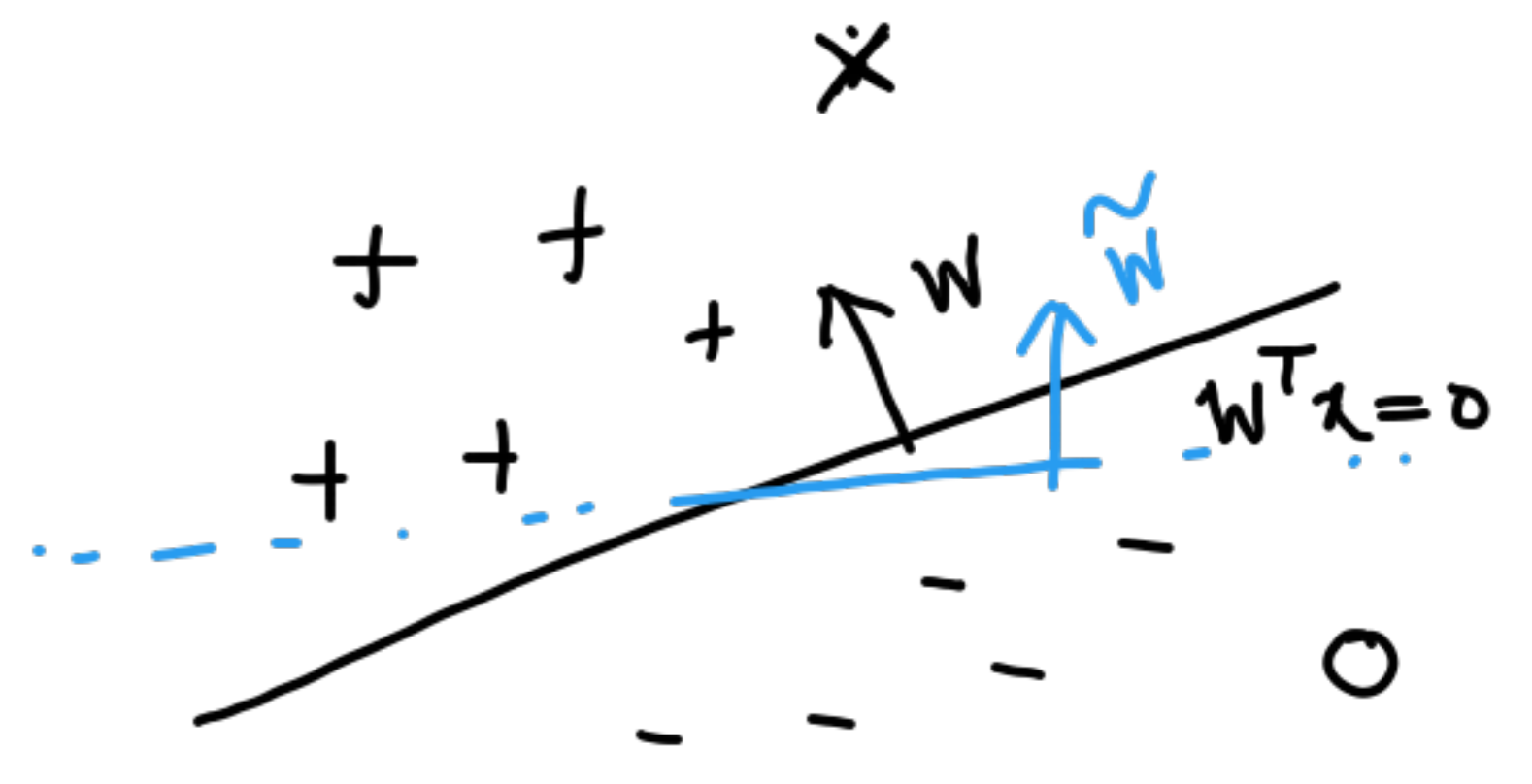


Lec 09: Perceptron : linear deterministic classification method

$$y_i = f(x_i) \in \{+1, -1\}$$



Goal: learn a weight vector w that linearly separates the training data points

$$\begin{bmatrix} 1 \\ x_i \end{bmatrix} w^T x$$

$$w^T x_i + w_0 \geq 0 \quad \text{for } y_i = 1$$

$$< 0 \quad \text{or } y_i = -1$$

Remark: the decision boundary is not unique.

$$f_w(x) = \text{sgn}(W^T x)$$

Q: How does perceptron find w ?

