

# Lecture 3

Today: mostly examples

Last time:  $\ell_1, \ell_\infty$  norm minimization - equivalent to LP

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$$x \in \mathbb{R}^n, \quad \min_x \|x\|_\infty \quad \ell_\infty \text{ infinity norm}$$

$$\begin{aligned} \|x\|_\infty &= \max \{ |x_1|, |x_2|, \dots, |x_n| \} \\ &= \max \{ x_1, -x_1, x_2, -x_2, \dots, x_n, -x_n \} \end{aligned}$$

$$\begin{aligned} \min t \\ \text{s.t.} \quad & x_i \leq t \quad i=1, \dots, n \\ & -x_i \leq t \end{aligned}$$

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$$\ell_1\text{-norm} \\ x \in \mathbb{R}^n$$

$$\min_x \|x\|_1$$

$$\|x\|_1 = \sum_{i=1}^n |x_i| = \sum_{i=1}^n \max \{ x_i, -x_i \}$$

$$\min_{x, t_1, \dots, t_n} t_1 + t_2 + \dots + t_n$$

$$\text{s.t. } \left. \begin{array}{l} x_i \leq t_i \\ -x_i \leq t_i \end{array} \right\} \quad -t_i \leq x_i \leq t_i \quad i=1, \dots, n.$$

$$\min \quad \mathbf{1}^T \mathbf{t}$$

$$\mathbf{t} = \begin{pmatrix} t_1 \\ \vdots \\ t_n \end{pmatrix}$$

$$\text{s.t. } -t \leq x \leq t$$


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• other norms: use approximation

$$A \|x\|_p \leq \|x\|_q \leq B \|x\|_p$$

Example

$$\|x\|_2 \leq \|x\|_1 \leq \sqrt{n} \|x\|_2$$

$$\min \|x\|_2$$

st

some constraints

$$Ax \leq b$$

Optimal value  $p^*$   
at  $x_0^*$

$$\min \|x\|_1$$

st

same constraints

$$Ax \leq b$$

Optimal value  $q^*$   
at  $x_1^*$

How far is  $q^*$  from  $p^*$ ?

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\* Difference, between  $\| \cdot \|_1$  and  $\| \cdot \|_2$

• small entries contribute <sup>more</sup> to  $\| \cdot \|_1$  and less to  $\| \cdot \|_2$   
 $x = (0.1, 10)$

• large entries contribute more to  $\| \cdot \|_2$

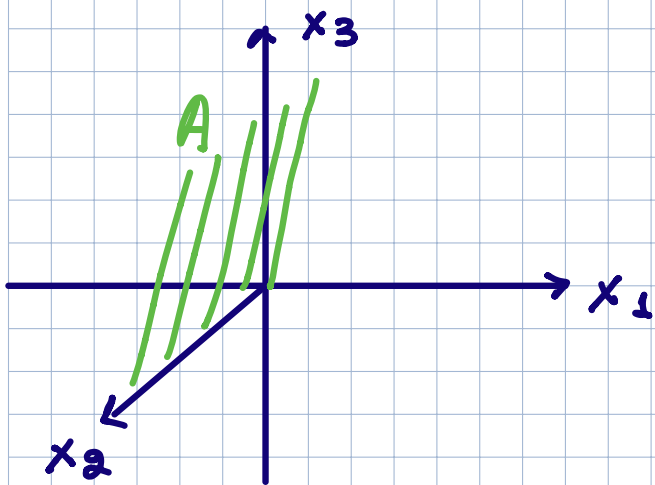
Error measurement  $\ell_2 \rightarrow$  lots of small errors  
 $\ell_1 \rightarrow$  most entries zero and a few larger ones

