

We say $(x^{(1)}, y_1), \dots, (x^{(n)}, y_n)$ are linearly separable with const $\gamma > 0$ if \exists a unit vector $w^* \in \mathbb{R}^p$, $\|w^*\| = 1$ such that

$$y_i \cdot (w^* \cdot x^{(i)}) > \gamma > 0 \quad i=1, \dots, n.$$

Perception Learning Algorithm

Input: sample pts with labels

$$(x^{(1)}, y_1), \dots, (x^{(n)}, y_n)$$

Output: weight $w = (w_1, \dots, w_p)^T$

Step 1: Set $k=0$, $w^{(0)} = 0$

Step 2: While $\exists (x^{(i)}, y_i)$ such that

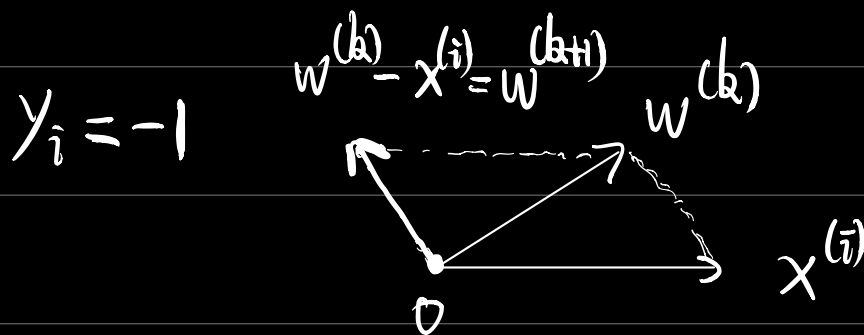
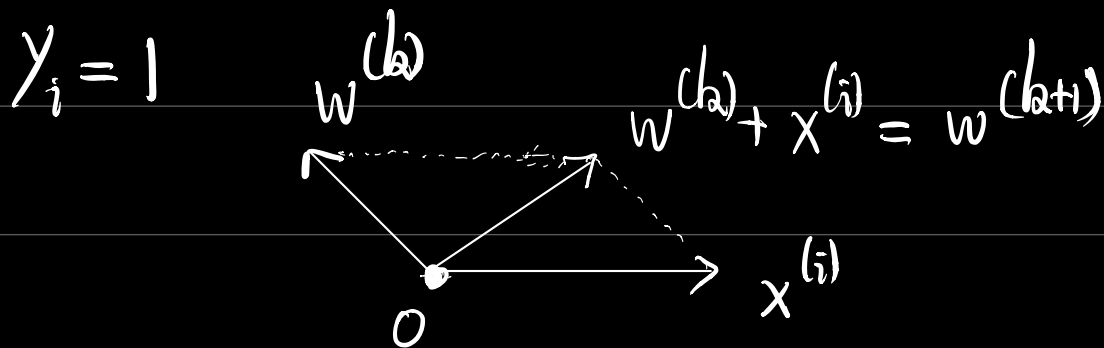
$$y_i (w^{(k)} \cdot x^{(i)}) < 0, \text{ update}$$

$$w^{(k+1)} = w^{(k)} + y_i x^{(i)}$$

$$k \leftarrow k+1$$

Remark: Here is a heuristic argument why $w^{(k+1)}$ is better than $w^{(k)}$ for classification

Suppose $(x^{(i)}, y_i)$ is misclassified by $\text{sign}(w^{(k)} \cdot x^{(i)})$.