1. Goes over the training examples (x_i, y_i) one by one
2. Check if the current classifier w_t , i.e.
$$y_i = \text{sgn}(w_t^T x_i)$$
3. If correct - no update

4. If not - correct w_{t+1}

$$w_{t+1} \leftarrow w_t + \underbrace{y_i}_{\text{vector (d=1)}} x_i$$

5. STOP if no update for a certain number of iteration.

Remarks: (1) Online algorithms

The data points are used one-by-one
 \leftrightarrow batch algorithms (LR, NB) - takes all data

Algorithm: Perceptron

- Initialize w_0

- for $t = 0, 1, 2, \dots, \text{maxRounds}$:

$$y_i = \text{sgn}(w^T x_i)$$

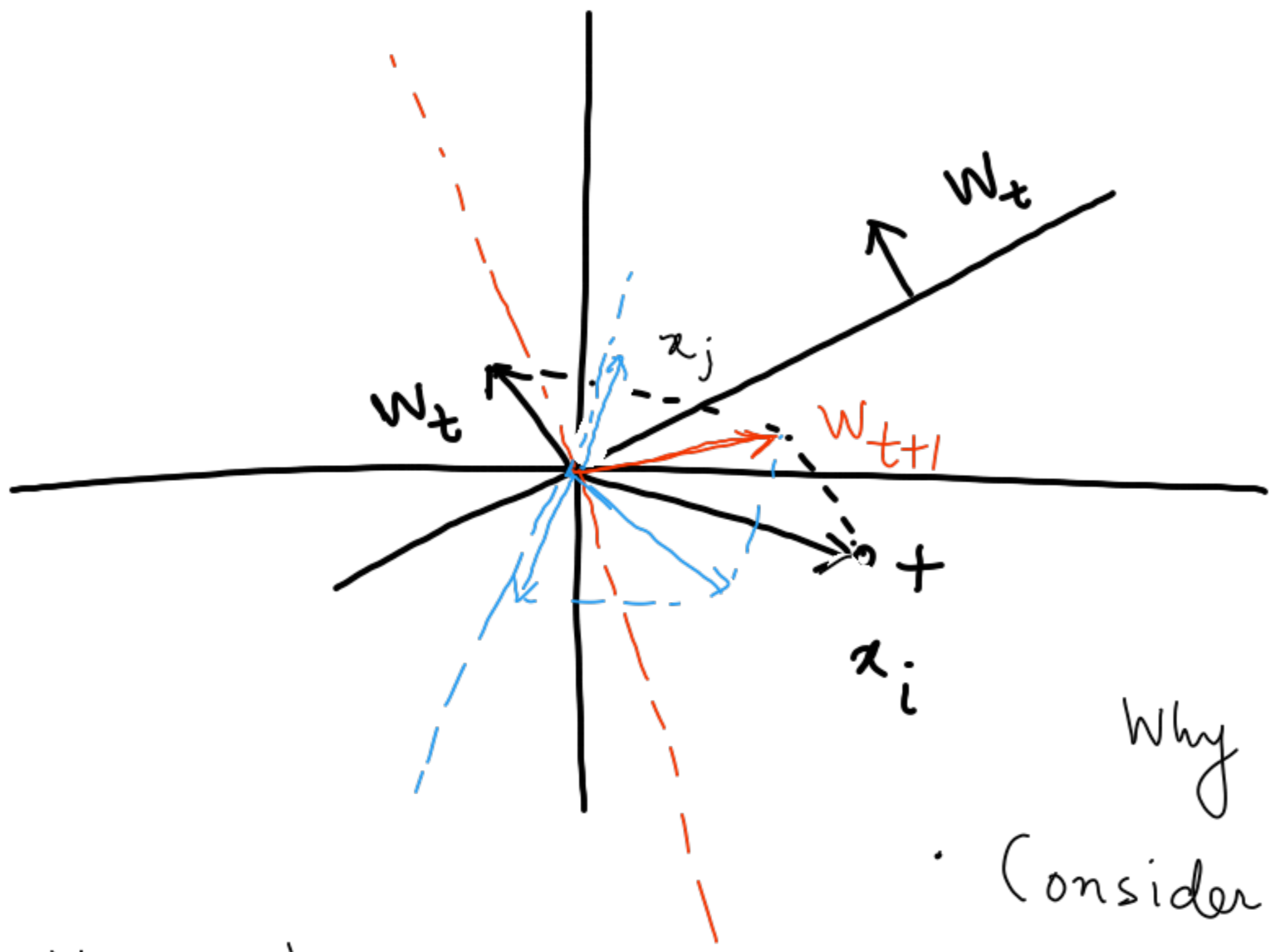
Randomly choose a training
example (x_i, y_i)

if $y_i(w_t^T x_i) < 0$, then

$$w_{t+1} \leftarrow w_t + y_i x_i$$

- STOP as before.

$$w_{t+1} \leftarrow w_t + \frac{1}{2} (y_i - \text{sgn}(w_t^T x_i)) x_i$$



$$W_{t+1} \leftarrow W_t + x_i$$

$$W_{t+2} \leftarrow W_{t+1} - x_j$$

Why is perceptron doing a meaningful update?