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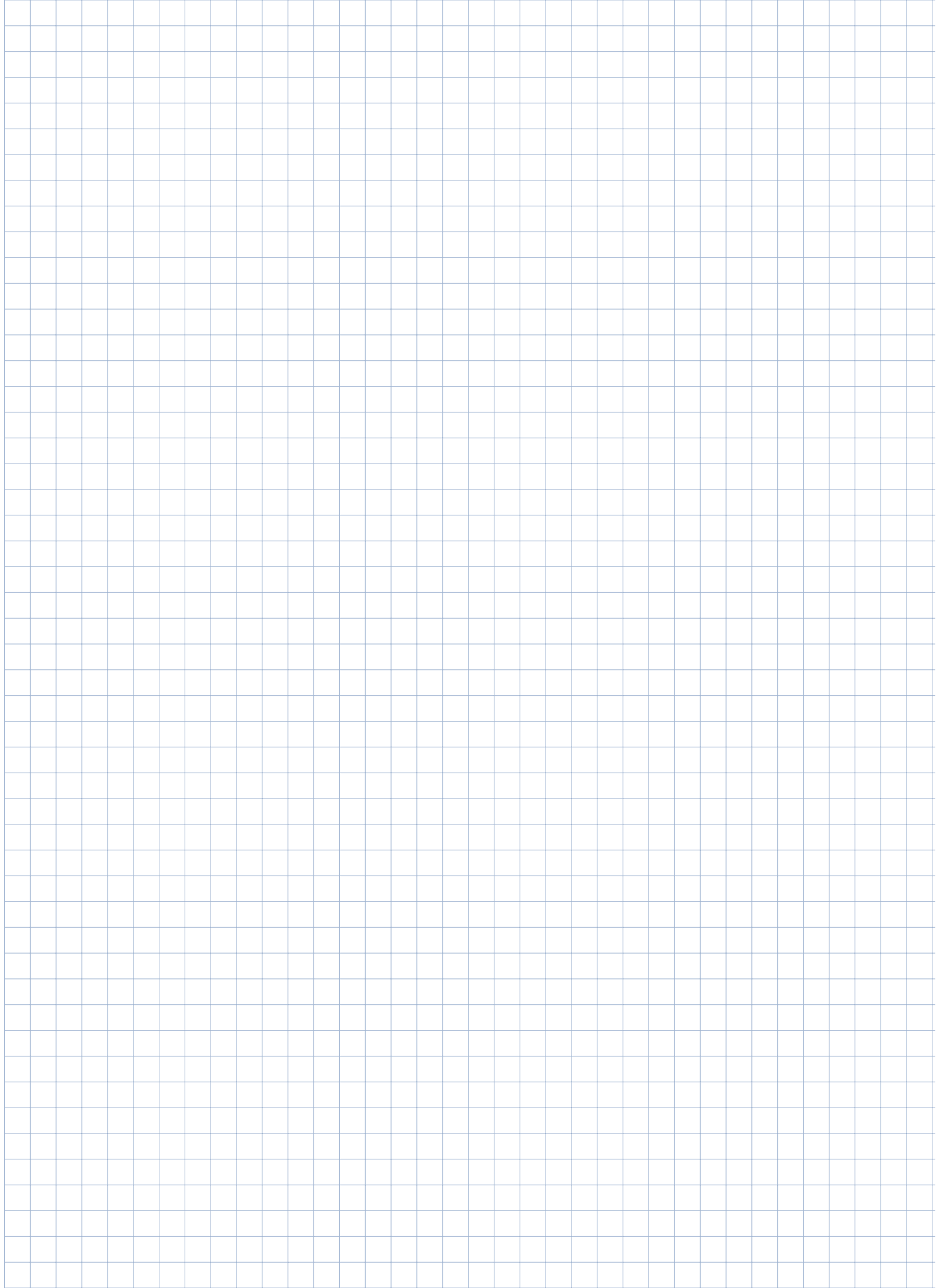
Example 1: Assume we are given a vector

$b \in \mathbb{R}^n$ . We want to find the "closest,"

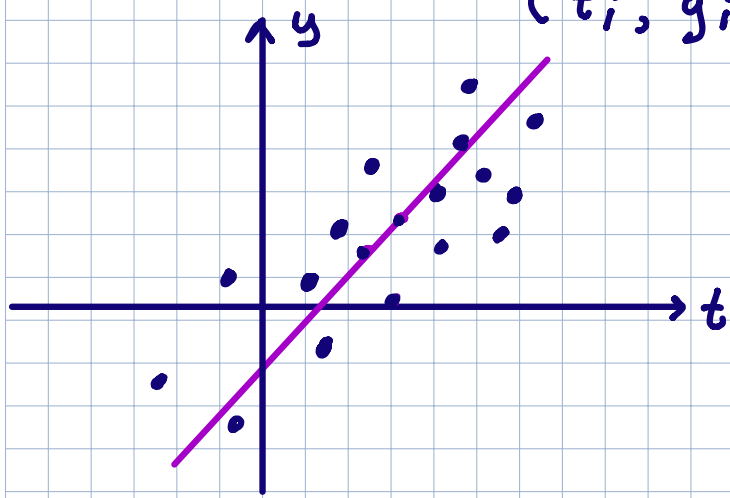
in the  $\| \cdot \|_\infty$  sense, vector  $y$ , inside a subspace spanned by the columns of a matrix  $A$ .



