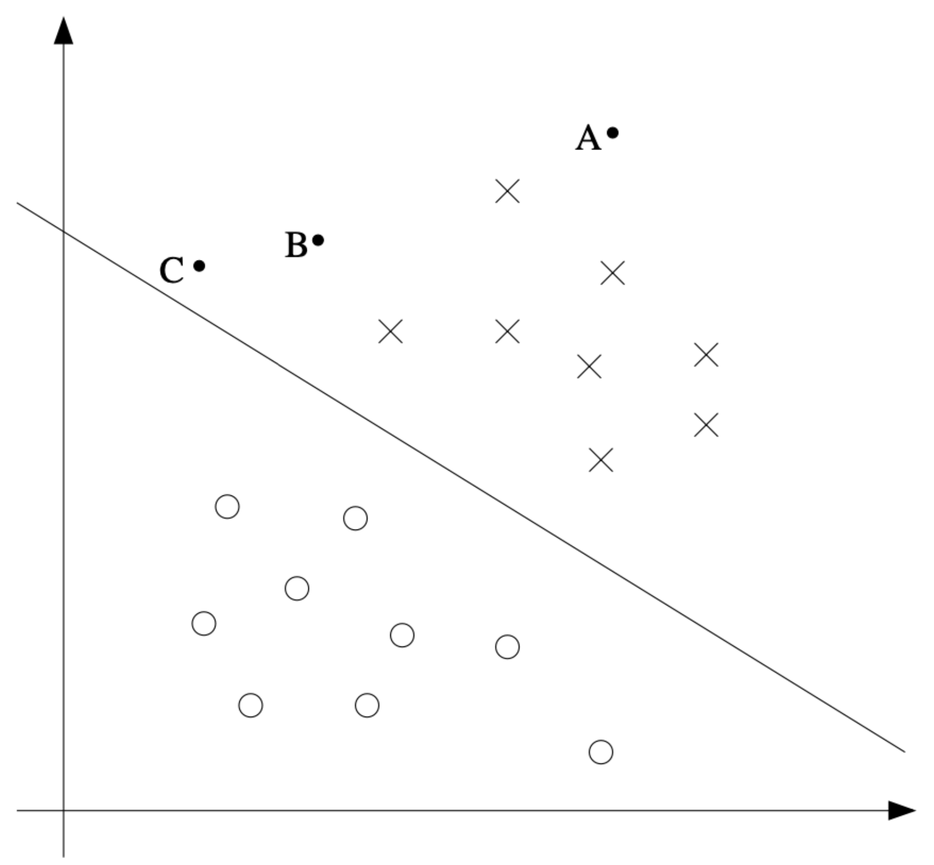
Maximize geometric margin

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



Review of the High-Level Logic

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Maximize geometric margin

Problem rewriting →