Consider a misclassified example (x_i, y_i)

i.e. $\text{sgn}(w_{\text{old}}^T x_i) \neq y_i$

$$y_i (w_{\text{new}}^T x_i) = y_i (w_{\text{old}} + y_i x_i)^T x_i = y_i w_{\text{old}}^T x_i + \underbrace{\|x_i\|^2}_{> y_i (w_{\text{old}}^T x_i)}$$

$$w_{\text{new}} = w_{\text{old}} + y_i x_i$$

Note: still not guaranteed to be correctly classified.

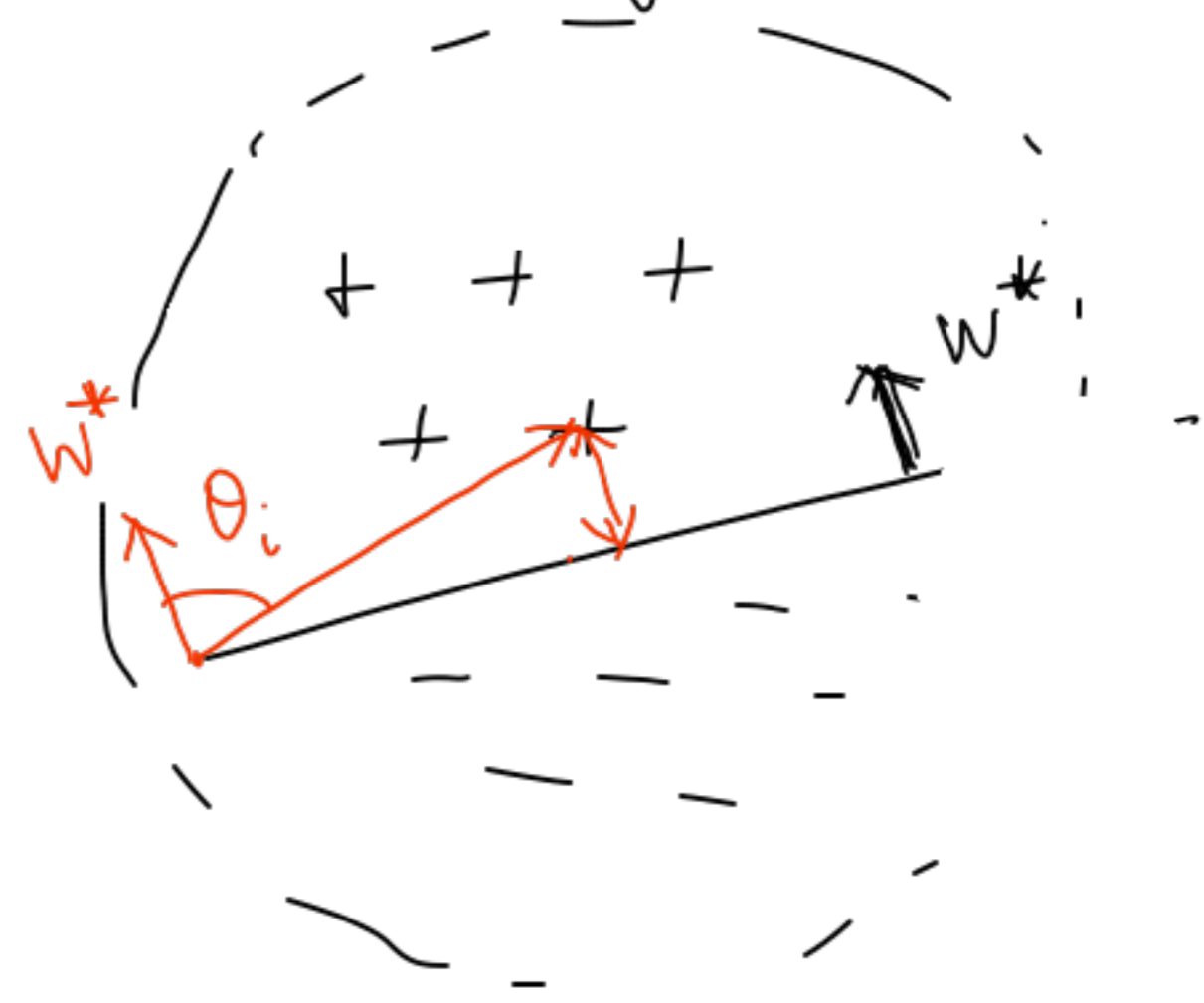
Summary: • Perceptron is a mistake-driven online learning algo.

