

Perceptron

training

$$w \in \mathbb{R}^{D \times 1}$$

for (x, y)

$$\alpha \leftarrow \left(\sum_{d=1}^D w_d x_d \right) + b$$

if $y\alpha \leq 0$:

$$\rightarrow w_d \leftarrow w_d + y x_d \text{ for all } d=1 \dots D$$

$$\rightarrow b \leftarrow b + y$$

end if

* find hyperplane to separate positive and negative examples in a linearly separable dataset

this is gradient descent

$$w_d \leftarrow w_d - (1-y)x_d$$

$$b \leftarrow b - (1-y)y$$

$\nabla_w L$

$$\frac{\partial L}{\partial b}$$

Perceptron uses the hinge loss variation

$\max \{0, 1 - y_n(w^T x_n)\}$ is the hinge loss function

we will use:

$$\max \{0, -y_n(w^T x_n + b)\}$$

implement the max function in code with an if statement

Objective:

$$\min_{w, b} L(w, b) = \min_{w, b} \sum_{n=1}^N \max \{0, -y_n(w^T x_n + b)\}$$

→ use gradient descent

$$\frac{\partial L}{\partial b} = \frac{\partial}{\partial b} \max \{0, -y_n(w^T x_n + b)\}$$

$$\frac{\partial L}{\partial b} = \begin{cases} 0 & \text{if } y_n(w^T x_n + b) > 1 \\ -y_n & \text{otherwise} \end{cases}$$

$$\nabla_w L = \nabla_w \max \{0, -y_n(w^T x_n + b)\}$$

$$\nabla_w L = \begin{cases} 0 & \text{if } y_n(w^T x_n + b) > 1 \\ -y_n x_n & \text{otherwise} \end{cases}$$

Testing

$$a \leftarrow \sum_{d=1}^D [w_d x_d] + b$$

$$\text{sign}(a)$$