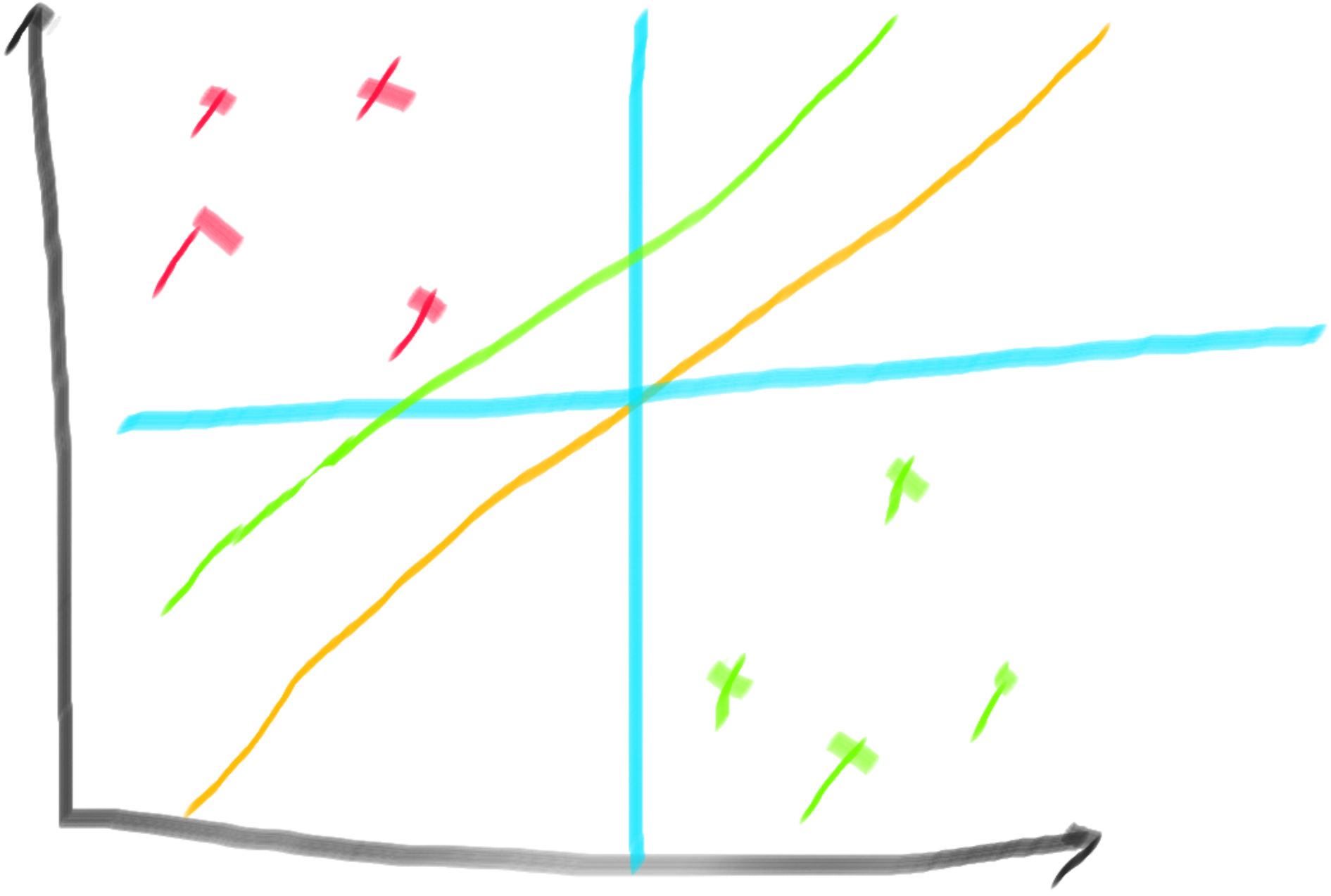
