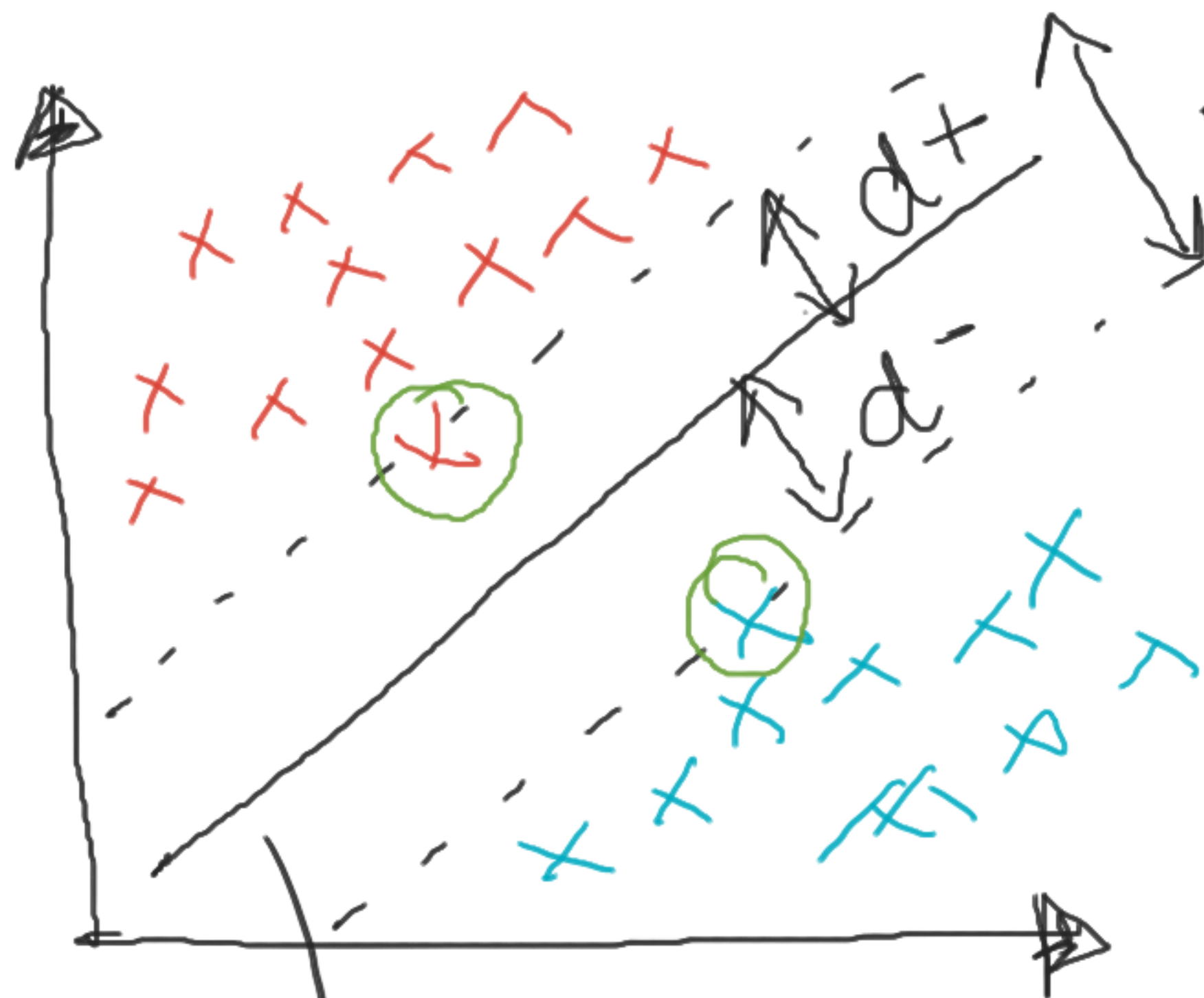


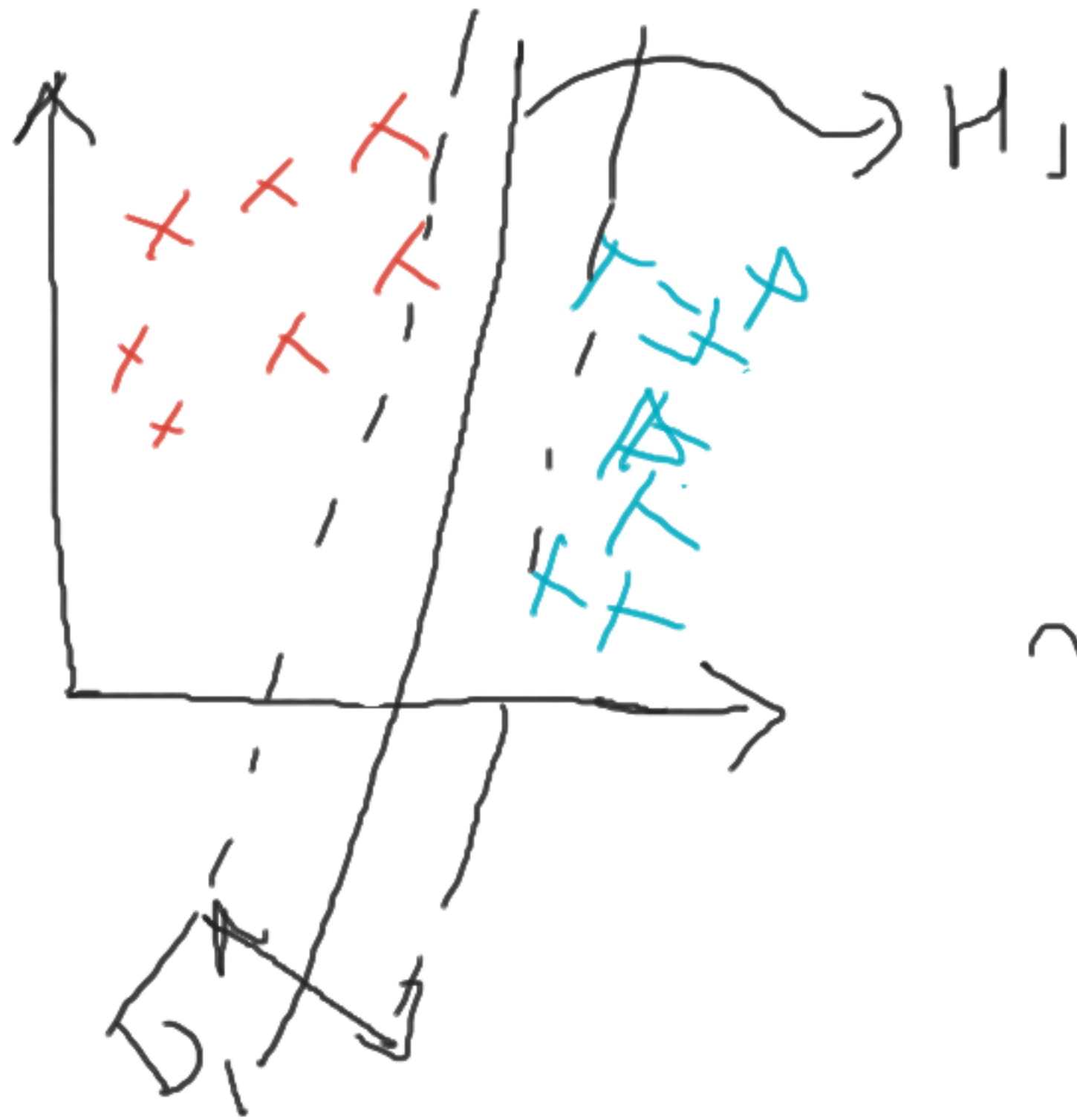
Support vector
Machine





They pick the
red region
support
vectors

There are
other possibilities
but we choose
this because



Our main aim is to
maximize $D \rightarrow$
marginal
distance

Note The hyperplane with max margin
is best hyperplane.

