

12/7/04

①

Line (and higher dimension) attractors.

Equilibrium:

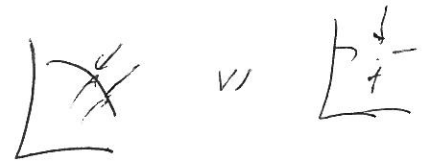
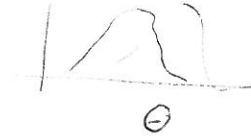
- Motivation:

Can be used to store continuous variables. Working memory + bias direct.

$$\dot{X}_i = \phi\left(\sum_j W_{ij} X_j\right) - X_i$$

 $X_{0i}$  is equilibrium:

$$X_{0i} = \phi\left(\sum_j W_{ij} X_{0j}\right)$$

Let  $W_{ij} = W_{i-j}$  $X_{0i+k}$  also a solution:

$$X_{0,i+k} = \phi\left(\sum_j W_{i-j} X_{0,j+k}\right)$$

$$i \rightarrow i-k$$

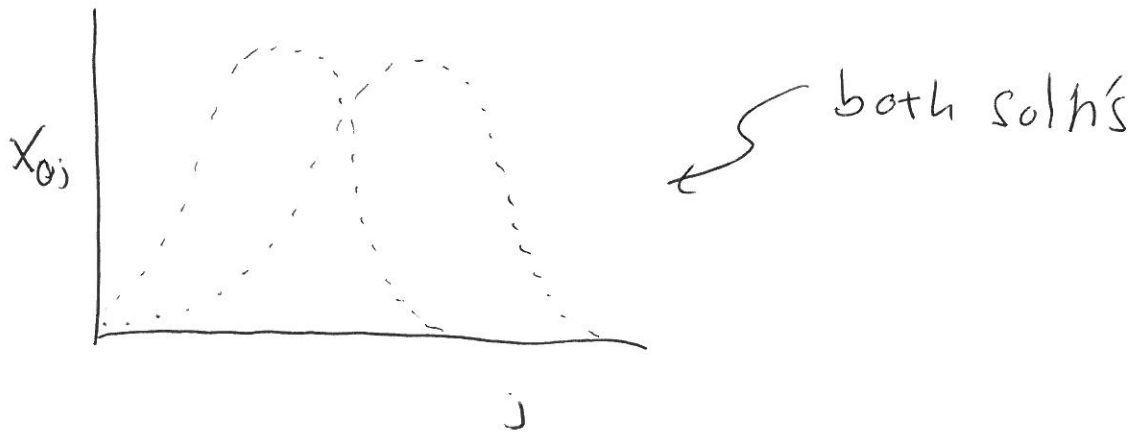
$$j \rightarrow j-k$$

$$X_{0,i} = \phi\left(\sum_j W_{i-k-(j-k)} X_{0,j}\right)$$

$$= \phi\left(\sum_j W_{i-j} X_{0j}\right)$$

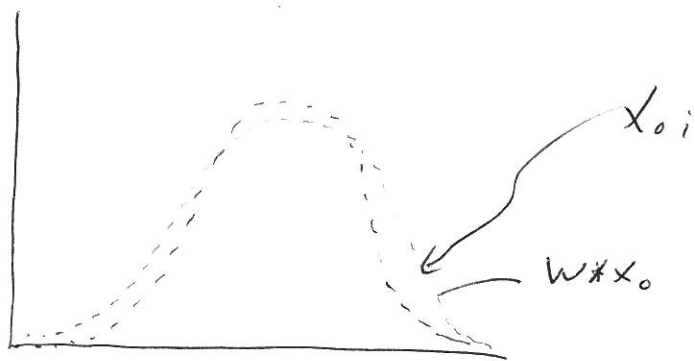
$$\approx X_{0i} = \phi\left(\sum_j W_{ij} X_{0j}\right)$$

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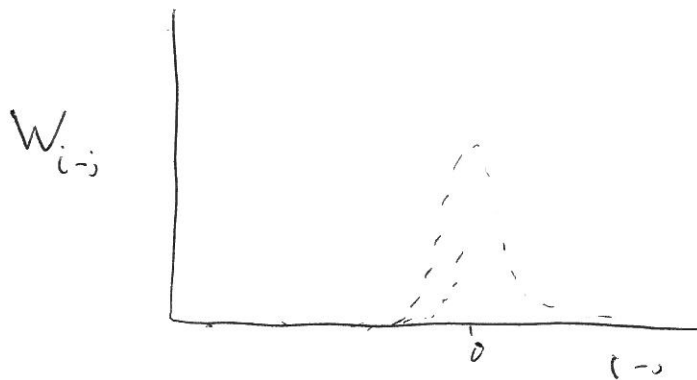


What's happening:  $W_{i-j}$  is a translation invariant operator (convolution).

