

Linear Binary Classification

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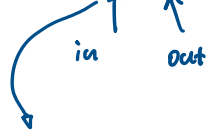
Binary Linear Classification (perceptron)

- Draw a linear geometry (line / plane ...) between 2 categories

\mathcal{H} is a set of lines/hyperplanes.

Model Setup

$$\mathcal{D} = \{(\underline{x}_1, y_1), (\underline{x}_2, y_2), \dots, (\underline{x}_N, y_N)\}$$



$$\underline{x}_i = [\underbrace{x_{i0}=1}_{\text{bias}}, \underbrace{x_{i1}, x_{i2}, \dots, x_{id}}_{d\text{-values}}]^T \in \mathbb{R}^{d+1}$$

$$y_i = -1 \text{ or } +1$$

$$y_i \in \{-1, +1\}$$

parameter/weights $W = [w_0, w_1, \dots, w_d] \in \mathbb{R}^{d+1}$

CLASSIFICATION RULE:

$$\text{function } h(\underline{x}_n) = \text{sign}(W^T \cdot \underline{x}_n) = \hat{y}_n \text{ (estimate)}$$

② how do we find values for W

we need a way to see how good/bad our weights are.

⇒ Loss Function:

→ one type is Mean Square Error

but in this classification case, we can just simply count the number of errors.

→ indicator function:

$$f(\text{event}) = 1 \text{ if } \{ \hat{y}_n \neq y_n \}$$

event is true

$$E_{in}(\underline{w}) = \frac{1}{N} \sum_{n=1}^N 1\{\hat{y}_n \neq y_n\}$$

in-sample error (for training data)

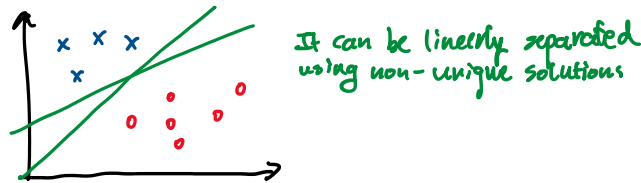
Training involves minimizing $E(\underline{w})$ for the available training data (\mathcal{D})

Perceptron Learning Algorithm (PLA)

INPUT: training set \mathcal{D} is linearly separable

we can put a line to separate data

ex. this is linearly separable



OUTPUT: PLA finds $\underline{w} \in \mathbb{R}^{d+1}$ such that $E_{in}(\underline{w}) = 0$

ALGORITHM

► Initialize $\underline{w}(0) = [0, 0, 0, \dots]$ $d+1$ dimensions

set $t = 0$

► While $E_{in}(\underline{w}(t)) \neq 0$ then

► pick any misclassified (x_n, y_n)

► update $\underline{w}(t+1) = \underline{w}(t) + y_n x_n$

► $t++$

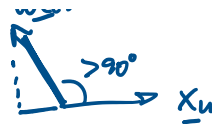
look at it in more detail

$$\underline{w}(t+1) = \underline{w}(t) + \underbrace{y_n x_n}_{\text{misclassified}}$$

case ① $y_n = +1$ $\hat{y}_n = -1 \iff \underline{w}(t)^T \cdot x_n < 0$

dot product negative

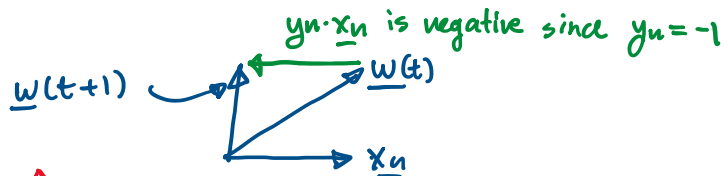




the idea is to add vector so that we get positive (correct classification)

$$\underline{w}(t+1) = \underline{w}(t) + y_n \cdot \underline{x}_n$$

case ② $y_n = -1$ $\hat{y}_n = +1 \Leftrightarrow \underline{w}(t)^T \cdot \underline{x}_n > 0$



⚠ notice in this case the "fix" doesn't fully succeed since the product is still ⊕

In summary

y_n	$\underline{w}(t)^T \underline{x}_n$	$y_n \underline{w}(t)^T \underline{x}_n$	classification
+1	> 0	> 0	✓
+1	< 0	< 0	✗
-1	> 0	< 0	✗
-1	< 0	> 0	✓

$$\text{PLA: } y_n \underline{w}(t+1)^T \underline{x}_n > y_n \underline{w}(t)^T \underline{x}_n$$

⚠ what if training data is not linearly separable?

→ the training will not converge and terminate
(and run forever ∞)

→ we can modify algorithm to just minimize E_{in} (keep the best, and continue look for better solution)

→ change objective E_{in}

Pocket algorithm: keep the best vector \underline{w} until it finds another better set. Terminates after some iterations.