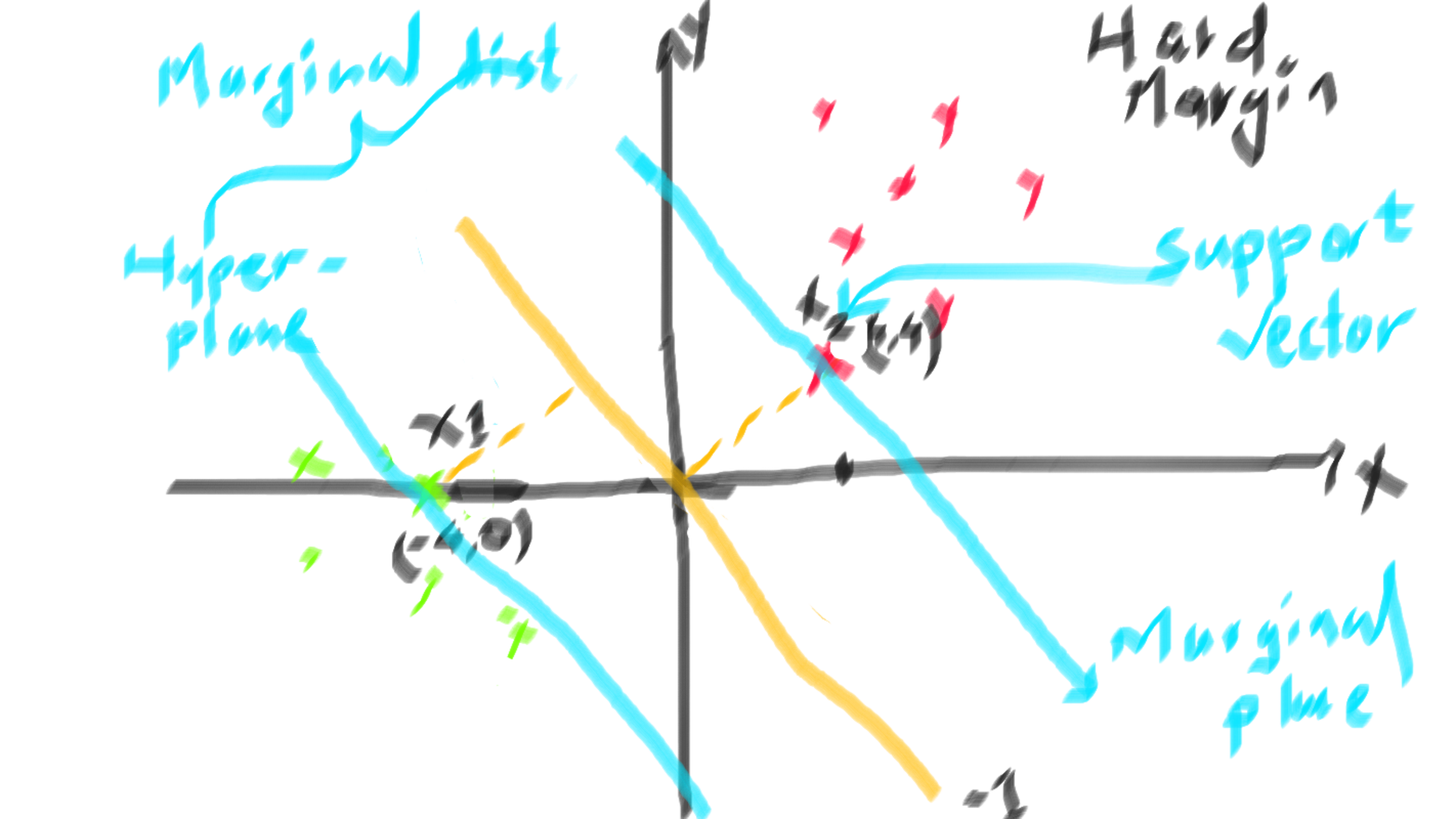



