

3- neural networks

biological neuron = all spikes (brief impulses) have the same magnitude and duration

↳ information is coded in the rate of the spikes

Synapses = inputs (x) → dendrites = weights (w) → soma = transfer func (Σ) → activation threshold

history of artificial neuron


↳ linear threshold logic unit = $x+y+2 \rightarrow \text{and}$, $x+y+1 \rightarrow \text{or}$, $-x \rightarrow \text{not}$ (no solution for xor)

↳ perceptron = $w^{\text{next}} = w^{\text{curr}} + \eta (y_i - \bar{y}_i) x_i$ $\bar{y}_i = \begin{cases} 1 & \text{if } w x_i > 0 \\ 0 & \text{otherwise} \end{cases}$

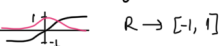
↳ adaline = $w^{\text{next}} = w^{\text{curr}} + \eta (y_i - w^{\text{curr}} \cdot x_i) x_i$ $y_i \in \{-1, 1\}$ → improved learning rule


↳ backpropagation = application of the chain rule in calculus

activation functions


↳ sigmoid = $\sigma(x) = \frac{1}{1+e^{-x}}$ $\frac{d\sigma(x)}{dx} = \sigma(x) \cdot (1 - \sigma(x))$  $R \rightarrow [0, 1]$

↳ since it is always positive, it introduces a bias for the next layer, which is not good

↳ hyperbolic tangent (tanh) = $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ $\frac{d\tanh(x)}{dx} = 1 - \tanh^2(x)$  $R \rightarrow [-1, 1]$

↳ rectified linear units (relu) = $p(x) = \max(0, x)$ $\frac{dp(x)}{dx} = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{else} \end{cases}$ 

↳ converges 6x faster than sigmoid/tanh

↳ leaky relu (LeLU) = $f(x) = \begin{cases} x & \text{if } x \geq 0 \\ \alpha x & \text{otherwise} \end{cases}$ $\alpha \rightarrow$ learned during training 

↳ parametric relu

↳ maxout = $\max(w_1^T x + b_1, w_2^T x + b_2, \dots)$ generalization of ReLU and Leaky ReLU

stochastic gradient descent

★ in stochastic gradient descent it is necessary to decrease the learning rate over time

↳ because noise (the random sampling of m training examples) may not vanish even the minimum is reached

momentum = helps accelerate gradients vectors in the right direction

↳ without = $w^{(t+1)} = w^{(t)} - \eta g^{(t)}$

↳ with momentum = $w^{(t+1)} = w^{(t)} + v^{(t)}$ $v^{(t)} = \alpha v^{(t-1)} - \eta g^{(t)}$ (exponential decay)

↳ size of the step depends on how large and aligned the subgradients are