• Guaranteed to converge for linearly separable training examples.

If the data is linearly separable,

$$\exists w^* \text{ s.t. } y_i (w^{*T} x_i) \geq 0 \quad \forall i = 1, \dots, n.$$

Assume $\|w^*\| = 1$, $\|x_i\| \leq 1$



Define, *margin of separation* $\gamma = \min_i |w^{*T} x_i| = \|w^*\| \|x_i\| \cos \theta_i$

Theorem: If \exists a unit vector w^* s.t. $y_i w^{*T} x_i \geq \gamma \quad \forall (x_i, y_i) \in D$

Then the # of weight updates by perceptron is at most $\frac{1}{\gamma^2}$.

Proof: track two quantities ① $W_t^T W^*$, ② $\|W_t\|_2^2$

① Claim: $W_t^T W^*$ on every update increases by at least γ

$$\begin{aligned} W_{t+1}^T W^* &= (W_t + \gamma_i x_i)^T W^* \\ &= W_t^T W^* + \underbrace{\gamma_i (W^{*T} x_i)}_{\geq \gamma} \geq W_t^T W^* + \gamma \end{aligned}$$

② Claim: $\|W_t\|^2$ increases by at most 1.

$$\|W_{t+1}\|^2 = (W_t + \gamma_i x_i)^T (W_t + \gamma_i x_i) = \|W_t\|^2 + \underbrace{2\gamma_i W_t^T x_i}_{< 0} + \underbrace{\|x_i\|^2}_{\leq 1} < \|W_t\|^2 + 1$$

Say $W_0 = 0$. After k updates

$$W_{k+1}^T W^* \geq k\gamma$$

$$\|W_{k+1}\|^2 < k$$

$$\sqrt{k} > \|W_{k+1}\| \geq W_{k+1}^T W^* \geq k\gamma \Rightarrow k < \frac{1}{\gamma^2}$$

$$W_{k+1}^T W^* = \|W_{k+1}\| \underbrace{\|W^*\|}_{=1} \underbrace{\cos \theta}_{\leq 1}$$

finite number of mistakes if data is linearly separable.

Limitations:

- ① Not giving a rate of convergence
- ② The # of iterations can be large if γ is small
- ③ May not converge if points are not linearly separable.

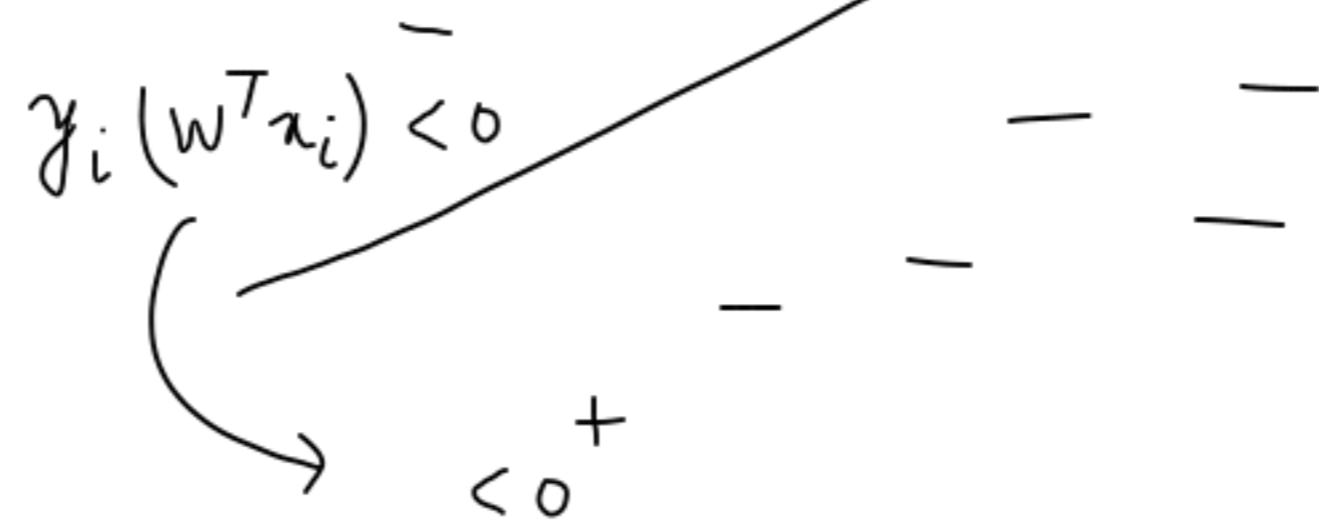
Find one such example of non convergence (HW)

