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Networks!!

1. Biology: The cortex
2. Excitation:
   - Unidirectional (transformations)
   - Local vs. distributed representations
   - Bidirectional (pattern completion, amplification)
3. Inhibition: Controlling bidirectional excitation.
4. Constraint Satisfaction: Putting it all together.

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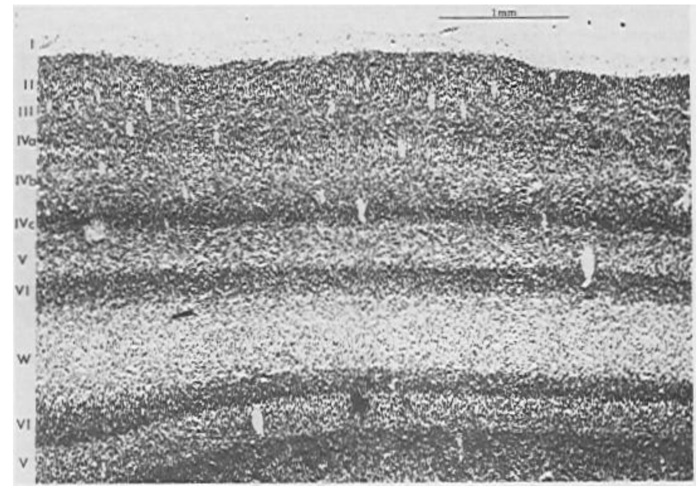
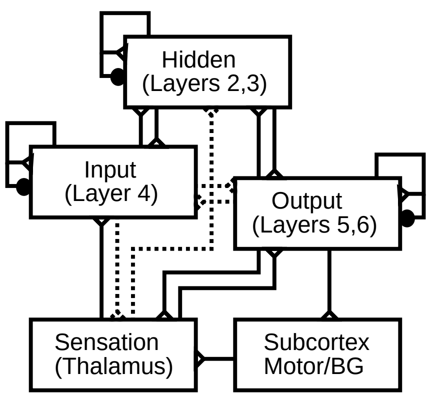
Laminar Structure of Cortex



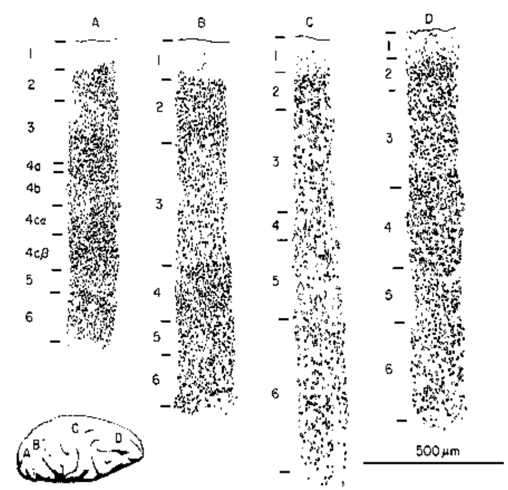
3

Laminar Structure of Cortex



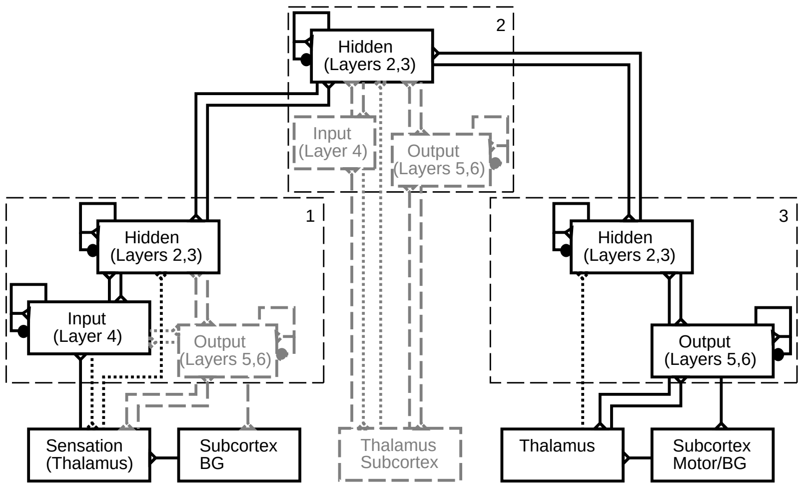
4

Area Structure of Cortex



5

Area Structure of Cortex



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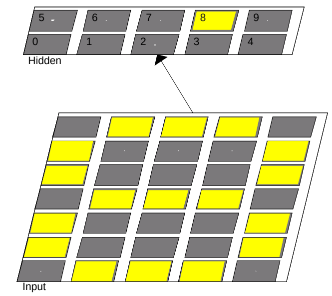
Excitation (Unidirectional): Transformations



- Detectors work in parallel to *transform* input activity pattern to hidden activity pattern.
- Emphasizes some distinctions, collapses across others.
- Function of what the detectors detect (and what they ignore).