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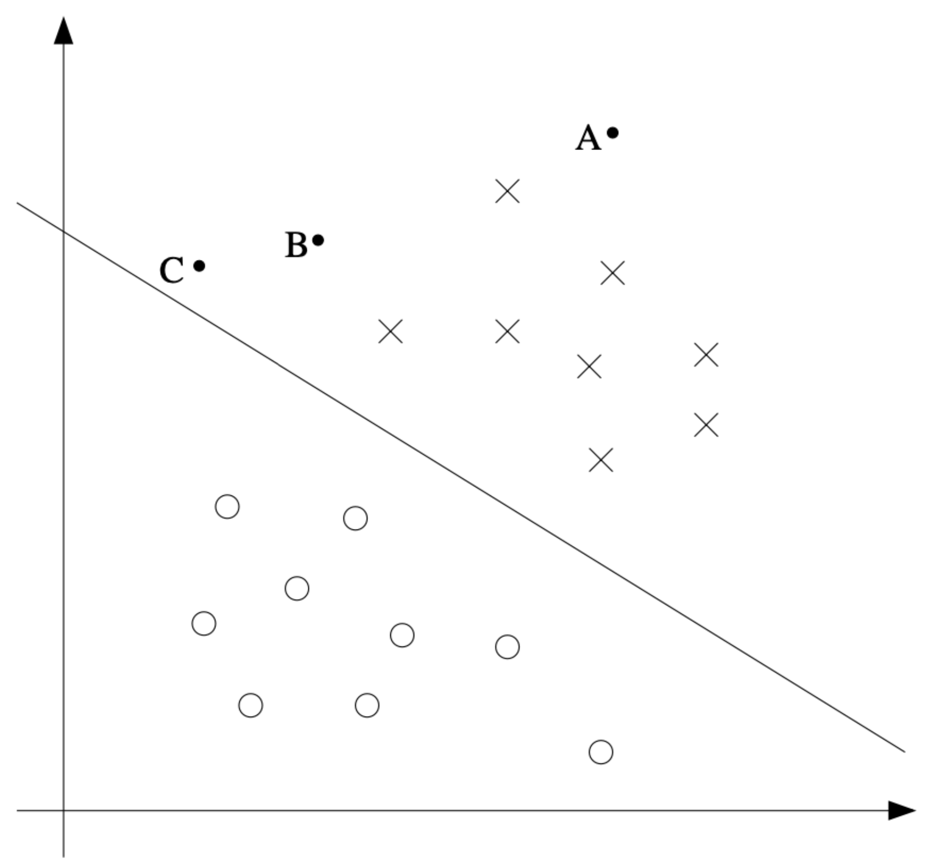
Review of the High-Level Logic

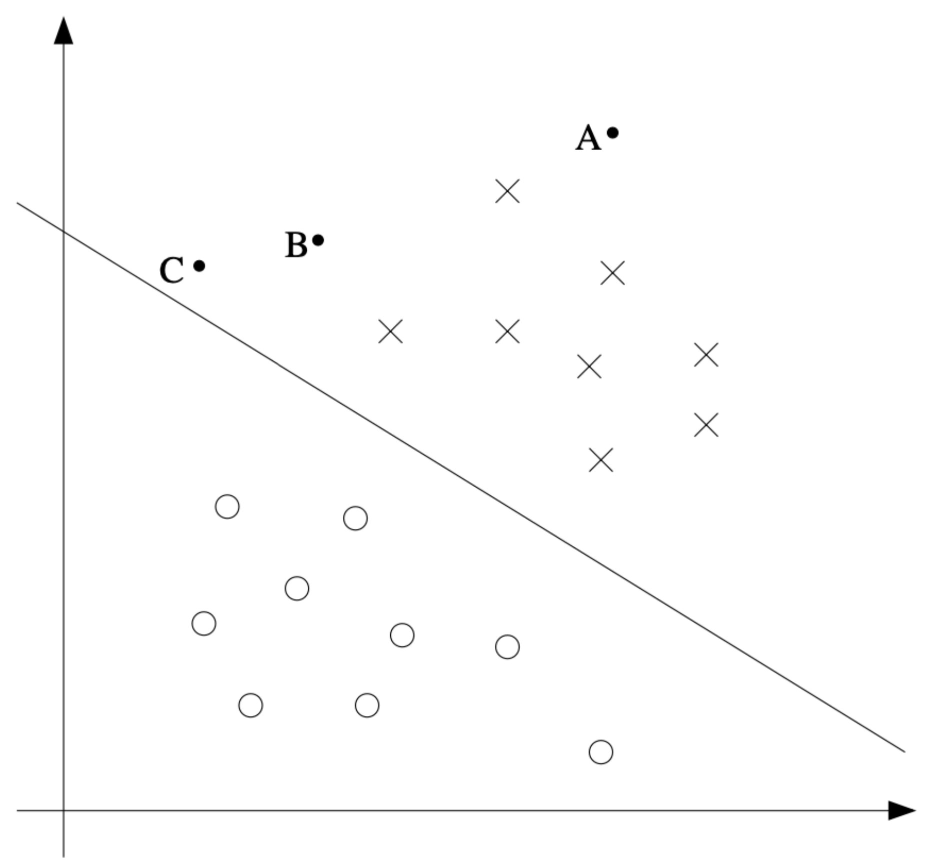


$$h_{w,b}(x) = g(w^T x + b).$$

Maximize geometric margin → (Problem rewriting) → **Quadratic Optimization Problem**

