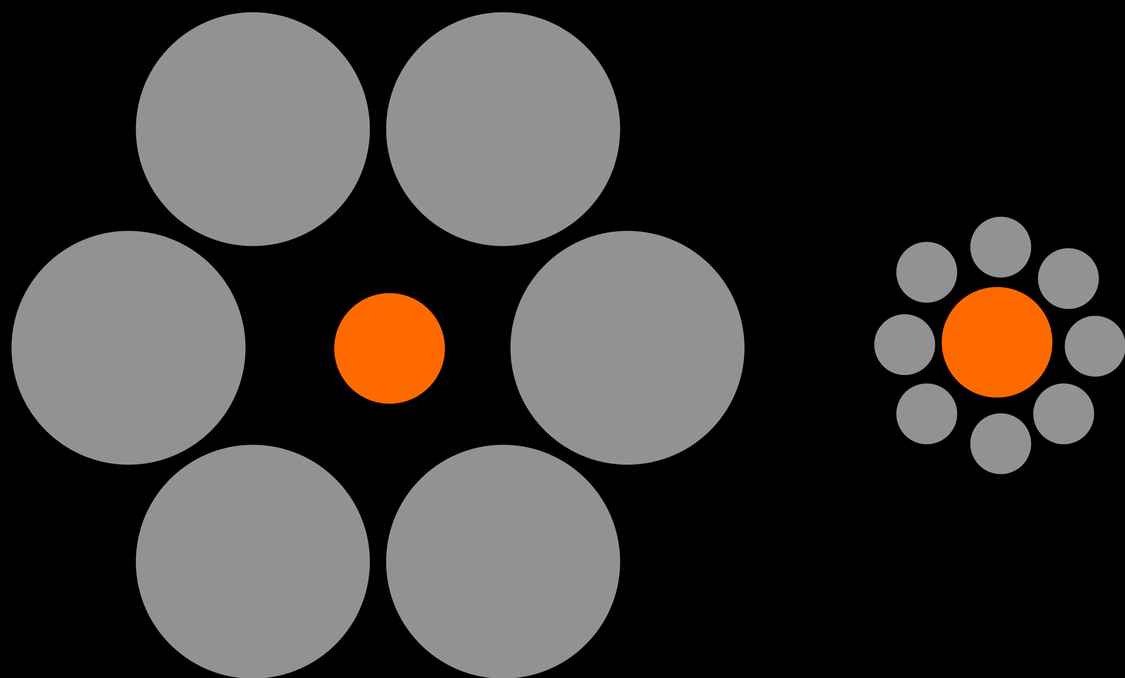
Constraint Satisfaction, Attractor Networks and Perception

Perceptual Illusions

Context influences perception



Ebbinghaus-Tichener Illusion (1901)

Perceptual Illusions

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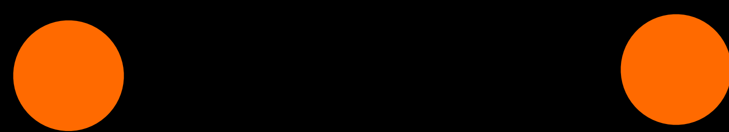

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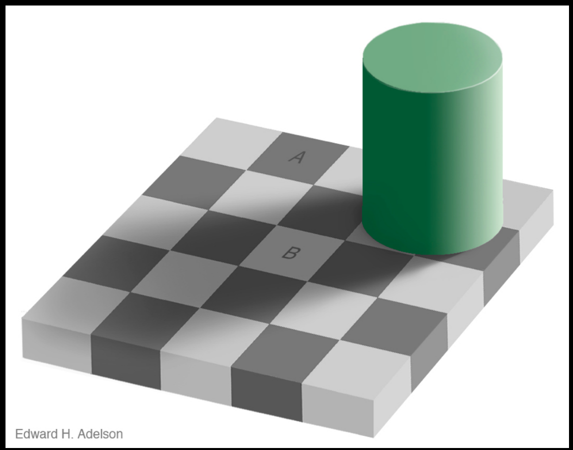