Picture



- nonlinearity can narrow the hill again



(3)

Example:

$$X_i = \left[ \sum_k \exp \left[ - \frac{[\Delta(c-k)]^2}{2\sigma^2} \right] X_k \right]^2$$

Sol'n  $X_i = A \exp \left[ - \frac{k\Delta^2}{2\sigma^2} \right]$

$$\sum_k \exp \left[ - \frac{\Delta(c-k)^2}{2\sigma^2} \right] A \exp \left[ - \frac{k\Delta^2}{2\sigma^2} \right]$$

$$= A \sum_k e^{-\frac{\Delta^2}{2\sigma^2} ((i-k)^2 + ik)}$$

$$= A \sum_k e^{-\frac{\Delta^2}{2\sigma^2} [i^2 + 2k^2 - 2ik]}$$

$$= A \sum_k e^{-\frac{\Delta^2}{2\sigma^2} [i^2 + 2(k^2 - ik + \frac{i^2}{4}) - \frac{i^2}{2}]}$$

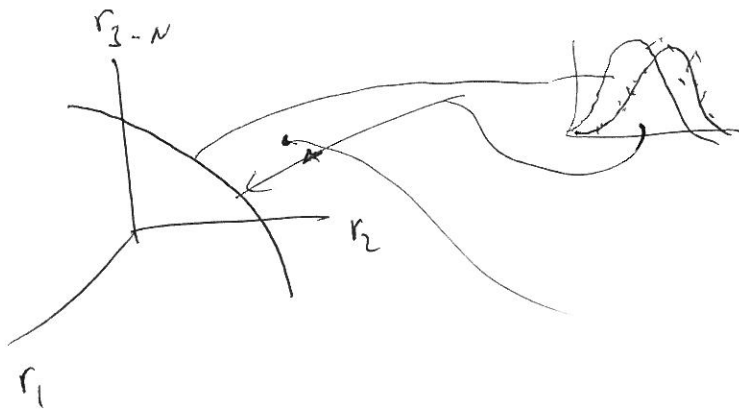
$$= A e^{-\frac{\Delta^2}{4\sigma^2} i^2} \sum_k e^{-\frac{\Delta^2}{\sigma^2} (k - \frac{i}{2})^2}$$

$$= A \sqrt{\frac{\pi\sigma^2}{\Delta^2}} e^{-\frac{\Delta^2}{4\sigma^2} i^2}$$

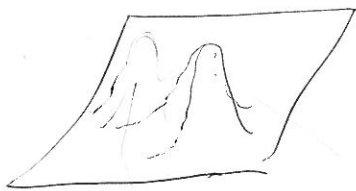
$$A e^{-\frac{\Delta^2}{2\sigma^2} i^2} = A \sqrt{\frac{\pi\sigma^2}{\Delta^2}} e^{-\frac{\Delta^2}{4\sigma^2} i^2} \Rightarrow A = \frac{\Delta^2}{\pi\sigma^2}$$

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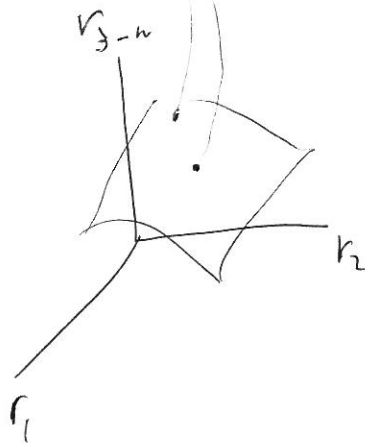
Abstract representation



D-dim attractors w/ symmetries



Abstract

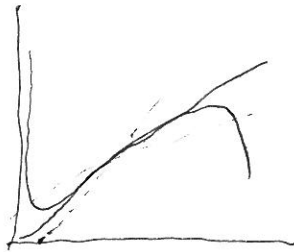


- Used to represent params in working / associative memory tasks
- Used for optimal computation

(5)

Also: firm rate attract.