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

$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2}||w||^2 \\ \text{s.t.} \quad & y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, n \end{aligned}$$



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Quadratic Optimization Problem

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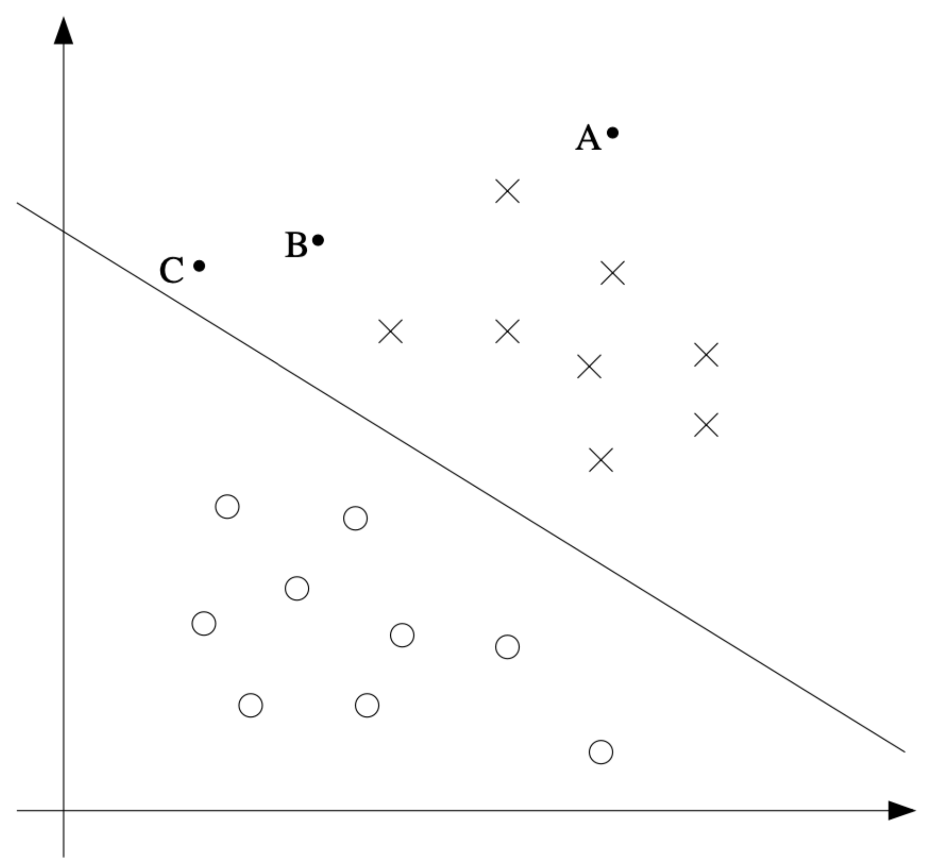
Not suitable for non-linear cases (high-dim feature map)