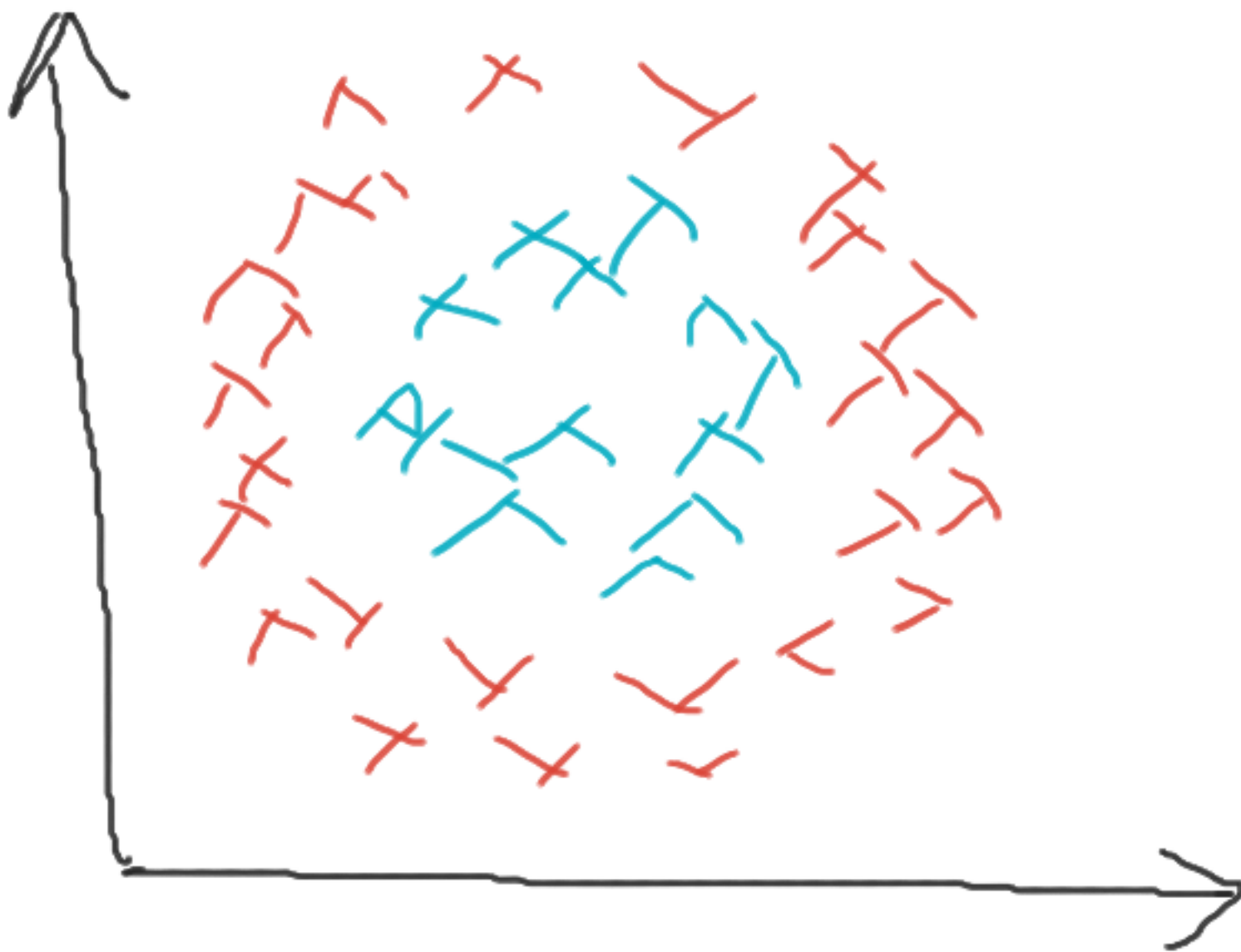
The previous examples were linearly

separable

E.g.