- von (sprms ~~evda~~ exp. evidence)
- integrate evidence (weak exp. evidence)



- Structurally uncond
- slow drain

Lim. analysis?

$$\lambda = \frac{T \pm \sqrt{T^2 - 4D}}{2}$$

$D=0 \Rightarrow$  par

~~Hot par~~  $\Rightarrow \lambda=0$

⑥

What about bumps? Also structure unstable:

$$\dot{\underline{V}} = \phi(\underline{W} \cdot \underline{V}_n) - \underline{V} \quad \left[ \dot{V}_i = \phi(\sum_j W_{ij} V_j + \sum_j \delta W_{ij} V_j) - V_i \right]$$

$$\underline{V} = \underline{V}_0(\theta) + \delta \underline{V}$$

$$\begin{aligned} \dot{\underline{V}} &= \underline{V}'_0(\theta) \dot{\theta} + \delta \dot{\underline{V}} = \phi(\underline{W} \cdot \underline{V}_0(\theta)) + \phi' \underline{W} \cdot \delta \underline{V} + \phi' \delta \underline{W} \cdot \underline{V}_0(\theta) - \underline{V} - \delta \underline{V} \\ &= \underline{J} \cdot \delta \underline{V} + \phi' \delta \underline{W} \cdot \underline{V}_0 \end{aligned}$$

$$\underline{J} \cdot \underline{V}'_0 = 0$$

$$\underline{J} \cdot \underline{V}_{1k} = -\lambda_k \underline{V}_{1k}$$

$$\underline{V}_{1k}^T \cdot \delta \underline{V} = -\lambda_k \underline{V}_{1k}^T \cdot \delta \underline{V} + \phi' \underline{V}_{1k}^T \cdot \delta \underline{W} \cdot \underline{V}_0(\theta) = 0$$

$$\dot{\theta} = \phi' \underline{V}_0^T \cdot \delta \underline{W} \cdot \underline{V}_0(\theta)$$

$$= F(\theta)$$

slow (hyperbolic) flow



(7)

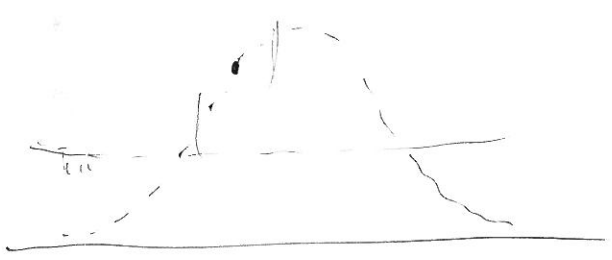
Implicatii pentru multitudine liniara in m.c. nu

$$W_{ij} = W_{i-1}^{\#} + W_{p(i)-p(i)}^{\#} + W_{p_2(p-p_2(i))}^{\#}$$

↑  
reorder

$$W_{i-1} X_{0j} + W_{p(i)-p(i)} X_{0j} + \dots + \bar{w} = 0$$

$\cdot \theta(n)$                        $\theta(\sqrt{n})$                        $\dots$                        $\theta(\sqrt{n})$



