

The Boltzmann Machine

- **Similarities to Hopfield Networks**
 1. state values +1, -1
 2. weights symmetric
 3. unit selected at random
 4. no self-feedback
- **Differences with Hopfield Networks**
 1. Boltzmann permits hidden neurons
 2. Boltzmann uses stochastic neurons
 3. Hopfield unsupervised while Boltzmann may operate supervised
- **Boltzmann Machine terminology**
 - hidden, visible
 - clamped, operating freely
 - training: input output
 - thermal equilibrium
- **Basic Operation**
 - select neuron at random
 - update stochastically
 - $\text{prob}(s_j \rightarrow -s_j) = 1/(1+\exp(-\text{delat_}E_j/T))$
- **Clamped and free probabilities: P^+_{alpha} and P^-_{alpha}**
- **Energy for $s_j \rightarrow -s_j$**
- **$\text{prob}(s_j \rightarrow -s_j) = 1/(1+\exp(2s_j v_j/T))$**
- **Operates like a stochastic neuron**

1. No self-feedback
 2. external threshold θ_j ($s_0 = -1$)
 3. 2^N states
- thermal equilibrium
 - Boltzmann Distribution
 - $P_{\alpha} = 1/Z \exp(-E_{\alpha}/T)$
 - $Z = \dots$
 - for large T all states are equiprobable
 - as $T \rightarrow 0$ only states with minimum energy level have non-zero probability
 - coarse search \rightarrow fine search
 - constraint- satisfaction: weak constraints
 - The Boltzmann Learning Rule
 - hidden neurons act as feature detectors
 - state = visible/hidden (α / β)
 - 2^K choices for α
 - 2^L choices for β , where $L = N-K$
 - N.B. text says α runs from 1 to 2^K
 - Clamped Probability: $P_{\alpha}^+ = \dots$
 - Running free probability: $P_{\alpha}^- = \dots$
 - actual /desired probabilities
 - relative entropy
 - gradient descent method
 - Correlations