

Binary classification task

inputs are associated with targets $t \in \{-1, 1\}$

(using same notation than for perceptron)

negative class positive class

Linear model : $z = \vec{w}^T \vec{x} + b$

$y = \begin{cases} 1 & \text{if } z \geq 0 \\ -1 & \text{if } z < 0 \end{cases} = \text{sign}(z)$

Error / loss / cost of our model:

$\mathcal{L}_{0-1}(y, t) = \begin{cases} 0 & \text{if } y = t \\ 1 & \text{if } y \neq t \end{cases}$

$z = \vec{w}^T \vec{x} + b$, if we replace $\vec{w} \leftarrow 2\vec{w}$
 $b \leftarrow 2b$

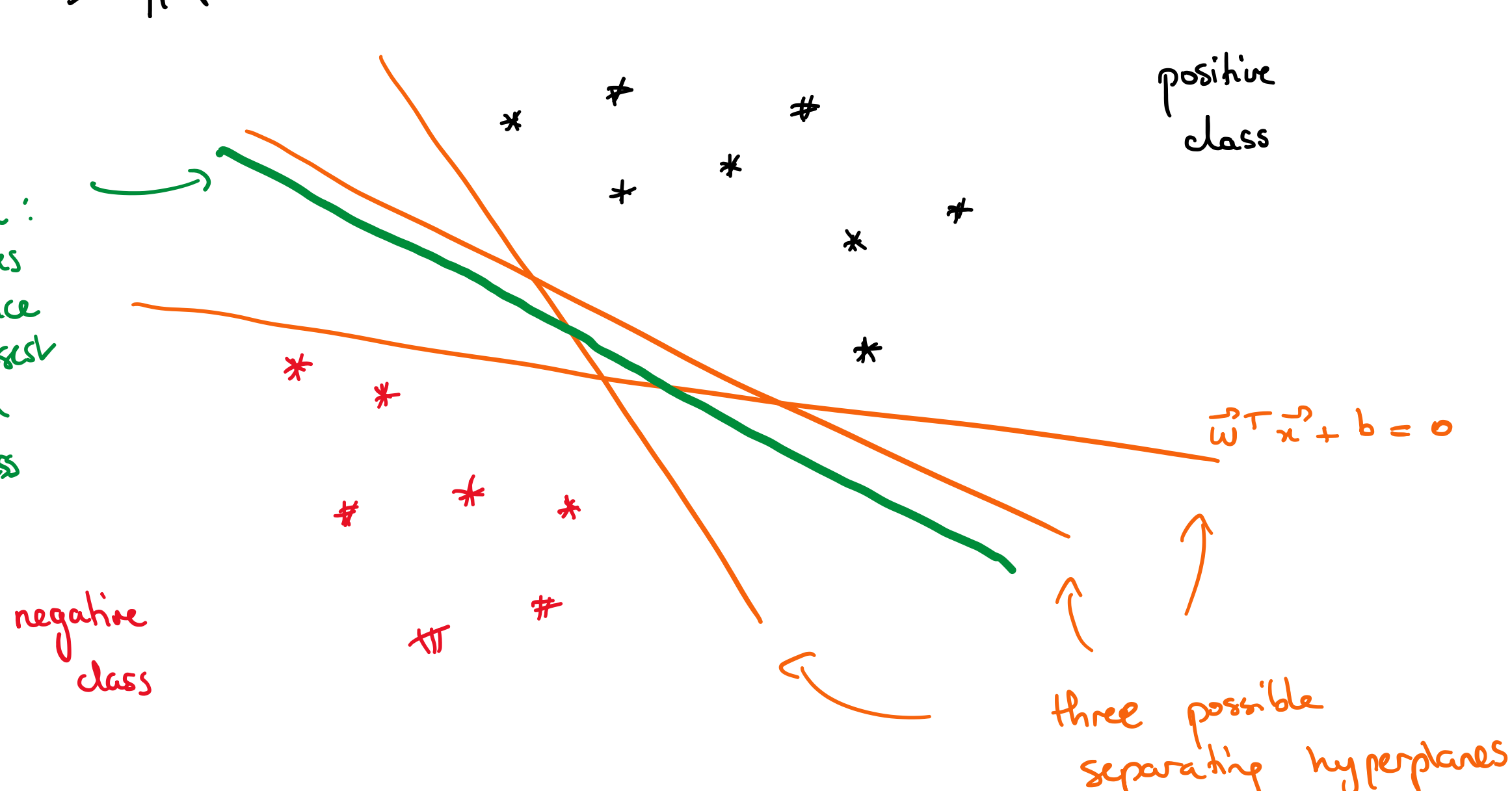
z gets modified but y is identical.