$$A = \begin{bmatrix} | & | & \dots & | \\ a_1 & a_2 & \dots & a_k \\ | & | & & | \end{bmatrix}$$



## Example 2



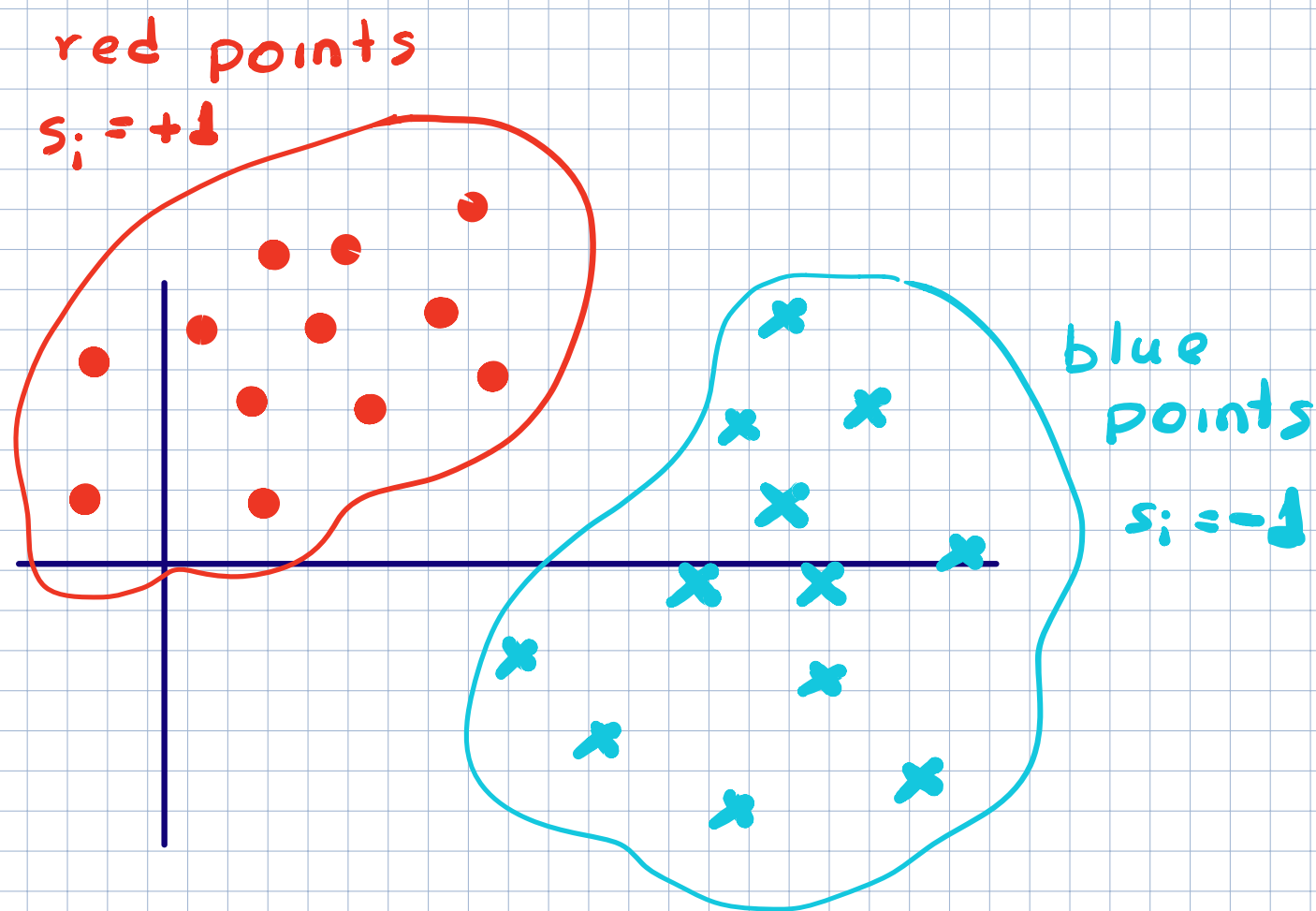
We are given  $m$  points  
 $(t_i, y_i) \in \mathbb{R}^2$

