

Agenda: perceptrons as linear separators; the on-line learning setting and the need, at least in the perceptron-learning case, for restrictions on the oracle. We may also get to Rosenblatt’s perceptron learning algorithm.

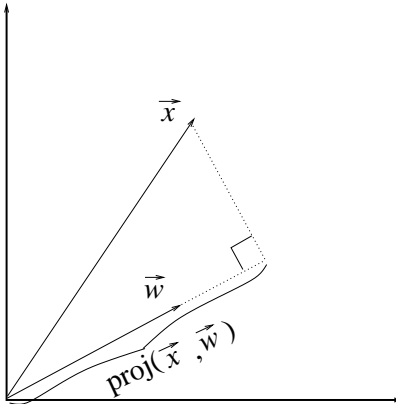
I. Recall: perceptron functions Given a weight vector \vec{w} in \mathbb{R}^n , $n \geq 1$, and a threshold value T , the function $f_{\vec{w},T} : \mathbb{R}^n \rightarrow \{+1, -1\}$ is given by

$$f_{\vec{w},T}(\vec{x}) = \begin{cases} +1, & \vec{w} \cdot \vec{x} \geq T \\ -1 & \text{otherwise} \end{cases} .$$

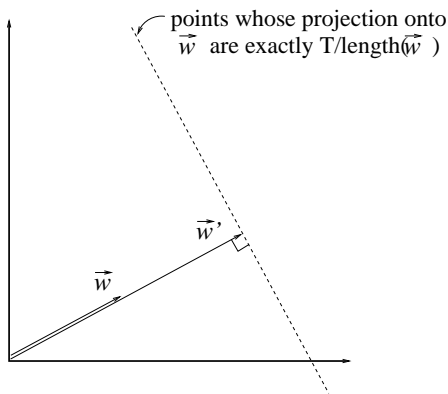
If $\text{length}(\vec{w}) > 0$, then this can be rewritten as

$$f_{\vec{w},T}(\vec{x}) = \begin{cases} +1, & \text{proj}(\vec{x}, \vec{w}) \geq \frac{T}{\text{length}(\vec{w})} \\ -1 & \text{otherwise} \end{cases} ,$$

where we are defining the projection of \vec{x} onto \vec{w} to be the (signed) length from the origin to the point on \vec{w} that results from dropping a perpendicular from \vec{x} to \vec{w} . (This is a signed distance because it can be negative if \vec{x} points “behind” \vec{w} .)



II. Linear separation Continuing with the above conditions, if we let \vec{w}' be the vector that points in the direction of \vec{w} but has length $T/\text{length}(\vec{w})$, we get this picture:



Hence, a perceptron function is a *linear separator* corresponding to a *half-plane* concept.

III. Conventions for the oracle's sequence of labeled examples We denote the instances by $\vec{x}^{(1)}, \vec{x}^{(2)}, \dots, \vec{x}^{(i)}, \dots$. Those that are given label +1 are known as *positive* examples; those that are given label -1 are known as *negative* examples.

IV. Identification in the limit (a success criterion for on-line learning) After seeing a finite number of examples,

- the learner always outputs the same hypothesis (\vec{w} and T) from then on, and
- this hypothesis correctly predicts the label of every subsequent example.