$y = \text{sign}(z)$
 $y = \text{sign}(2z)$ equal

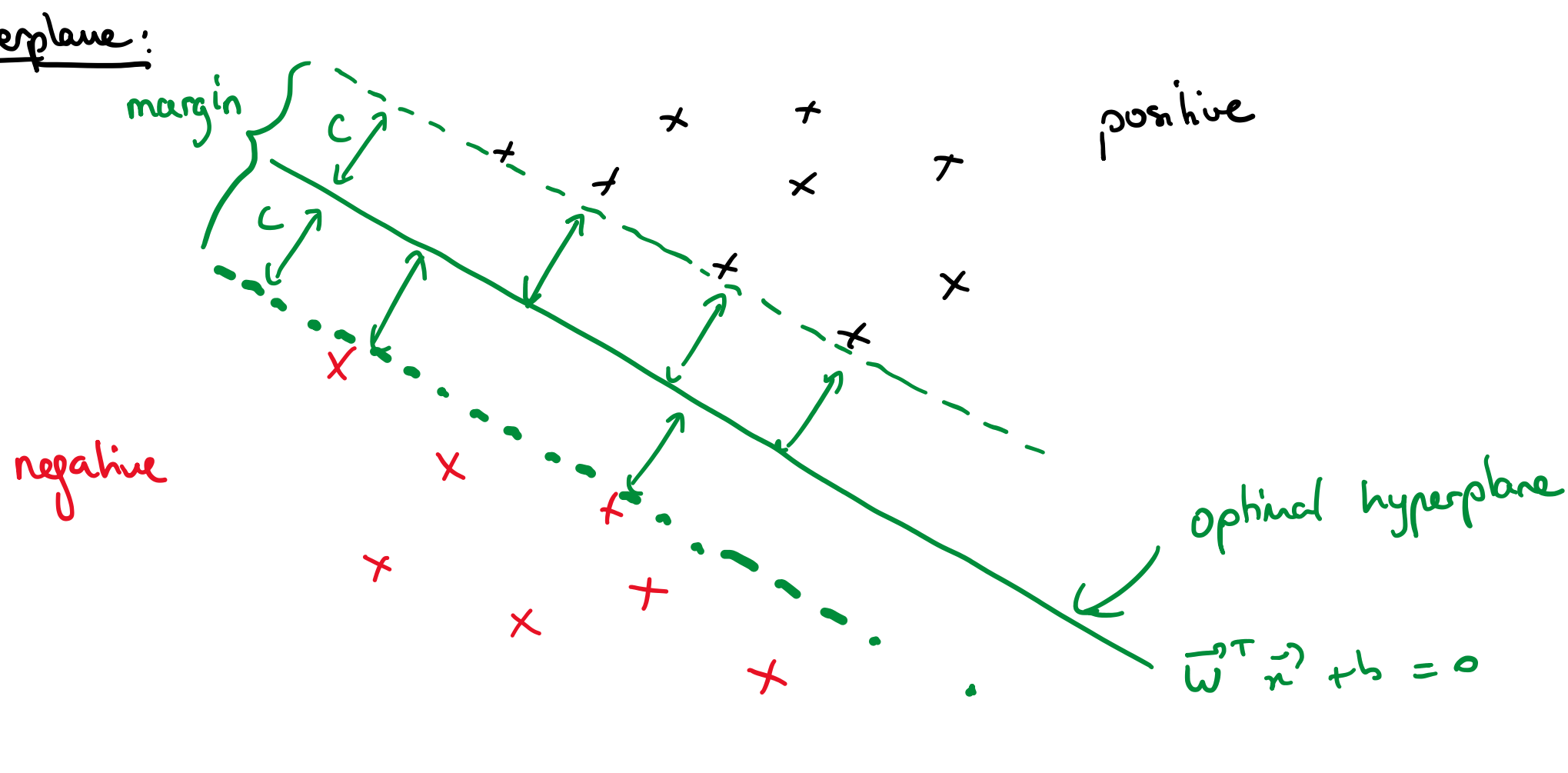
\Rightarrow The classifier's confidence is not captured by this loss.