Marginal dist.
Hyper-plane
Hard Margin
support vector
x1
(-2,0)
(2,4)
Marginal plane

$y = mx + c$

$y = w^T x + b$

$= \begin{bmatrix} -1 \\ 0 \end{bmatrix} x_1$

$= \begin{bmatrix} -1 \\ 0 \end{bmatrix} [-4, 0]$

$y = +4$

$\begin{bmatrix} -1 \\ 0 \end{bmatrix} x_2$

$y = \begin{bmatrix} -1 \\ 0 \end{bmatrix} [4, 4]$

$y = -4$

$w^T x_1 + b = 4$

$- w^T x_2 + b = -4$

$w^T [x_1 - x_2] = 8$

eqn of marginal distn.

$$w^T[x_1 - x_2] = -b$$

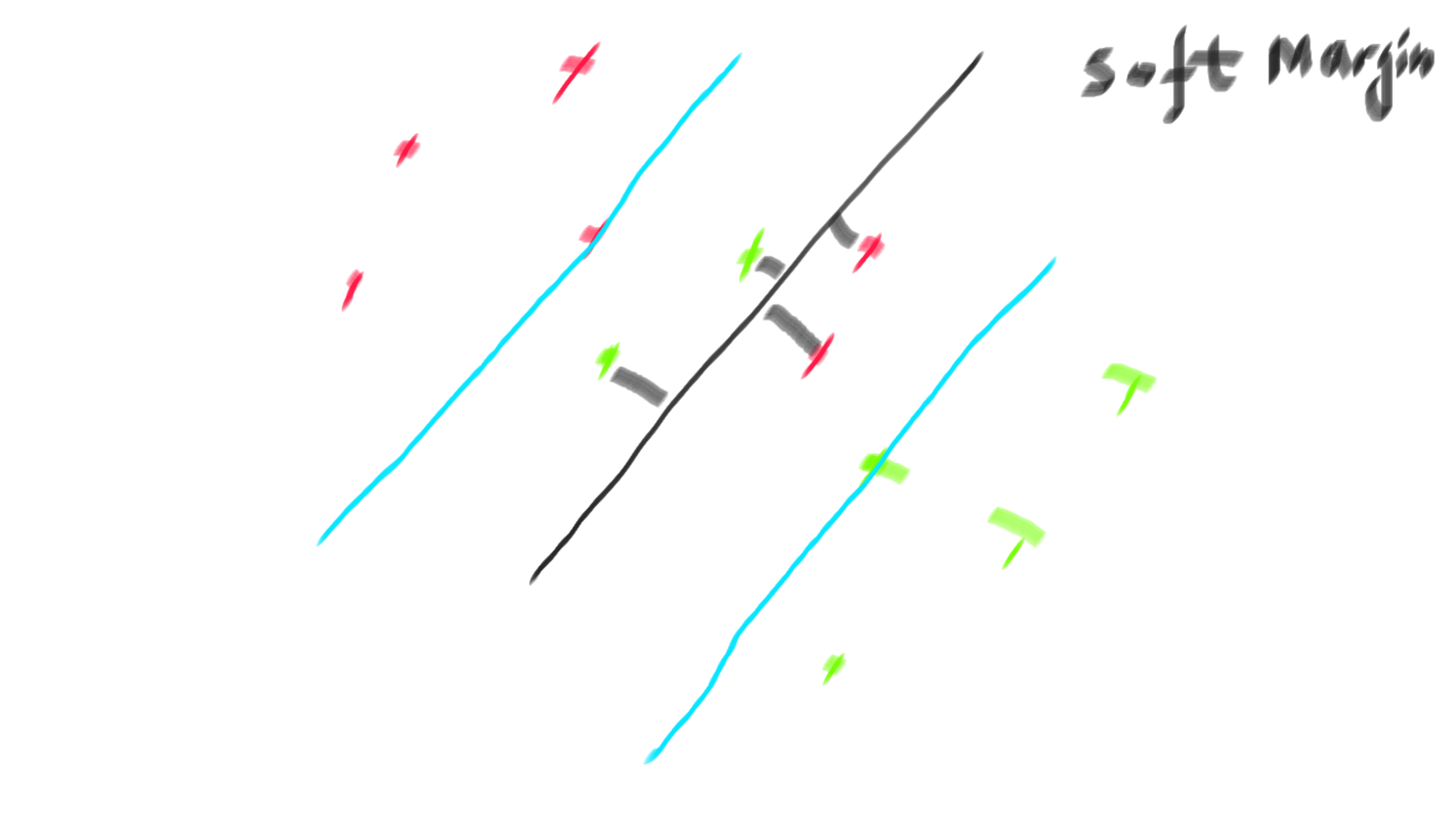
$$\frac{w^T}{\|w\|}[x_1 - x_2] = -\frac{b}{\|w\|}$$