Review of the High-Level Logic

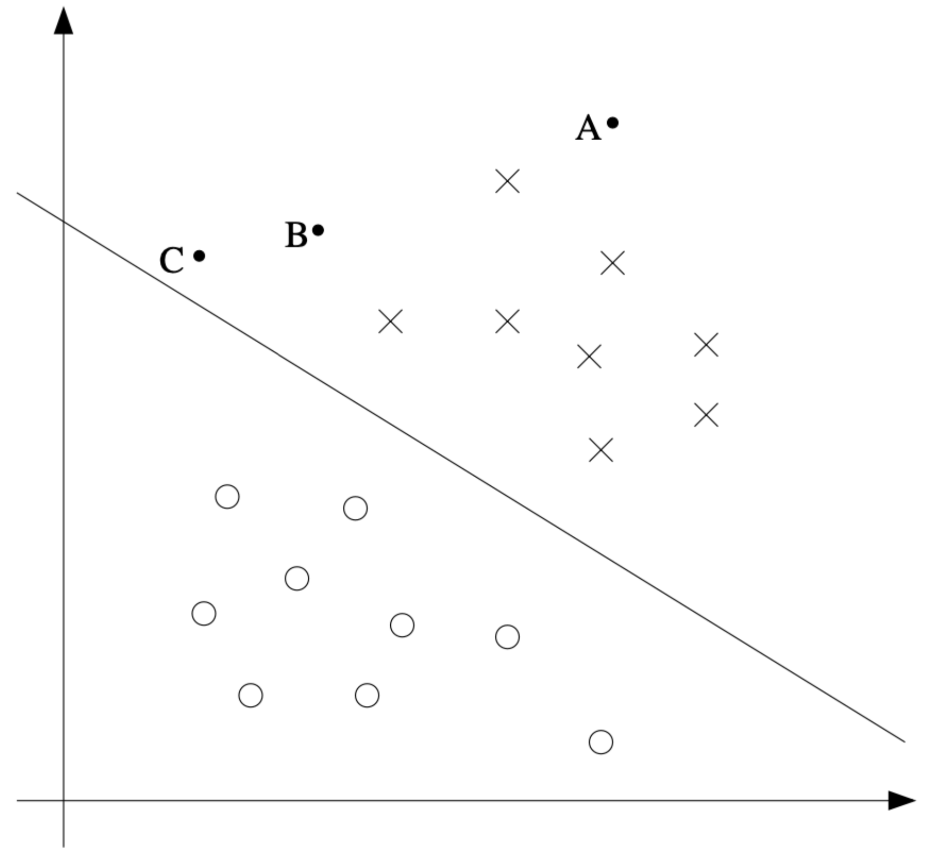
$$h_{w,b}(x) = g(w^T x + b).$$

Maximize geometric margin → (Problem rewriting) → Quadratic Optimization Problem → (Finding a related optimization problem that is easier)

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

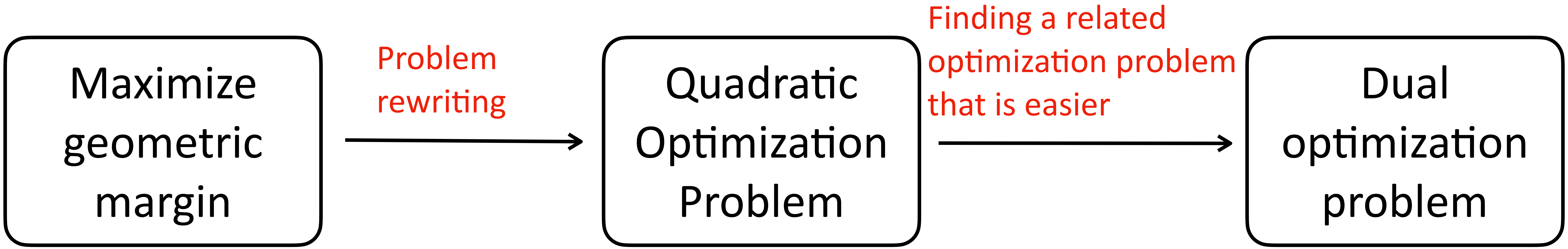
$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2}||w||^2 \\ \text{s.t.} \quad & y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, n \end{aligned}$$

Not suitable for non-linear cases (high-dim feature map)