We want to  
find an affine  
function  
 $f(t) = at + b$   
such that, for  
every  $t_i$ ,  $f(t_i)$   
is close to  $y_i$  in  $l_1$   
distance

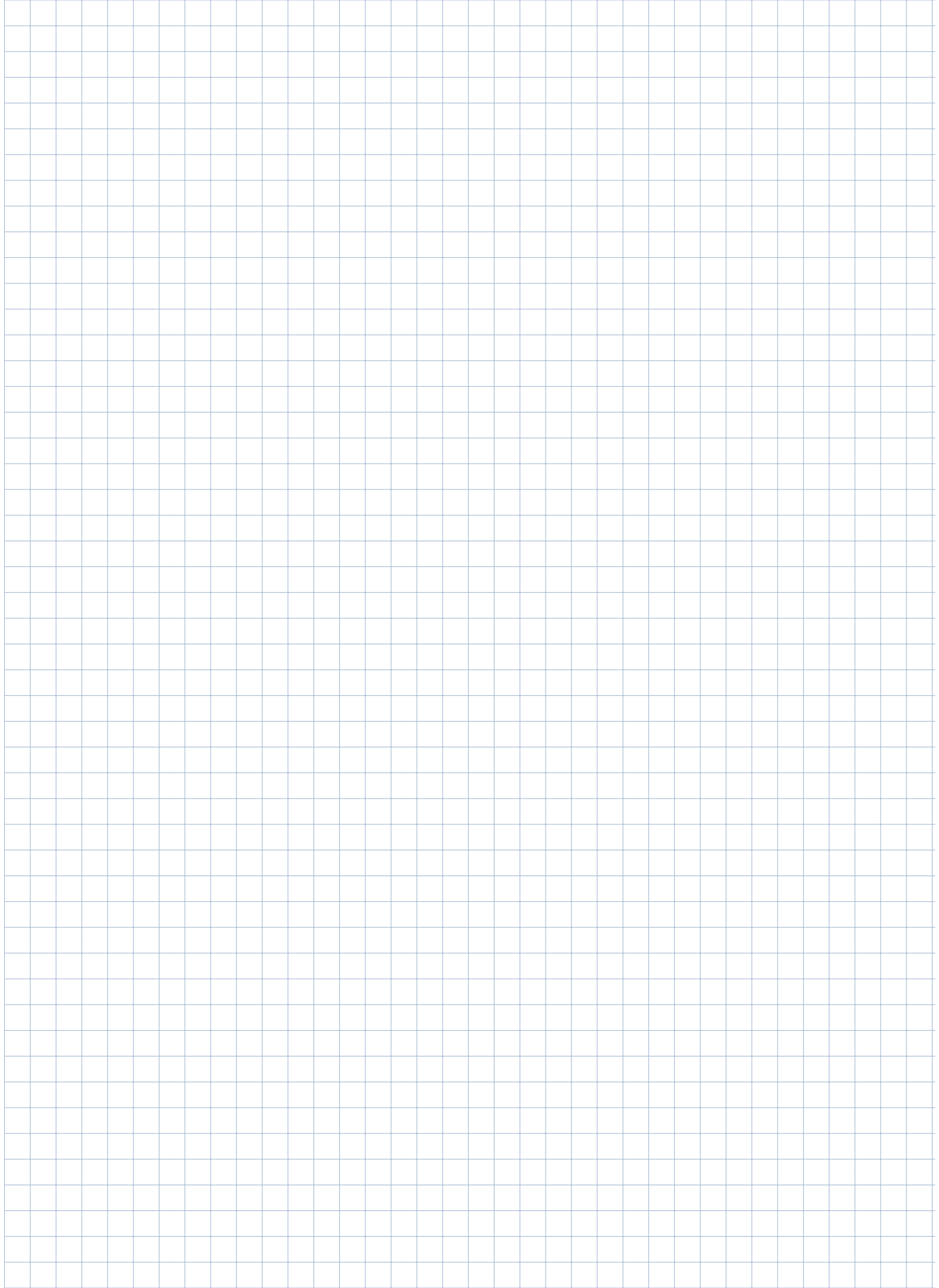