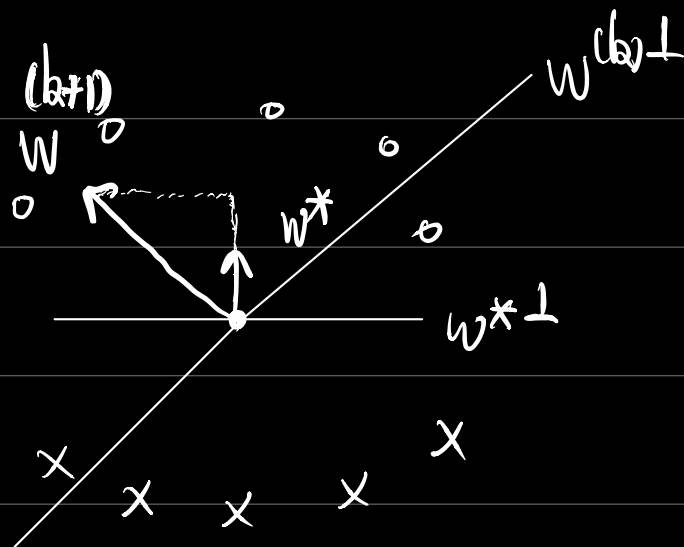
Theorem: Suppose

- (1) the sample pts with labels $(x^{(1)}, y_1), \dots, (x^{(n)}, y_n)$ are linearly separable with const $\gamma > 0$.

(z) $x^{(1)}, \dots, x^{(n)}$ are bounded, i.e. $\exists R > 0$,
such that $\|x^{(i)}\| \leq R$

Then the perceptron learning algorithm makes
at most $\frac{R^2}{\gamma^2}$ updates before returning a
separating hyperplane.

Proof:



Let w^* be the unit vector in the definition
of linear separability, then

$$y_j \cdot (w^* \cdot x^{(j)}) > \gamma > 0 \quad j = 1, \dots, n. \textcircled{1}$$

Compute the projection of $w^{(k+1)}$ on w^* ,
if $(x^{(i)}, y_i)$ is misclassified,

$$\begin{aligned}
 w^{(k+1)} \cdot w^* &= (w^{(k)} + \gamma_i x^{(i)}) \cdot w^* \\
 &= w^{(k)} \cdot w^* + \gamma_i (x^{(i)} \cdot w^*)
 \end{aligned}$$

$$\begin{aligned}
 &\textcircled{1} \\
 &> w^{(k)} \cdot w^* + \gamma
 \end{aligned}$$

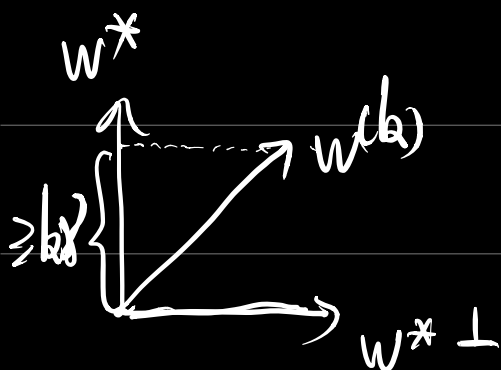
This shows: $w^{(k+1)} \cdot w^* > w^{(k)} \cdot w^* + \gamma$

$$\begin{aligned}
 \text{Similarly: } &w^{(k)} \cdot w^* > \cancel{w^{(k-1)}} \cdot w^* + \gamma \\
 &\cancel{w^{(k-1)} \cdot w^*} > \cancel{w^{(k-2)}} \cdot w^* + \gamma \\
 &\vdots \\
 &\cancel{w^{(1)} \cdot w^*} > \cancel{w^{(0)}} \cdot w^* + \gamma = \gamma
 \end{aligned}
 \left. \vphantom{\begin{aligned} &w^{(k)} \cdot w^* > \cancel{w^{(k-1)}} \cdot w^* + \gamma \\ &\cancel{w^{(k-1)} \cdot w^*} > \cancel{w^{(k-2)}} \cdot w^* + \gamma \\ &\vdots \\ &\cancel{w^{(1)} \cdot w^*} > \cancel{w^{(0)}} \cdot w^* + \gamma = \gamma \end{aligned}} \right\} \text{add}$$

Add the inequalities to get

$$w^{(k)} \cdot w^* > k\gamma > 0$$

$$\text{Thus } \|w^{(k)}\| \geq |w^{(k)} \cdot w^*| = w^{(k)} \cdot w^* > k\gamma > 0$$



(to be continued)