The loss function view of perceptron

$$y_i w^T x_i < 0$$

maximize $y_i (w^T x_i)$

$\Rightarrow \min_w \sum_{i \in \text{misclassified examples}} (-y_i (w^T x_i))$



for any i

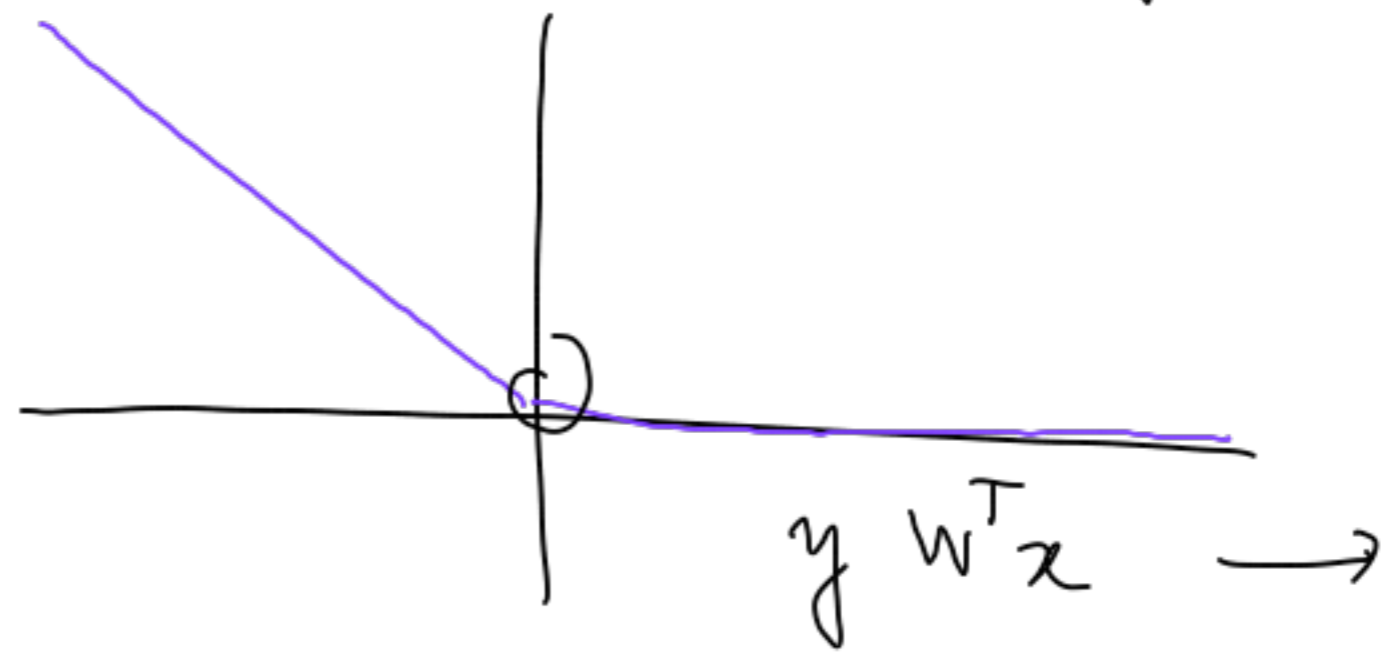
$$y_i w^T x_i \geq 0 \rightarrow \text{loss} = 0$$

$$< 0 \rightarrow \text{loss} = -y_i w^T x_i$$

$$L_i(w, D) = \max \{ 0, -y_i w^T x_i \}$$

Hinge loss

$$L(w, D) = \sum L_i(w, D)$$



Apply SGD: \rightarrow randomly pick i , compute $\nabla_w L_i(w, D)$

$$w_{t+1} \leftarrow w_t - \underbrace{\nabla_w L_i(w, D)}_{-y_i x_i}$$

$$-y_i w^T x_i$$

Hinge loss with SGD

is the perceptron algo.

$$w_t + y_i x_i$$

Decision Trees

Fuel efficiency	cyl	disp	Origin	Year
good	3	low		
	4	med		
bad	5			
	6	high		