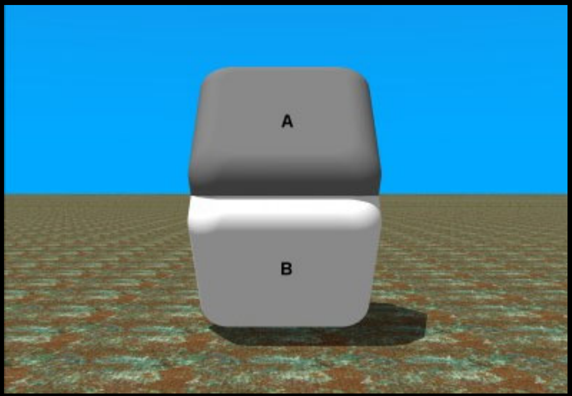

Edward Adelson (1995)

Perceptual Illusions

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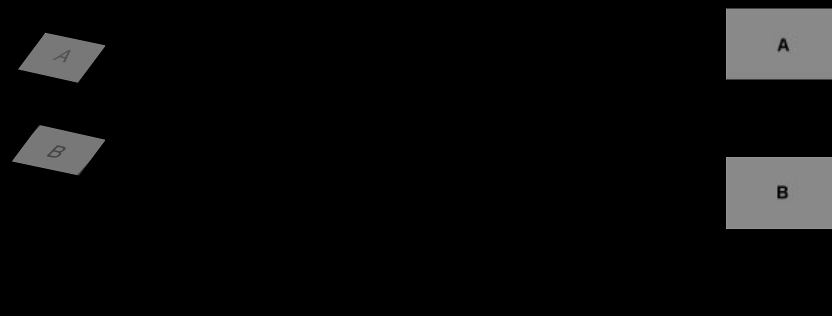

Edward Adelson (1995)

Top-down Effects

Mask Illusion - Richard Gregory (1970)

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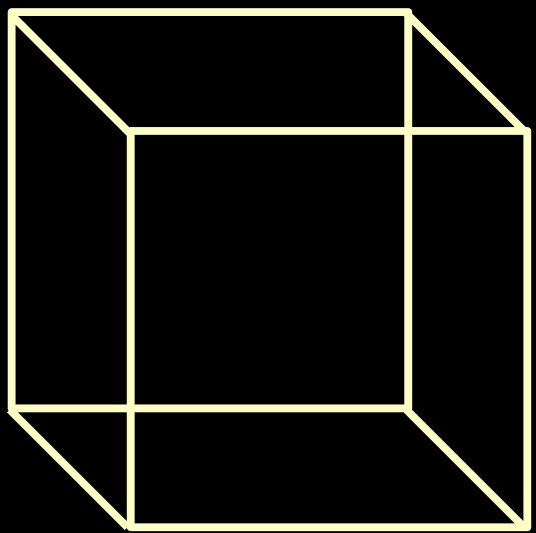
Top-down Effects

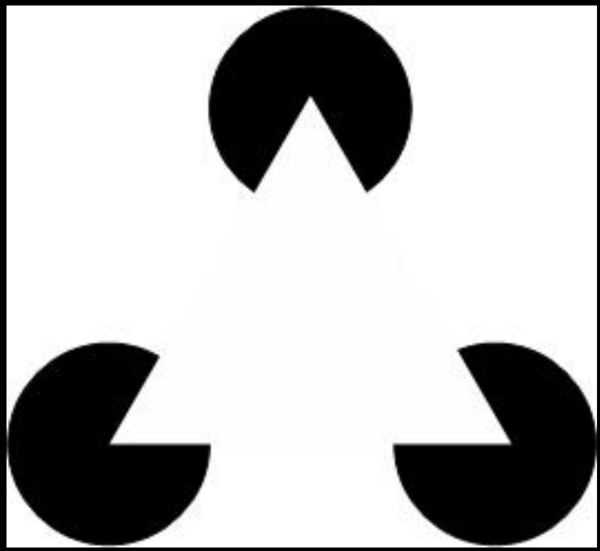
Instruction can also be a source of context