Review of the High-Level Logic

$$h_{w,b}(x) = g(w^T x + b).$$

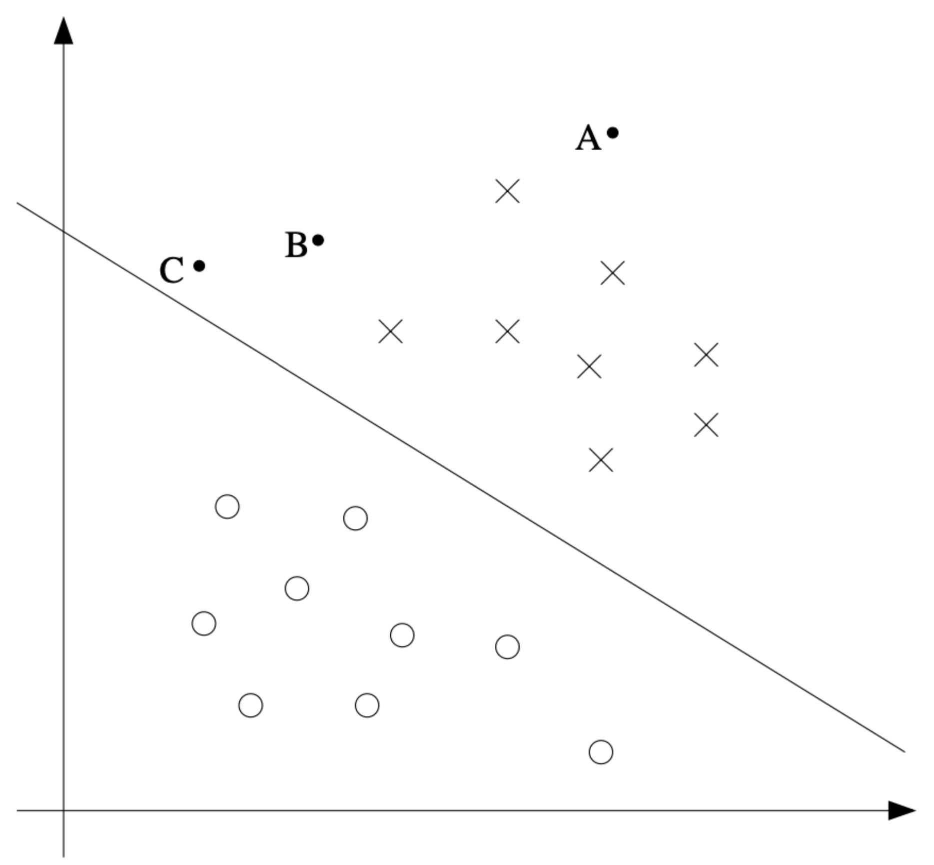


$$\gamma^{(i)} = y^{(i)} \left(\left(\frac{w}{||w||} \right)^T x^{(i)} + \frac{b}{||w||} \right)$$

$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2}||w||^2 \\ \text{s.t.} \quad & y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, n \end{aligned}$$

$$\begin{aligned} \max_\alpha \quad & W(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n y^{(i)} y^{(j)} \alpha_i \alpha_j \langle x^{(i)}, x^{(j)} \rangle \\ \text{s.t.} \quad & \alpha_i \geq 0, \quad i = 1, \ldots, n \\ & \sum_{i=1}^n \alpha_i y^{(i)} = 0, \end{aligned}$$

Not suitable for non-linear cases (high-dim feature map)



Review of the High-Level Logic

$$h_{w,b}(x) = g(w^T x + b)$$

Maximize geometric margin → (Problem rewriting) → **Quadratic Optimization Problem** → (Finding a related optimization problem that is easier) → **Dual optimization problem**

