



From circuit model shown at left, we require that:

- 1. Assume that V is the output (no spikes)
- 2. g_m is linear, $E_m = E_{rest} = 0$ 3. $I_{sym} = s \left[\sum w_i V_i\right]$, where s is a squashing fn, i.e.

$$S = \frac{1}{1 + e^{-x}}$$

Perceptron

$$V = s \left[\overrightarrow{w} \cdot \overrightarrow{u} \right]$$

$$V(t \to \infty) = \begin{cases} 1, \ \overrightarrow{w} \cdot \overrightarrow{u} \ge \gamma \\ -1, \ \overrightarrow{w} \cdot \overrightarrow{u} < \gamma \end{cases}$$

Where u is input, and w is weight, and γ is a learned constant

- 3-layer perceptron can solve any continuous mapping function
- 4-layer perceptron can solve any mapping

Supervised Learning (differentiable s(x))

Patterns: $\vec{u}^1, \dots, \vec{u}^p$

Empty → Excitatory

Desired outputs: $\vec{v}^1, \dots, \vec{v}^p$

$$\begin{split} Err[\overrightarrow{w}] &= \frac{1}{2} \sum_{p} (v^{p} - s(\overrightarrow{w} \cdot \overrightarrow{u}^{p}))^{2} \\ \frac{\partial Err}{\partial w_{k}} &= -\sum_{p} [v^{p} - s(\overrightarrow{w} \cdot \overrightarrow{u}^{p})] \left. \frac{\partial s}{\partial h} \right| \overrightarrow{u}_{k}^{p} \end{split}$$

Where $h = \vec{w} \cdot \vec{u}^p$

$$\nabla Err = [\frac{\partial Err}{\partial w_1}, \dots, \frac{\partial Err}{\partial w_k}]$$

Gradient Descent

$$\Delta \vec{w} = -\epsilon \vec{\nabla} Err$$

Hebbian (unsupervised) Learning

$$\tau \frac{dV}{dt} = -V + \vec{w} \cdot \vec{u}$$
$$\Delta \vec{w} = \frac{1}{\tau_w} V \vec{u} = \frac{1}{\tau_w} \langle V \vec{u} \rangle$$

$$\|\varDelta \overrightarrow{w}\|^2 \approx \frac{2}{\tau_w} V^2 > 0$$

Weights can unboundedly grow... so Oja's Rule is req'd:

$$\Delta \vec{w} = \frac{1}{\tau_w} [V\vec{u} - V^2 \vec{w}]$$

Hopfield Nets

$$\tau = -S_i + F\left[\sum_i w_{ij} x_j\right]$$

Assume Steady State for analysis → discrete steps from $\vec{S} \rightarrow \vec{S}'$ F can be any fn (sign(), for instance)

 $\vec{S}' = \vec{S}$ is a stable state. Patterns are stable states.

For patterns ξ :

$$\vec{\xi}^{j} = \{\xi_{1}^{j}, \dots, \xi_{N}^{j}\}, j = 1 \to P$$

$$w_{ij} = \frac{1}{N} \sum_{k=1} \xi_i^k \xi_j^k$$

Where $w_{ii} = \frac{P}{N}$; $w_{ij} = w_{ji}$

Noisy patterns require more signal than noise for the pattern to be recovered consistently.