## Example 3 Linear Classification

Consider a set of points  $x_1, x_2, \dots, x_m \in \mathbb{R}^n$

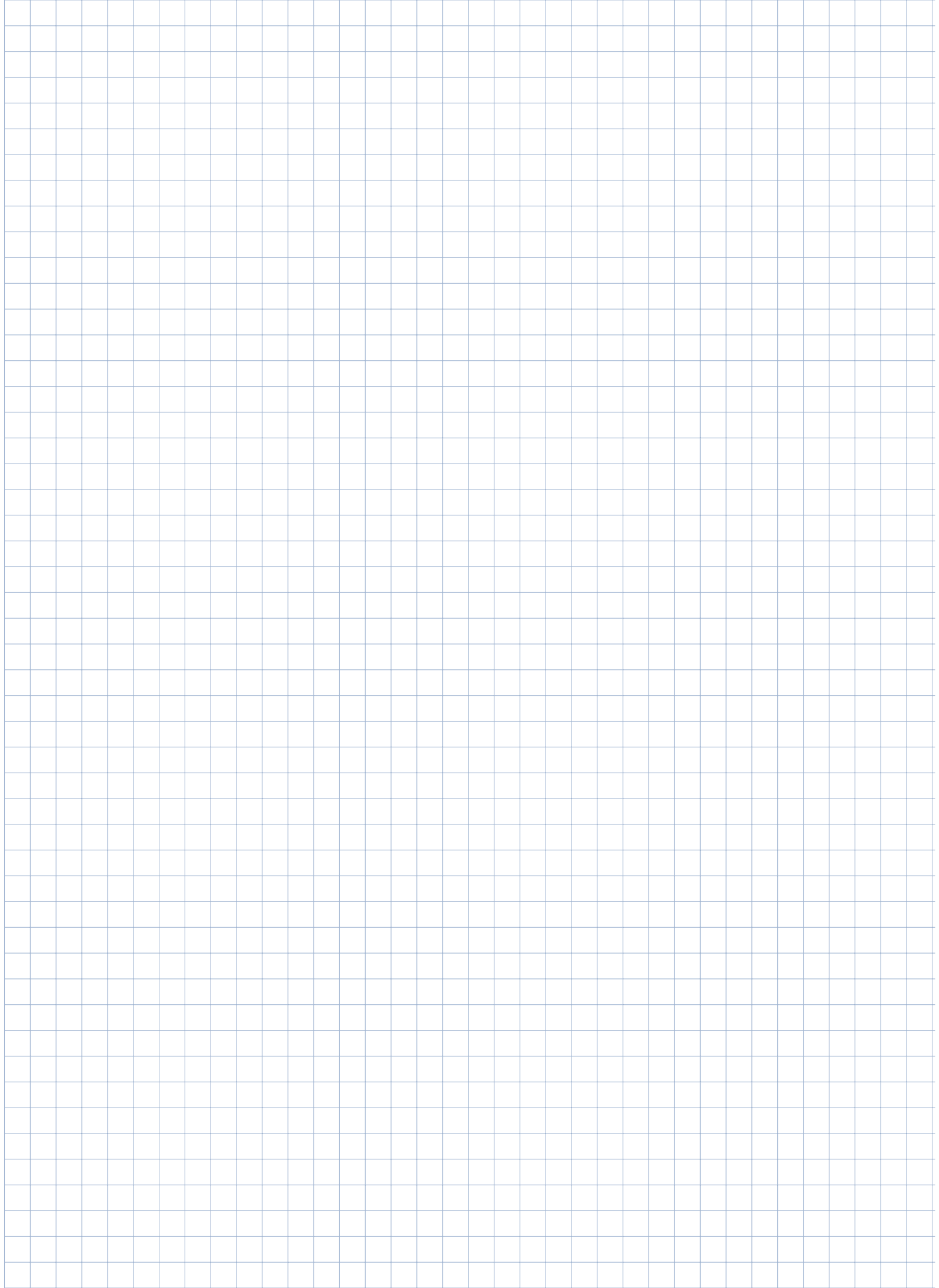
Each point comes with an associated label  $s_i \in \{+1, -1\}$