$$V_i = \phi \left( \sum_n \sum_j W_{ij}^{\#} v_j \right) - v_r$$

~~$$V_i = v_i^{\#}(\theta)$$~~

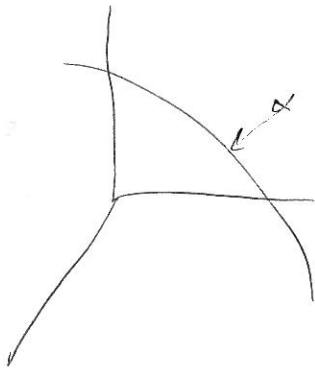
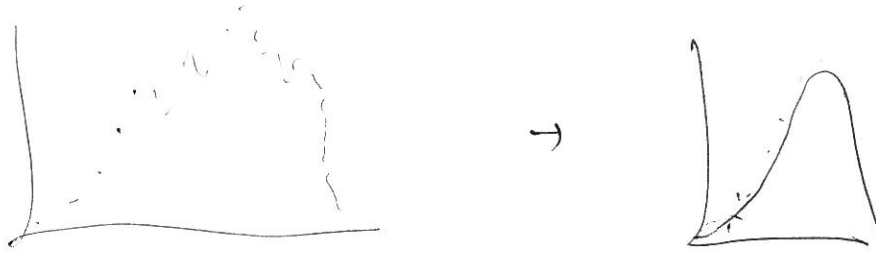
$$= \phi \left( \sum_j W_{ij}^{\#} v_j + f(v_{ij}) \right) - v_r$$

$$\Theta^{\#} = \sum_j \phi' v_j \Rightarrow \text{direct}$$

for the limit

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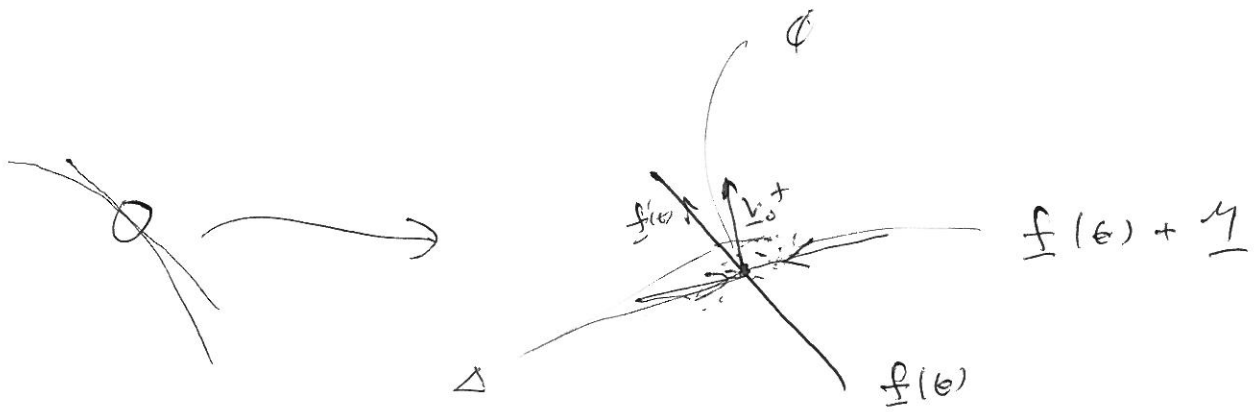
Noise clamp



how do we choose  
network dynm?



(9)



$$\Delta \cos \phi = \frac{v_0^+ \cdot y}{\Delta}$$

$$\Delta = \frac{v_0^+ \cdot y}{\cos \phi} = \frac{v_0^+ \cdot y}{f'(x_0)}$$

$$\langle \Delta^2 \rangle = \frac{v_0^+ \cdot n \cdot v_0^+}{|f'(x_0)|^2}$$

where:  $(f'(x_0))^2 v_0^+ \cdot n = v_0^+ \cdot n \cdot v_0^+ \leq v_0^+ \cdot v_0^+ = 1$

$$f' \sim v_0^+ \cdot n$$

$$v_0^+ \sim n^{-1/2} \cdot f'$$

(10)

$$d\underline{V} = \underline{J} \cdot d\underline{x}$$

$$\sum_k \lambda_k \underline{V}_k \underline{V}_k^T$$

$$d\underline{V} = \underline{0}$$

$$d\underline{V} = \sum_k q_k \underline{V}_k$$

$$\sum_k q_k \underline{V}_k = \sum_k \lambda_k \underline{V}_k \underline{V}_k^T \cdot \sum_k q_k \underline{V}_k$$

$$= \sum_k q_k \lambda_k \underline{V}_k$$

$$q_k = \lambda_k q_k$$

$$\frac{d}{dt} \underline{V}_0^T \cdot d\underline{x} = \underline{V}_0^T \cdot \sum_k \lambda_k \underline{V}_k \underline{V}_k^T \cdot d\underline{x}$$

$$= \lambda_0 \underline{V}_0^T d\underline{x}$$

$$= 0$$