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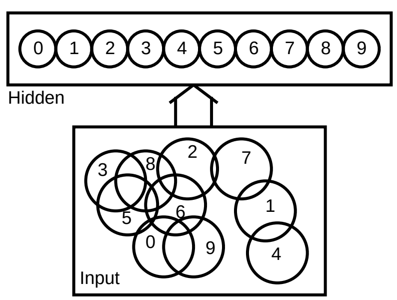
Transformations



Emphasize distinctions: Different digits non-overlapping.
Collapse distinctions: Noisy digits categorized as same.

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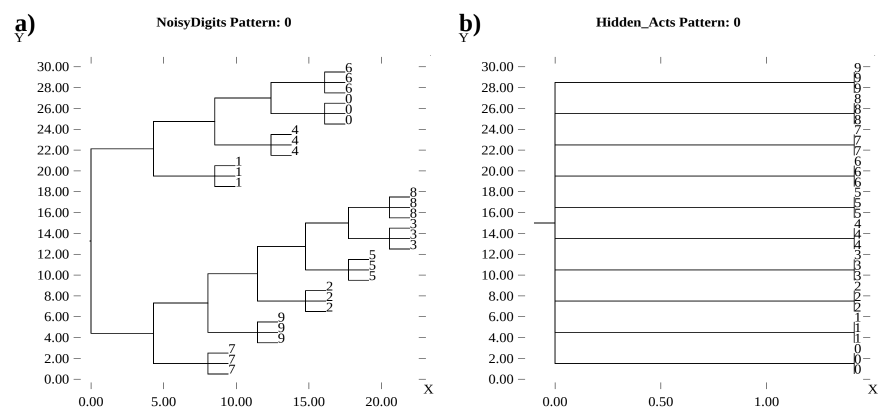
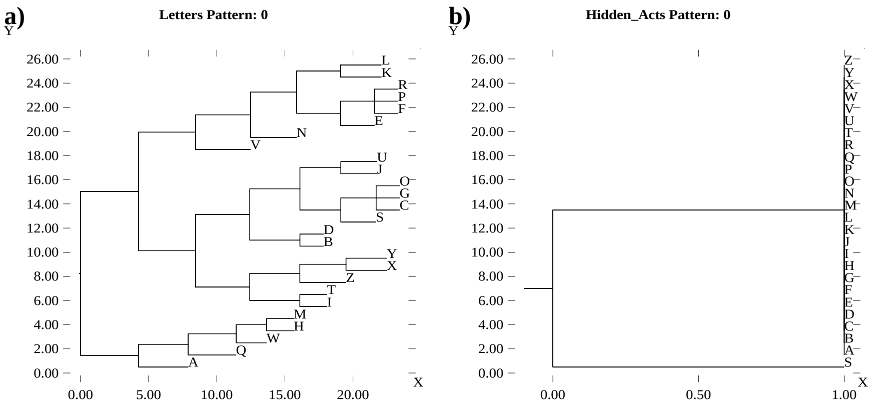
Distinctions: Cluster Plot

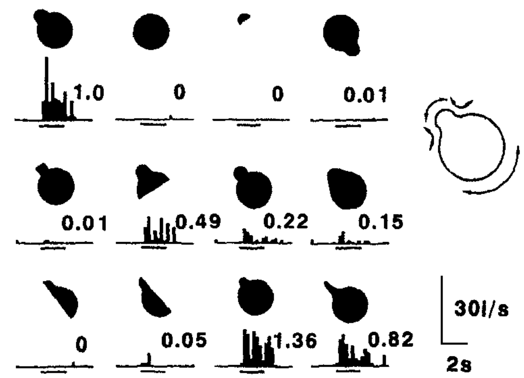


9 Detectors are Dedicated, Content-Specific

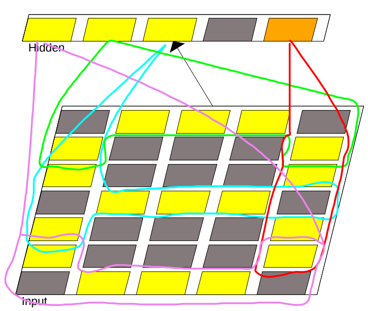


10 Distributed vs Localist Representations

Localist = 1 unit active at a time (e.g., digits).
Distributed = many units active, for multiple inputs (the brain!).



11 Digits With Distributed Representations



12 Advantages of Distributed Representations

Efficiency: Fewer total units required.

Similarity: As a function of overlap.

Generalization: Can use novel combinations.

Robustness: Redundancy.

Accuracy: By coarse-coding.

Learning: Bootstrapping of small changes.