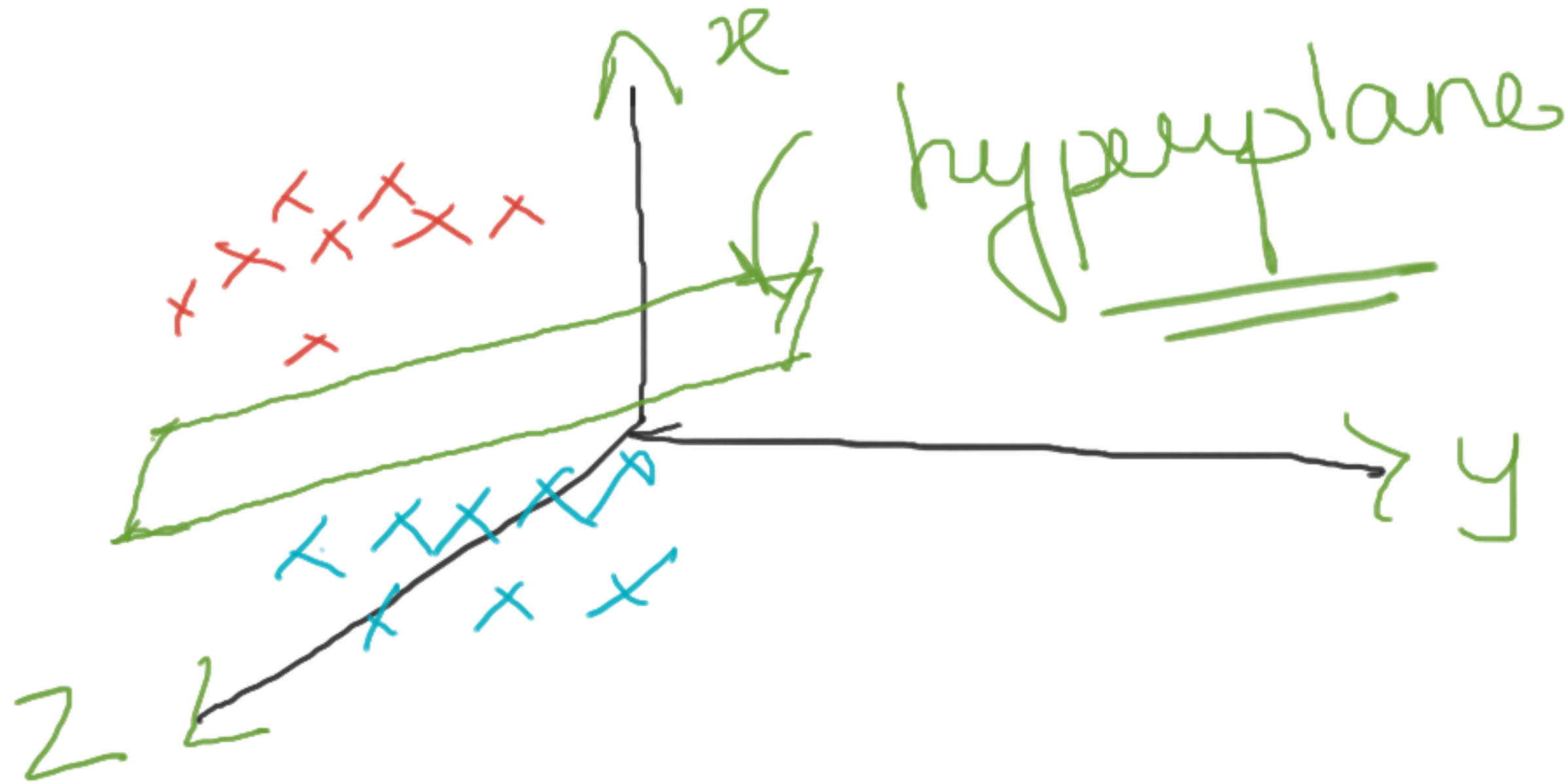
But there may
be non-linear

separable

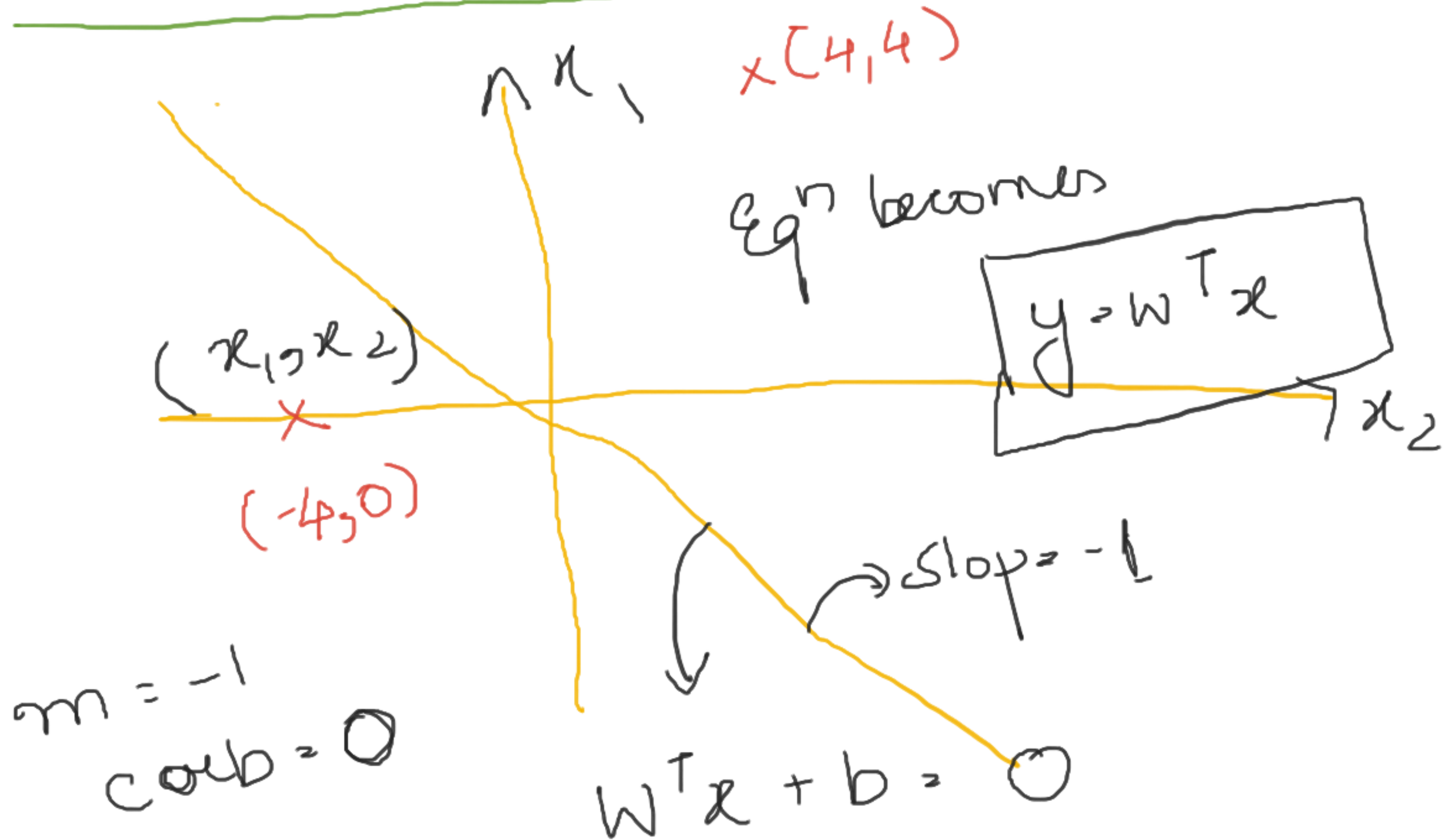


To solve ^{non} linearly separable data, we use
SVM Kernels.

↳ convert 2D \rightarrow 3D



SVM maths intuition



$$- \begin{matrix} \omega \\ \begin{bmatrix} -1 \\ 0 \end{bmatrix} \end{matrix} \begin{matrix} \begin{bmatrix} -4 & 0 \end{bmatrix} \\ 2 \times 2 \end{matrix}$$