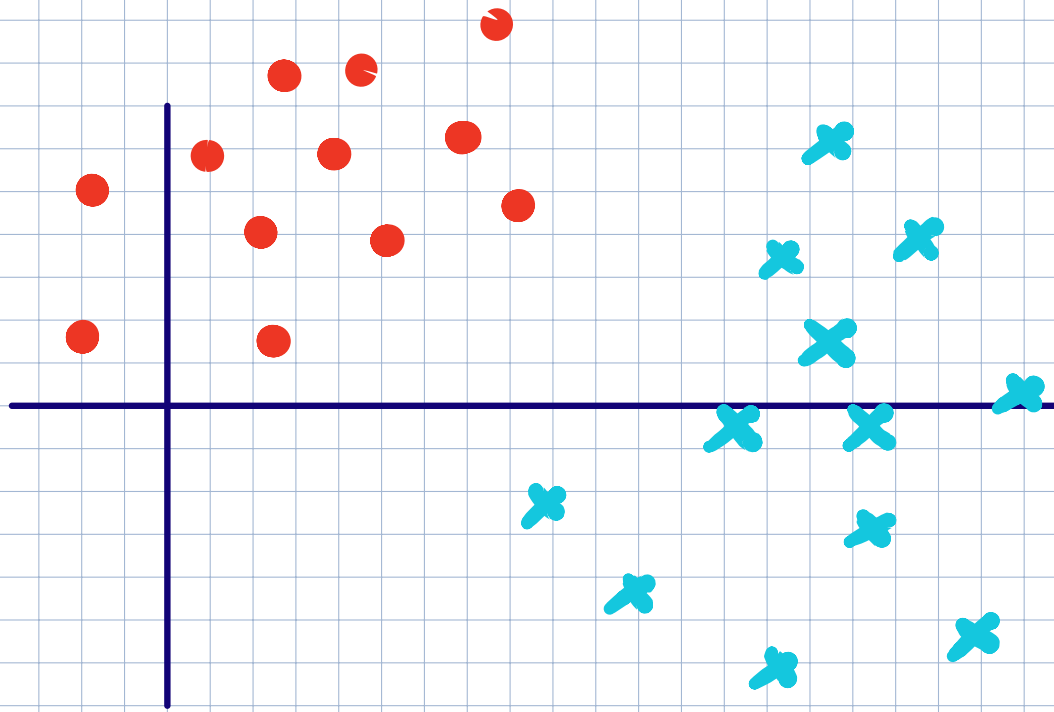
Find a hyperplane  $H = \{x \mid a^T x + b = 0\}$   
that separates "as well as possible,"  
the training points







