

11/17/06

①

① finish off linear analysis ← slope

② fluctuation: quenched noise

a) simple 1-D model

b) 2-D model - balance

3) temporal fluctuations

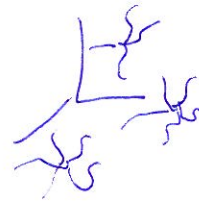
} emphasize:
fluctuations smooth
out gain function



③ Structured connectivity - $\frac{1}{k}$ scaling

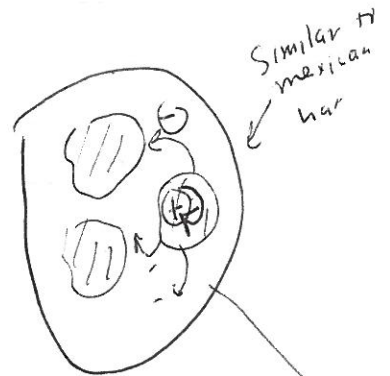
④ Hopfield network

- pattern completion
- associative memory
- what weight matrix will give us that?
- Very simple model



$$X_i(t+1) = f\left(\sum_j W_{ij} X_j\right) \quad w \rightarrow j$$

$$\rightarrow \text{sign}\left(\sum_j W_{ij} X_j\right)$$



Want a nonlinear equation w/ lots of fixed points

$$z_i^{\mu} = \text{sign}\left(\sum_j W_{ij} z_j^{\mu}\right) \quad \mu=1, \dots, p$$

Genius:

$$W_{ij} = \frac{1}{n} \sum_{\mu} z_i^{\mu} z_j^{\mu}$$

↑ random vector: $\frac{1}{2}$ 1's + $\frac{1}{2}$ -1's

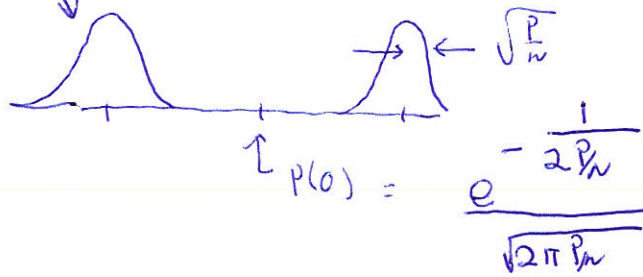
$$z_i^{\mu} = \begin{cases} 1 & \text{prob } 0.5 \\ -1 & \text{prob } 0.5 \end{cases}$$

②

— why it works:

$$\begin{aligned} \sum_j W_{ij} s_j^v &= \frac{1}{N} \sum_{u,j} s_i^u s_j^u s_j^v \\ &= \frac{1}{N} \sum_{j} s_i^v s_j^v s_j^v + \sum_{u \neq v} s_i^u \frac{1}{N} \sum_j s_j^u s_j^v \\ &= s_i^v + \sum_{u \neq v} s_i^u \frac{1}{\sqrt{N}} \sum_j s_j^u s_j^v \\ &\quad + \sqrt{\frac{P}{N}} \sum_j \xi_j^u \end{aligned}$$

quenched noise just like in randomly connected network case.



$$= \frac{e^{-\frac{N}{2P}}}{\sqrt{2\pi P/N}} \rightarrow \text{if } P \ll 1$$

$$s_i^u = \text{sign}(s_i^u)$$

Stability???

$$X_i(t+1) = \text{sign}\left(\frac{1}{N} \sum_j W_{ij} X_j\right)$$

$$W_{ij} = W_{ji} \quad w_{ii} = 0$$

$$H^{(1)} = -\frac{1}{2} \sum_{i,j} X_i(t) W_{ij} X_j(t)$$

Asynchronous update:

$$H(t+1) - H(t) = -\frac{1}{2} \sum_{i,j} X_i(t+1) W_{ij} X_j(t+1) - X_i(t) W_{ij} X_j(t)$$

Unit k update:

$$X_k(t+1) \neq X_k(t) \text{ (maybe)}$$

$$X_{i \neq k}(t+1) = X_{i \neq k}(t)$$

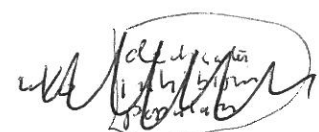
$$\begin{aligned} \Delta H &= -\frac{1}{2} \sum_j \left[X_{ik}(t+1) W_{kj} X_j + X_j(t) W_{jk} X_k(t+1) \right] \\ &\quad - \left[X_k(t+1) - X_k(t) \right] \sum_j W_{kj} X_j \\ &= -\frac{1}{2} \left[\text{sign}\left(\sum_j W_{kj} X_j(t)\right) - X_k(t) \right] \sum_j W_{kj} X_j(t) \end{aligned}$$

3

Problems: ~~Violates~~

Capacity: $\frac{P}{N} = 0.138$ (hard!!)