Separating hyperplanes

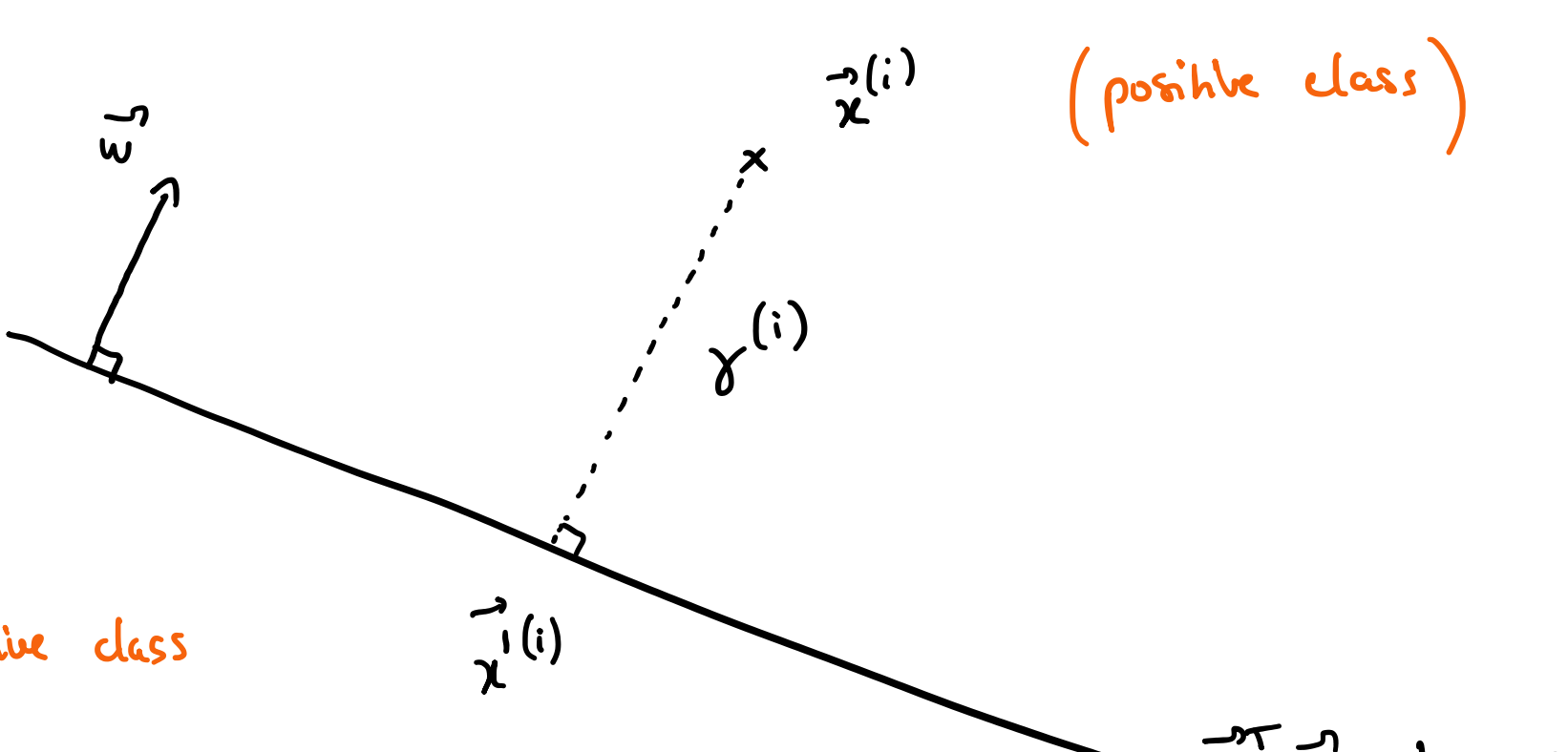
optimal separating hyperplane: it maximizes the distance to the closest point from each class