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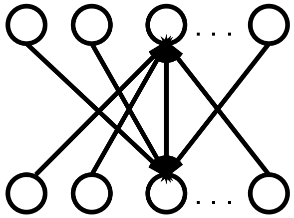
Bidirectional Excitation



1. Top-down processing ("imagery").
2. Pattern completion.
3. Amplification/bootstrapping.
4. Attractor dynamics.

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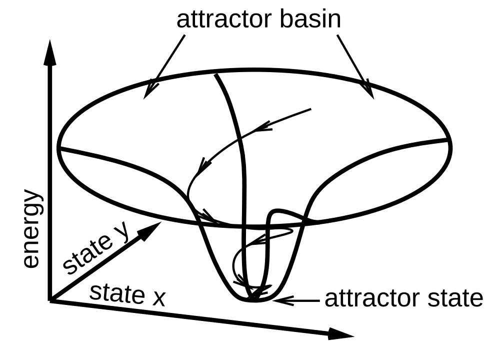
Attractor Dynamics



Bidirectional excitation caused network to *settle* into a particular *stable state* over time: the *attractor*.

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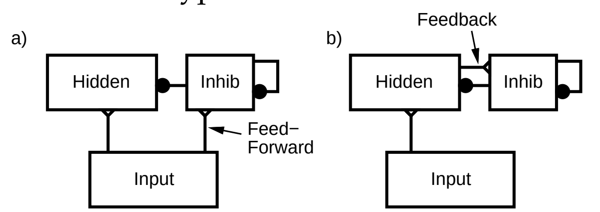
Need Inhibition!

- Controls activity (bidirectional excitation).
- Competition -> selection (Darwin!).

1. Biology: Feedforward and feedback inhibition.
2. Critical Parameters.
3. Simplification.

17 Types of Inhibition



Anticipates excitation — Reacts to excitation

Critical Parameters

- Inhib conductance into hidden units (`g_bar_i.hidden`)
- Strength of feedforward weights to inhib (`scale.ff`)
- Strength of feedback weights to inhib (`scale.fb`)

18 Simplification: KWTA Approximation

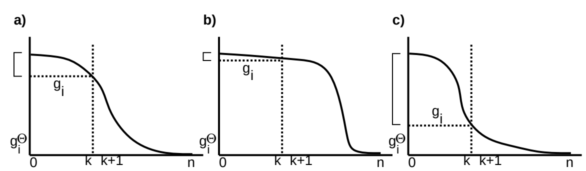
Very computationally expensive to simulate all inhibitory interneurons.

Approximate inhibition by allowing maximum of k units to be active at any time (the most active k units).

Approximates *set point* behavior of negative feedback systems

Implemented by computing g_i for entire layer, such that k units can get active, but rest will be too inhibited.

19 KWTA Approximation: Simple

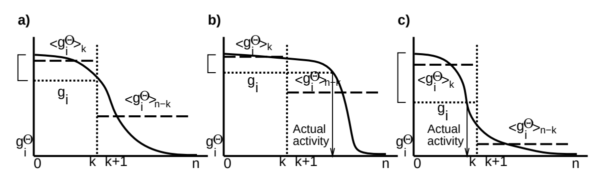


$$V_m = \frac{g_e \bar{g}_e E_e + g_i \bar{g}_i E_i + g_l \bar{g}_l E_l}{g_e \bar{g}_e + g_i \bar{g}_i + g_l \bar{g}_l} \quad (1)$$

$$g_i^{\Theta} = \frac{g_e^* \bar{g}_e (E_e - \Theta) + g_l \bar{g}_l (E_l - \Theta)}{\Theta - E_i} \quad (2)$$

$$g_i = g_i^{\Theta}(k+1) + q(g_i^{\Theta}(k) - g_i^{\Theta}(k+1)) \quad (3)$$

20 KWTA Approximation: Average-Based



$$\langle g_i^{\Theta} \rangle_k = \frac{1}{k} \sum_{i=1}^{k} g_i^{\Theta}(i) \quad (4)$$

$$\langle g_i^{\Theta} \rangle_{n-k} = \frac{1}{n-k} \sum_{i=k}^{n} g_i^{\Theta}(i) \quad (5)$$

$$g_i = \langle g_i^{\Theta} \rangle_{n-k} + q(\langle g_i^{\Theta} \rangle_k - \langle g_i^{\Theta} \rangle_{n-k}) \quad (6)$$

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Constraint Satisfaction

1. Energy Function.
2. Noise.
3. Inhibition.

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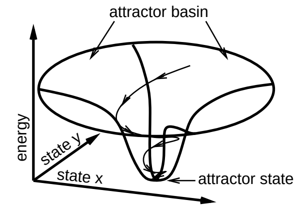
The Energy Function



Falling things are minimizing their potential energy: nature always seeks to minimize the energy of a system.

If we can write an expression for the energy of a network, will the "nature' of the network minimize it?

Yes!

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Energy, Harmony

$$E = -\frac{1}{2} \sum_j \sum_i x_i w_{ij} y_j$$

$$H = \frac{1}{2} \sum_j \sum_i x_i w_{ij} y_j$$

Best when activations consistent w/weights.

Just updating activations locally increases global constraint satisfaction!

$$y_j = \sum_i x_i w_{ij}$$

$$\frac{\partial H}{\partial y_j} = \sum_i x_i w_{ij}$$

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The Role of Noise