Problems: Dale's law - ~~fixable~~ - capacity $\sim \frac{0.138}{\sqrt{2}}$
↑
clip

Saturation: not ~~fixable~~ ^{so easily} fixable 

Neurms: $W_{ij}^{EE} \rightarrow W_{ij}^{EE} + \frac{\beta}{N} \sum_{\mu} \sum_i \sum_j \underbrace{C_{ij}}_{\text{input}} \frac{\beta}{N f(1-f)} \sum_n \varphi_i^n (\varphi_j^n - f)$

~~$\sum_j W_{ij} V_j \rightarrow \sum_j W_{ij} V_j + \frac{\beta}{N} \Sigma$~~ $\varphi_i = \begin{cases} 1 & \text{prob } f \\ 0 & \text{prob } 1-f \end{cases}$

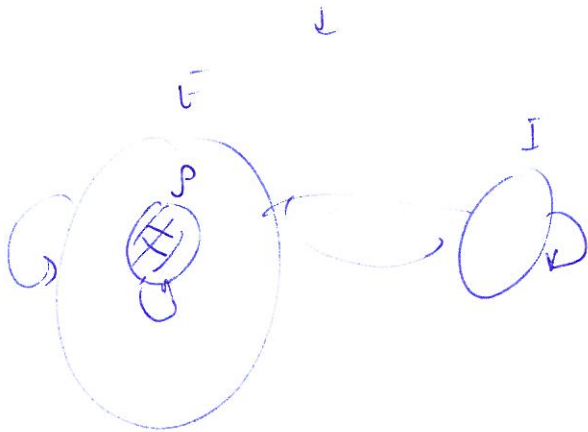
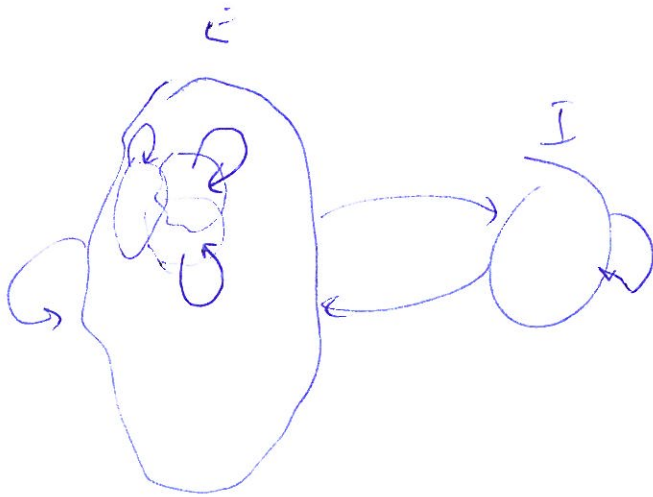
$V_{Ei} = \Phi_E \left(\sqrt{K} (\tilde{W}_{EE} V_E - \tilde{W}_{EI} V_I) + \sigma_E \varphi_{Ei} + \frac{\beta}{N f(1-f)} \sum_{\mu} \sum_j \varphi_i^{\mu} (\varphi_j^{\mu} - f) V_{Ej} \right)$

$V_{Ii} = \dots$

~~$\frac{\beta}{N f(1-f)}$~~

4

Memory Pic



$$M_p = \frac{1}{N+1} \sum_j g_j^p \quad \frac{1}{1+f} \left[\frac{1}{N+1} \sum_j g_j^p V_{Ej} - \frac{1}{N} \sum_j V_{Ej} \right]$$

$$= \frac{1}{N+1} \sum_j (g_j^p - f) V_{Ej}$$

$$V_E =$$

$$V_E =$$

\rightarrow

(5)

$$\frac{1}{Nf(1+f)} \sum_{i,j} \varphi_i^M (\varphi_j^M - f) V_{Eij}$$

$$= \sum_i \varphi_i^A m_p + \frac{1}{N+(1+1)} \underbrace{\sum_{i \neq p, j} \varphi_i^M (\varphi_j^M - f) V_{Eij}}_{\sqrt{Pn}} \underbrace{\hspace{10em}}_{\sqrt{\frac{P}{n}}}$$

$$V_{Ei} = \Phi_E \left(\sqrt{11} \left(\quad \right) + \beta \sum_i \varphi_i^P m_p + \sigma_E' \eta_i \right)$$

$$V_E = \sum_i \rightarrow \int dz \frac{e^{-z^2}}{\sqrt{2\pi}} f \quad \begin{matrix} (\beta=1) \\ (1+) \quad (\beta=0) \end{matrix}$$

$$V_E = \frac{1}{N} \sum_i \Phi_E \left(\quad \varphi_i^P \right)$$

$$= \frac{1}{N} \sum_i (1 - \varphi_i^P + \varphi_i^P) a_i$$

$$= \frac{1}{N} \sum_i^{(1-1)} \Phi_E \left(\quad 0 \right) + f \left(\quad + \right)$$

$$V_E = \tilde{\Phi}_E \left(\sqrt{11} \left(\quad \right) + \beta m_p \right) (1+1) + (7) +$$

↑
L_{in}ln

(A) f → 0

(B) f > 0