$$x_1 - x_2 = -\frac{b}{\|w\|}$$

$$x_1 - x_2 = \frac{-\delta}{\|w\|} \uparrow\uparrow$$

$$x_1 - x_2 = \max \frac{-\delta}{\|w\|} \rightarrow \|w\|^2 b^2$$

$$x_1 - x_2 = \min -\frac{\|w\|}{\delta}$$


soft Margin

$$\max_{w,b} \frac{2}{\|w\|} + C \sum_{i=1}^{n} \xi_i$$

ξ_i → Zeta → dist. of error from optimal line

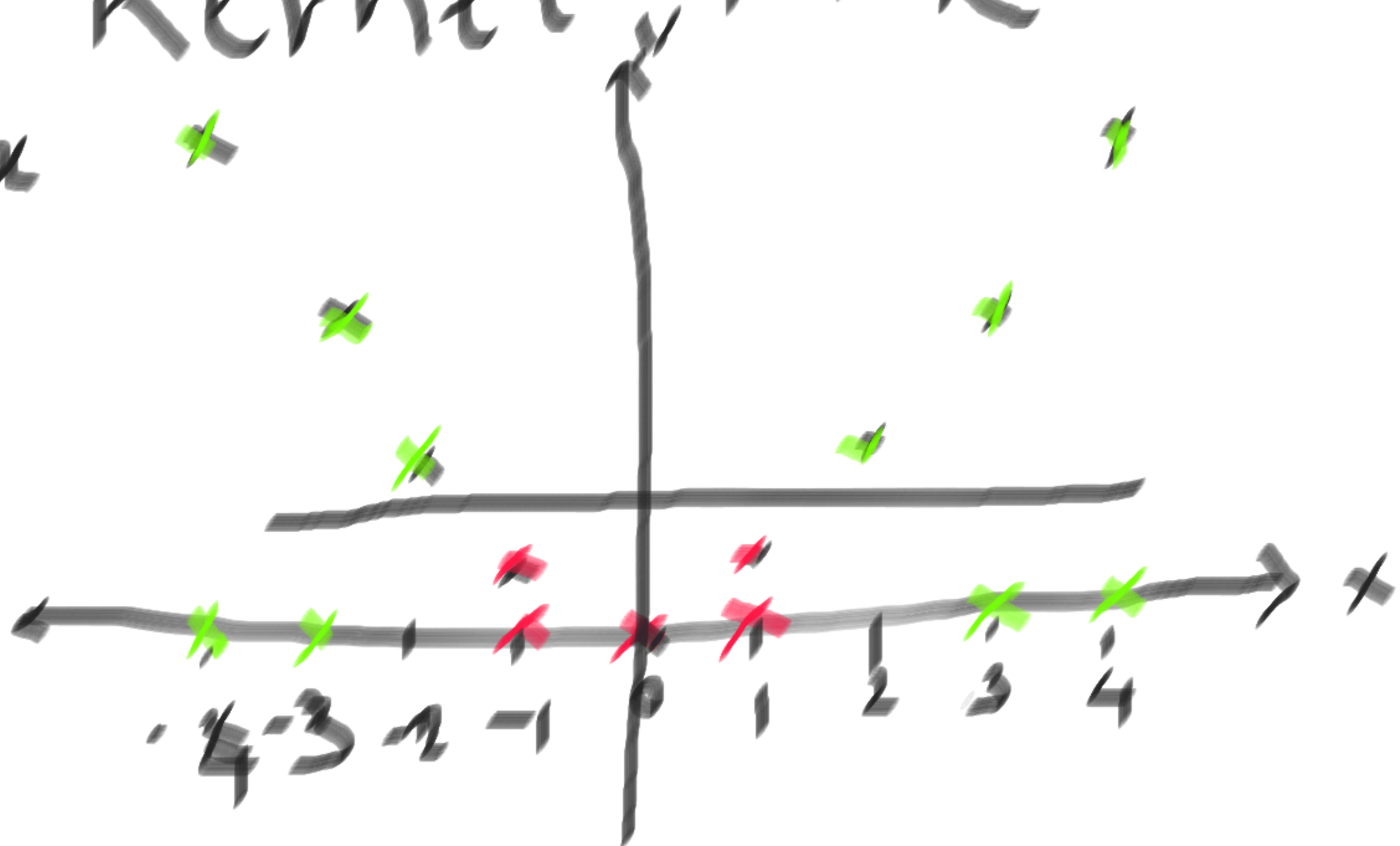
C → Regularization → no. of acceptable errors

c range (0-100)