Max-margin hyperplane:



Geometry reminders



for positive class
 $\vec{x}^{(i)} = \vec{x} - \gamma^{(i)} \frac{\vec{w}}{\|\vec{w}\|}$

(if negative class - becomes +)

How to measure $\gamma^{(i)}$:

Given that $\vec{x}^{(i)}$ is on the hyperplane: $\vec{w}^T \vec{x}^{(i)} + b = 0$

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

$\vec{w}^T \vec{w} = \|\vec{w}\|^2$

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

$\vec{w}^T \vec{x}^{(i)} - \gamma^{(i)} \|\vec{w}\| + b = 0$

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

(this holds when the example is in the positive class)

The following holds for both positive and negative examples.

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

Enforcing the geometric margin:

For an example $\vec{x}^{(i)}$,

$\gamma^{(i)} \geq C$

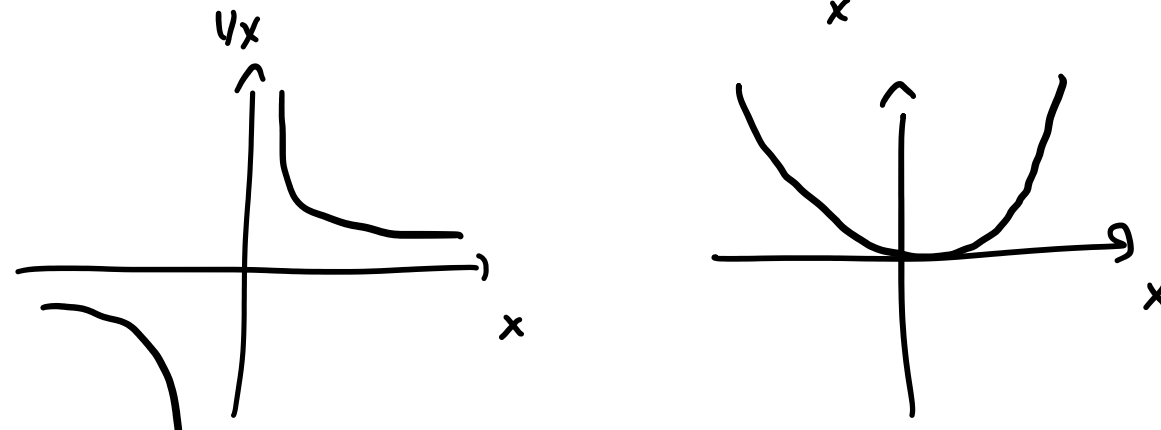
minimum distance between the training point $\vec{x}^{(i)}$ and the classifier's decision boundary (the hyperplane)

We want a classifier such that:

$\max_{\vec{w}, b} C \quad \text{s.t.} \quad t^{(i)} \frac{\vec{w}^T \vec{x}^{(i)} + b}{\|\vec{w}\|} \geq C \quad \forall i \in 1..N$

* Set $C = \frac{1}{\|\vec{w}\|}$ (because the classifier is invariant to rescaling of \vec{w})

* $\max \frac{1}{x} \Leftrightarrow \min x^2$



$\min_{\vec{w}, b} \|\vec{w}\|^2 \quad \text{s.t.} \quad t^{(i)} \frac{\vec{w}^T \vec{x}^{(i)} + b}{\|\vec{w}\|} \geq \frac{1}{\|\vec{w}\|} \quad \forall i \in 1..N$

$\min_{\vec{w}, b} \|\vec{w}\|^2 \quad \text{s.t.} \quad t^{(i)} (\vec{w}^T \vec{x}^{(i)} + b) \geq 1 \quad \forall i \in 1..N$