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

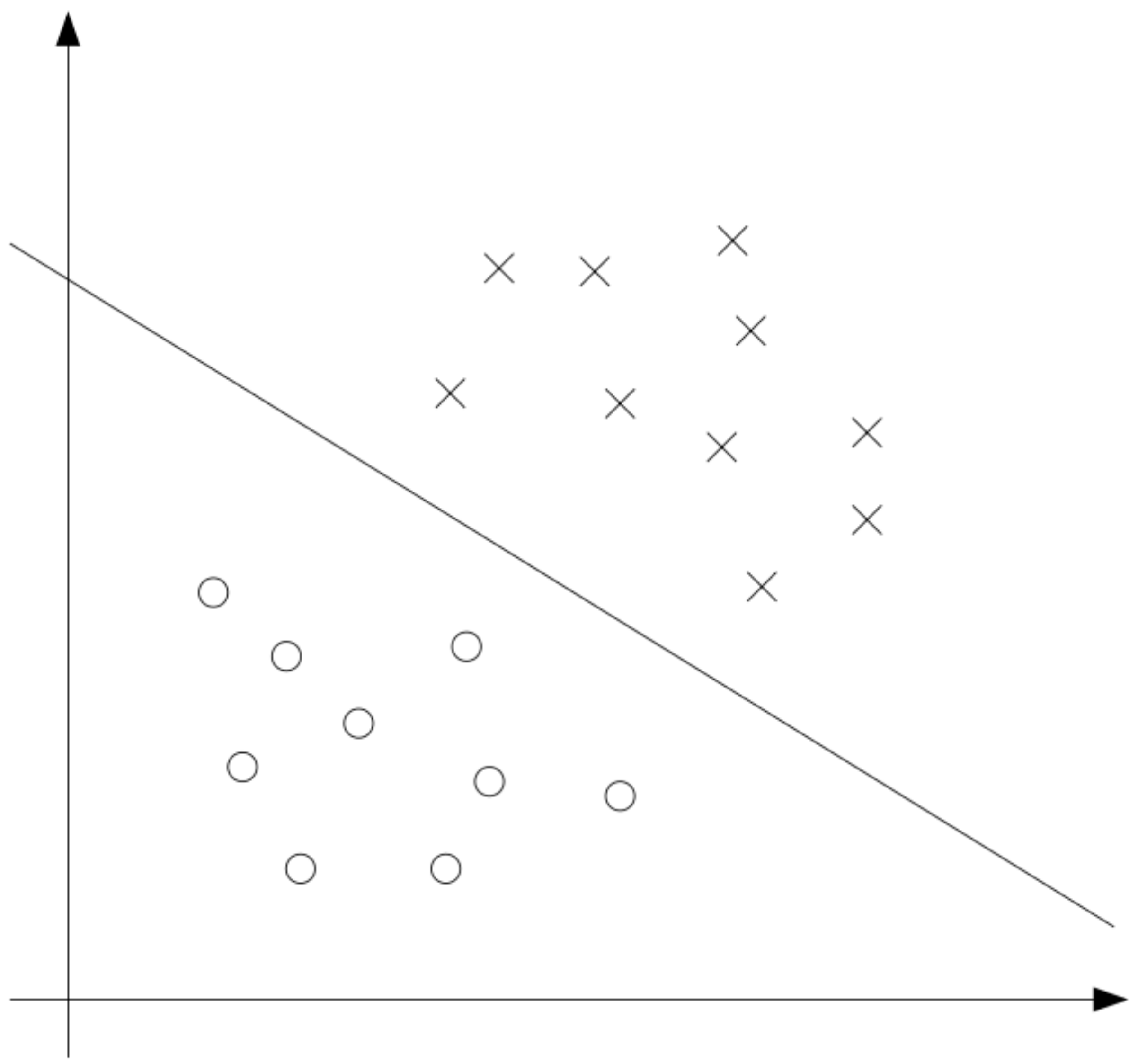
$$\begin{aligned} \min_{w,b} \quad & \frac{1}{2}||w||^2 \\ \text{s.t.} \quad & y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, n \end{aligned}$$

Not suitable for non-linear cases (high-dim feature map)