Kernel Trick

$f(y) = x$

$f(y) = x^2$



$$poly\ k = (x_1^T x_2 + 1)^d$$

$$= \left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \cdot [x_1 \ x_2] + 1\right)^1$$

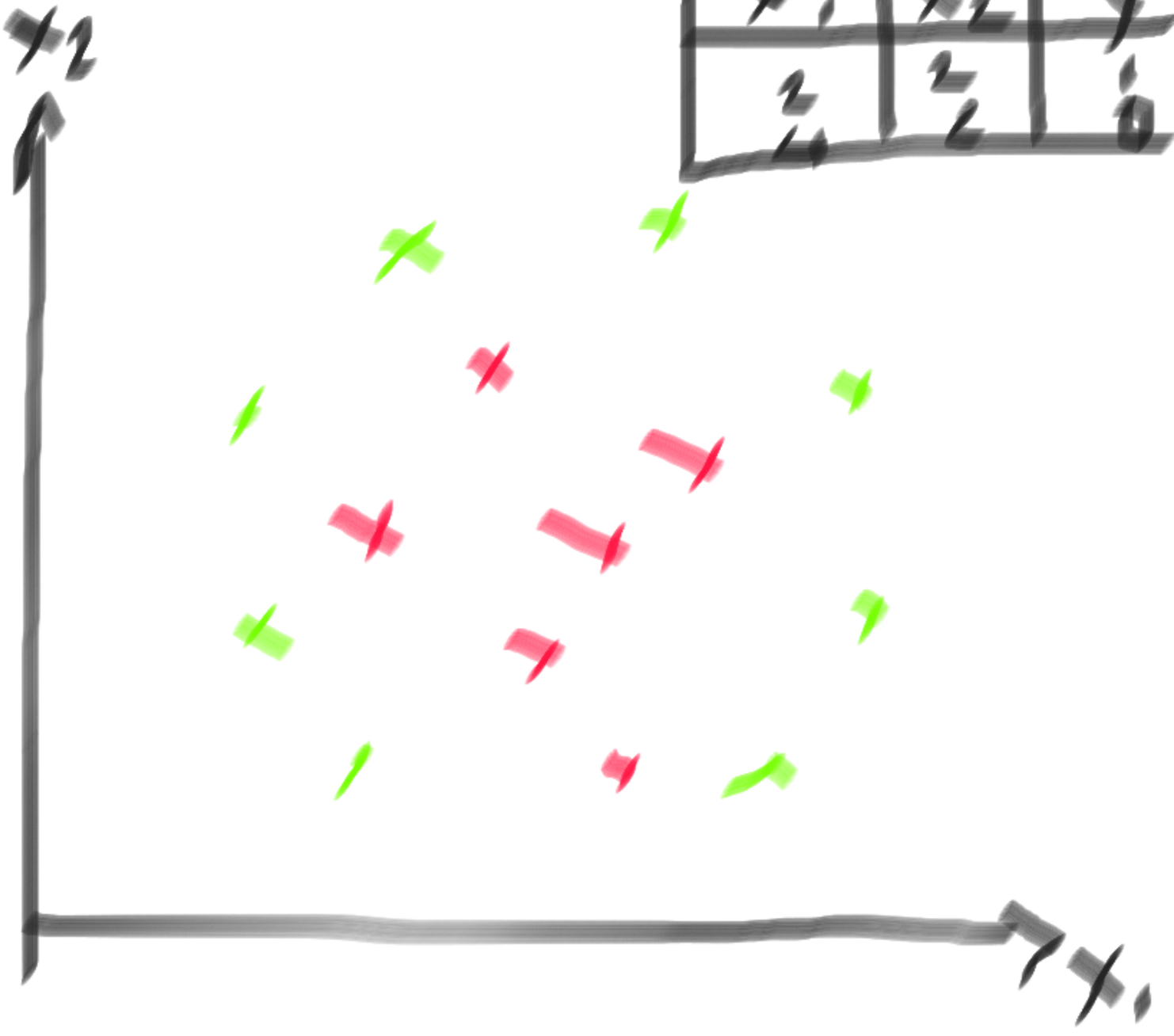
$$= (x_1 + x_2)^2$$