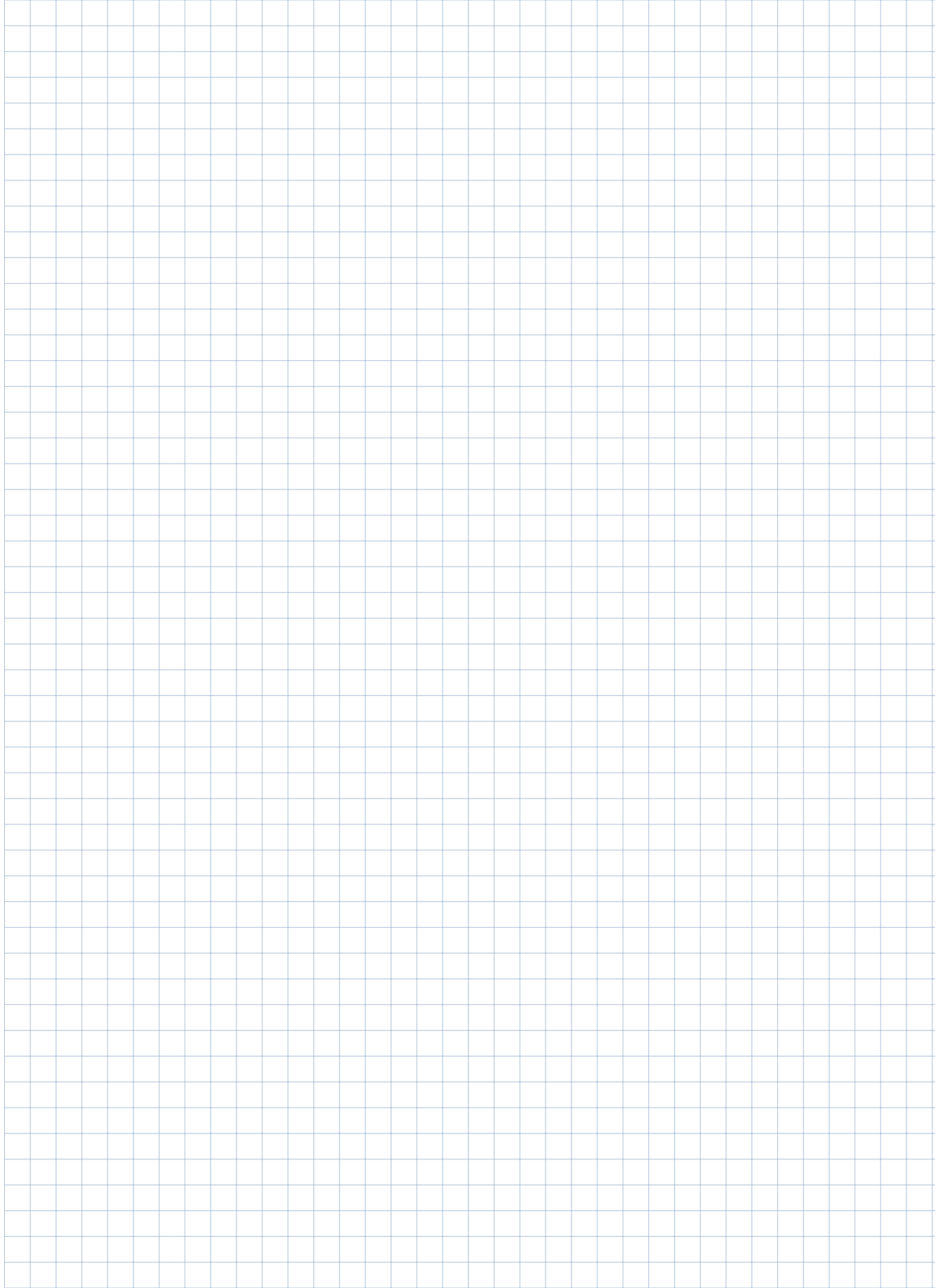
If the training data are linearly separable (there exists a hyperplane that perfectly separates them) the objective value is zero.



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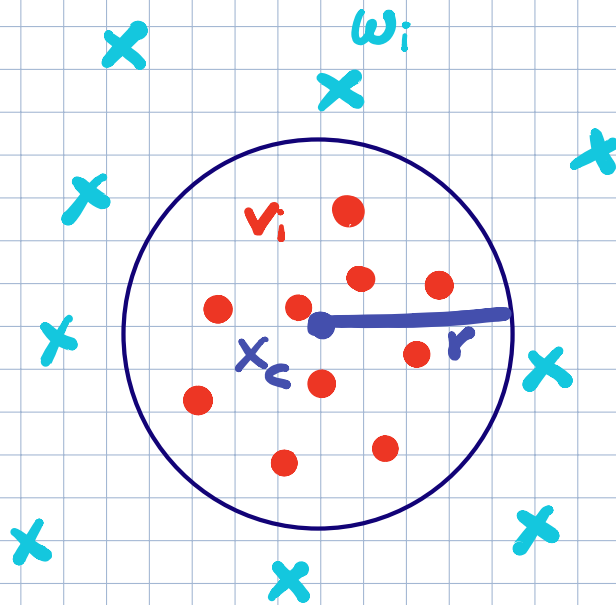
SVM (support vector machine):

maximize the "margin" around the separating hyperplanes



## Example 4

Find a sphere that separates two sets of points  $v_i$  and  $w_i$ :



Sphere: all points within distance  $r$  from a center  $x_c$ .

$$S = \{ x \mid \|x - x_c\|_2 \leq r \}$$