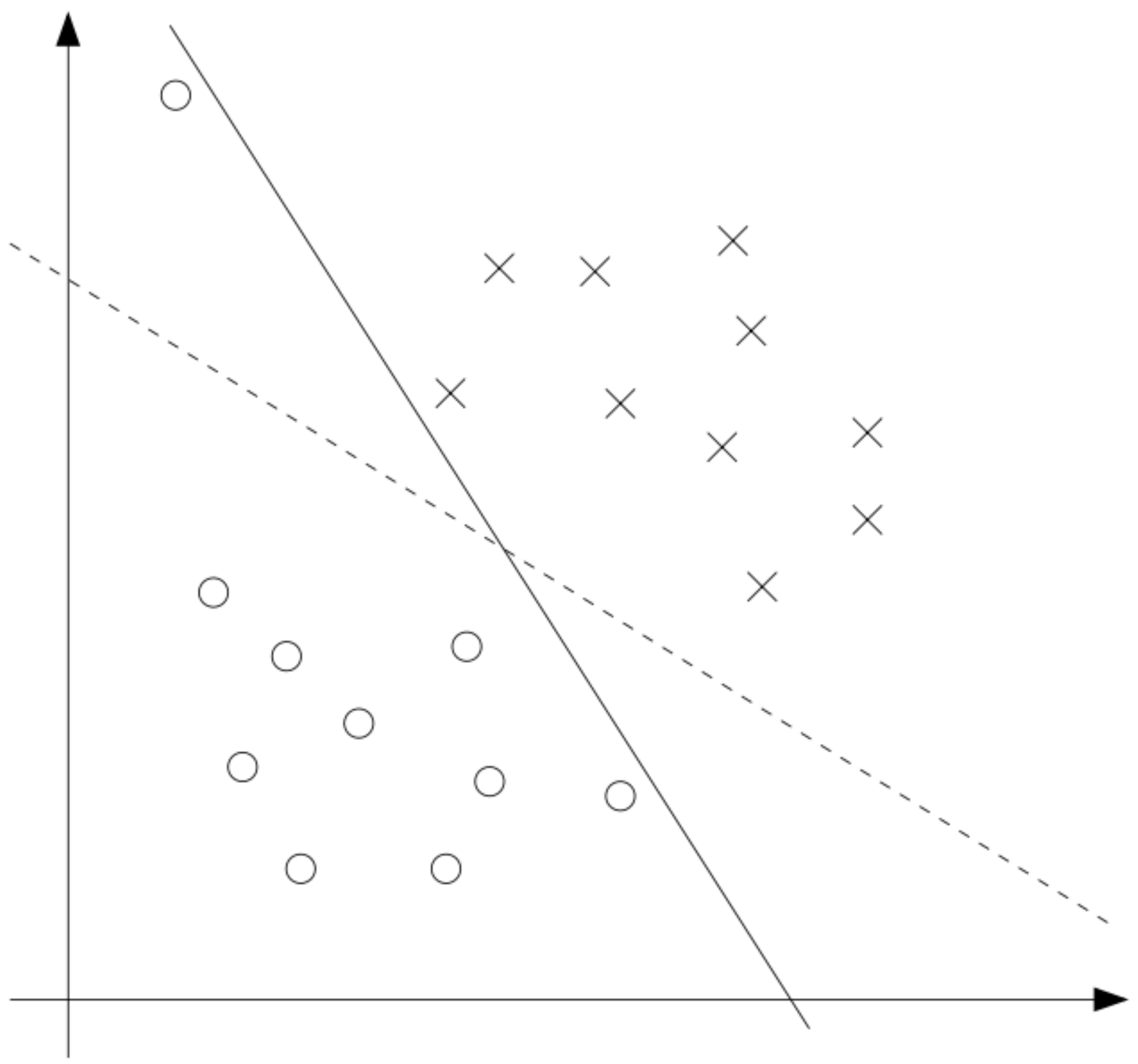
$$\begin{aligned} \max_\alpha \quad & W(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n y^{(i)} y^{(j)} \alpha_i \alpha_j \langle x^{(i)}, x^{(j)} \rangle \\ \text{s.t.} \quad & \alpha_i \geq 0, \quad i = 1, \ldots, n \\ & \sum_{i=1}^n \alpha_i y^{(i)} = 0, \end{aligned}$$

Kernel makes it very flexible in non-linear cases!

The Non-Separable Case



Linearly Separable



Linearly Non-Separable

The Non-Separable Case

Primal opt problem:

$$\begin{aligned} \min_{\gamma,w,b} \quad & \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi_i \\ \text{s.t.} \quad & y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i, \quad i = 1,\ldots,n \\ & \xi_i \geq 0, \quad i = 1,\ldots,n. \end{aligned}$$

Dual opt problem

$$\begin{aligned} \max_{\alpha} \quad & W(\alpha) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} y^{(i)}y^{(j)}\alpha_i\alpha_j\langle x^{(i)}, x^{(j)}\rangle \\ \text{s.t.} \quad & 0 \leq \alpha_i \leq C, \quad i = 1,\ldots,n \\ & \sum_{i=1}^{n}\alpha_i y^{(i)} = 0, \end{aligned}$$

Thank You!

Q & A