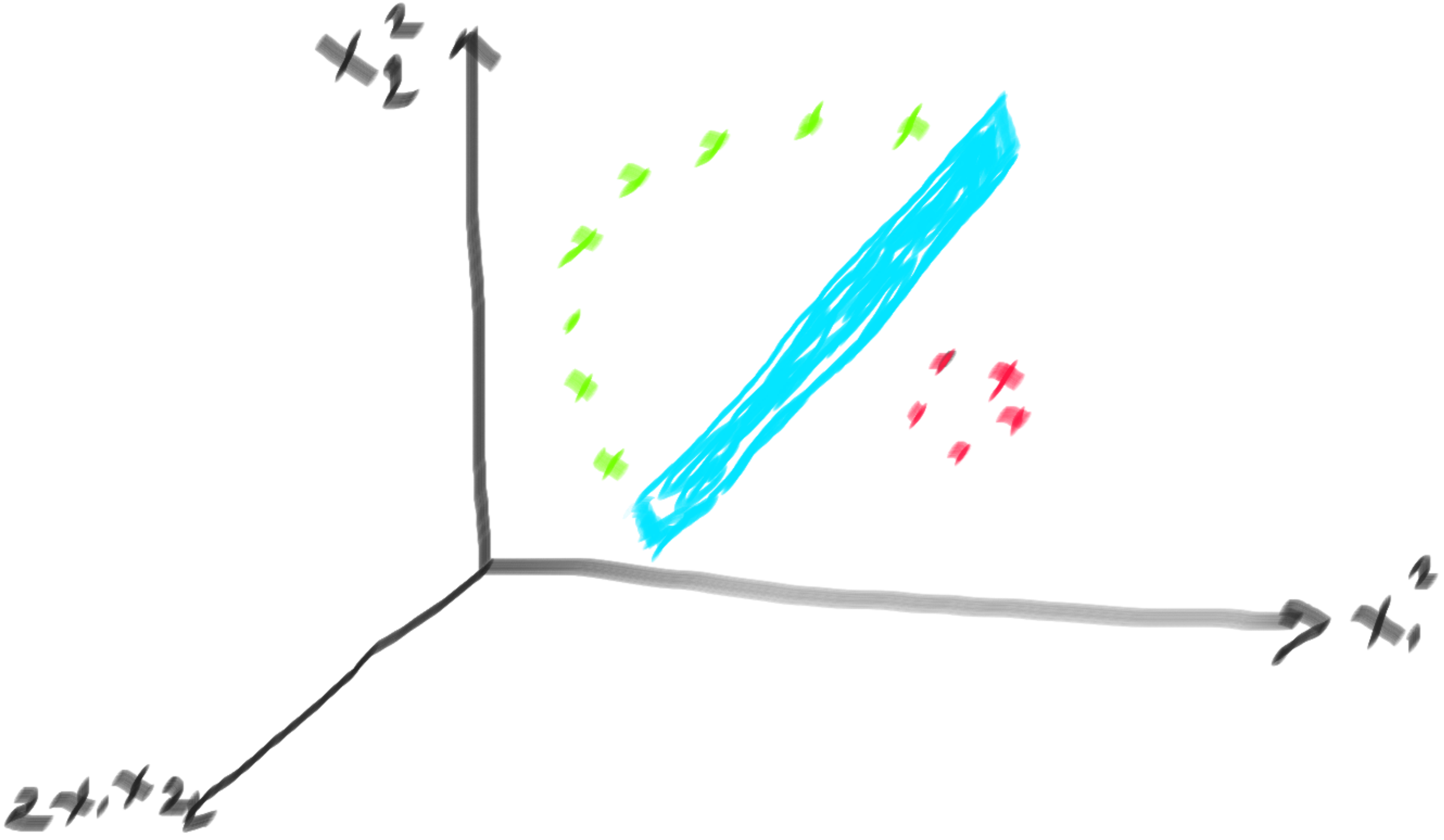
$$= x_1^2 + 2x_1x_2 + x_2^2$$

$$\begin{bmatrix} x_1^2 & x_1 x_2 \\ x_1 x_2 & x_2^2 \end{bmatrix}$$

x_1^2	x_2^2	$x_1 x_2$	y
1	2	2	0
0.5	0.5	0.25	1

x_1	x_2	y
2	2	0




x_2^2
x_1^2
x_1, x_2

SVM Regression