1×2

z is $4 - 1$ +ve value

Any point in red below line, it will always be +ve ✓

For above point-

$$y = w^T x$$

$$= \begin{bmatrix} -1 \\ 0 \end{bmatrix} \begin{bmatrix} 4 & 4 \end{bmatrix}$$

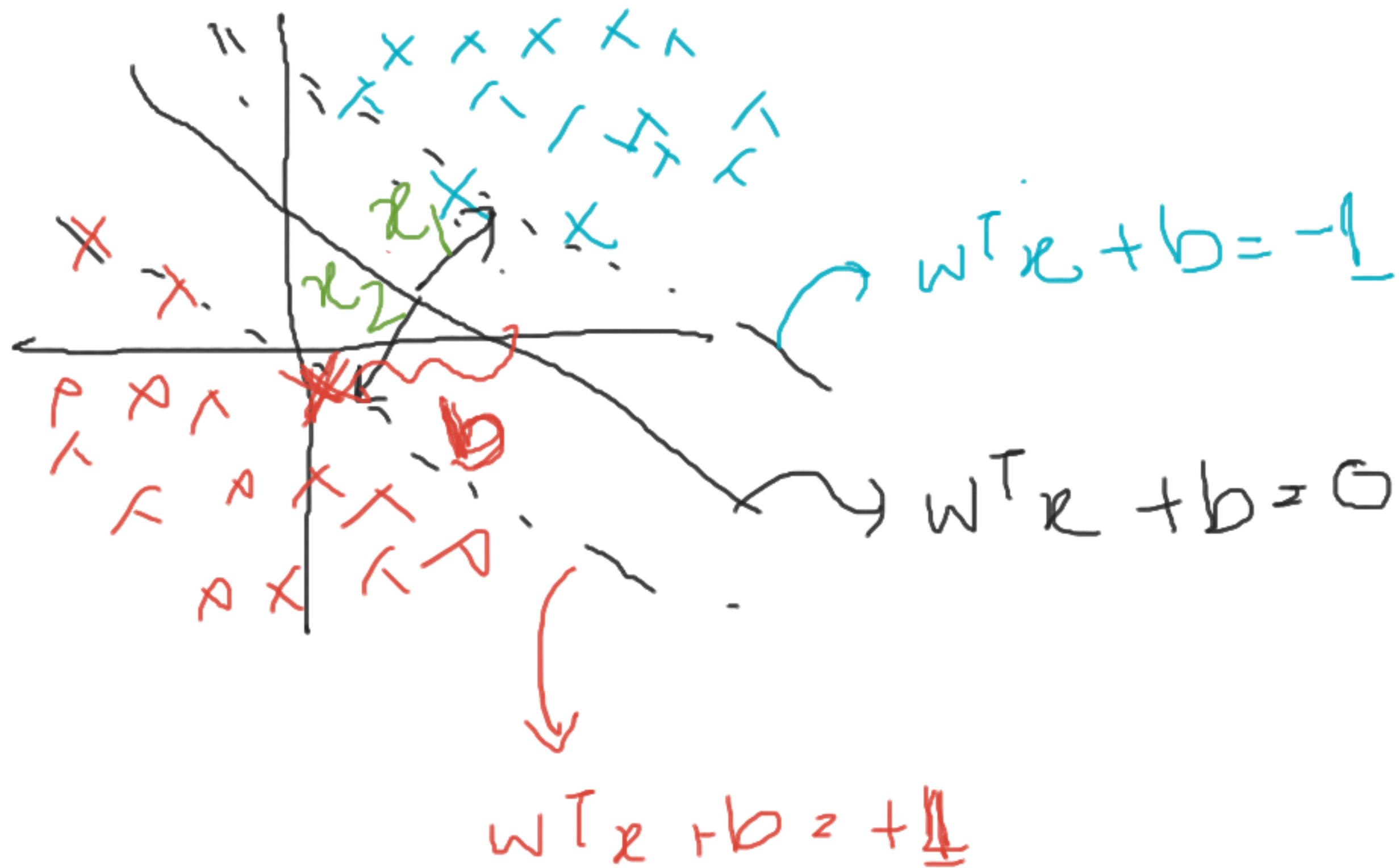
$$z - 4 \Rightarrow -ve$$

Always -ve above line

$$+ve \rightarrow +1$$

$$-ve \rightarrow -1$$

→ For simplification



$$w^T x_1 + b = -1$$

$$\frac{w^T x_2 + b}{(-1)(-1)(-1)} = +1$$

$$w^T (x_1 - x_2) = -2$$

$$\Rightarrow w^T (x_2 - x_1) = 2$$

$$\Rightarrow \frac{w^T}{\|w\|} (x_2 - x_1) = \frac{2}{\|w\|}$$

↑ maximize this

Update w^*, b^* such that

we maximize $\frac{2}{\|w\|}$

Such that $\begin{cases} +1 \rightarrow w^T x + b \geq 1 \\ -1 \rightarrow w^T x + b \leq -1 \end{cases}$

$y_i \neq w^T x_i + b_i \geq 1 \rightarrow \text{okay}$

$$(w^*, b^*) = \min \frac{\|w\|^2}{2} + C \sum_{i=1}^n \xi_i \rightarrow \text{value of error}$$

SVM
optimization
fn

How many errors my model
can consider

Regularization