Gestalt Figures

The parts interact to determine the whole



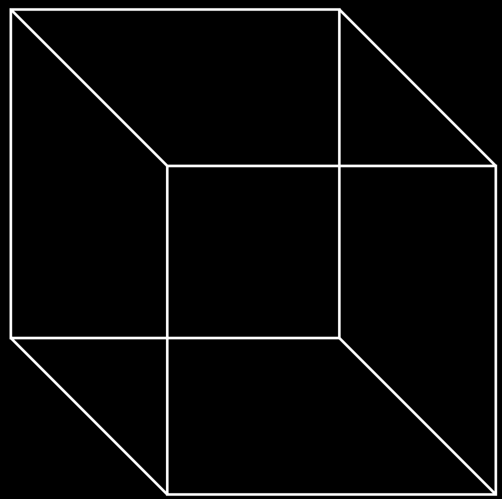
Necker Cube *(1832)*



Kanizsa Triangle *(1976)*

Perceptual Bistability

- **Instantly perceive a coherent figure** *(more or less)*
- **Two different interpretations**
- **Can't perceive both at once**
- **Alternate between perceptions:** ***bistablility…***



The Necker Cube

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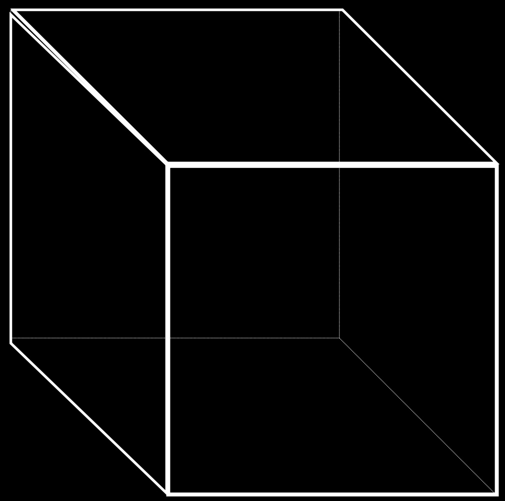

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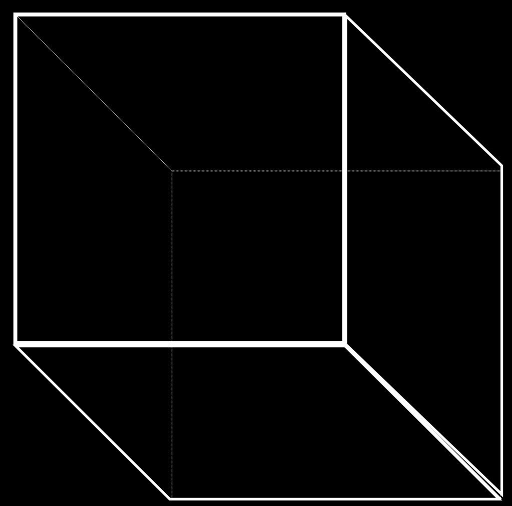
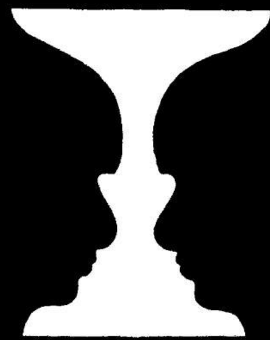
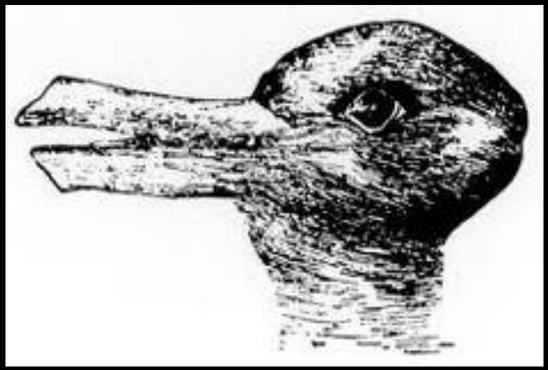


The Necker Cube

Other Examples





Gestalt Perception

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- **Principles that guide perception of the "whole"**
  - Similarity
  - Contiguity
  - Continuity
  - Closure
  - Symmetry

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  - **–Emergence**

Gestalt Perception

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  - Symmetry
  - **Emergence**

- **Nice heuristic description, but how do these work?**
  - How do we assess images along all of these dimensions at once, seemingly instantaneously?

    (remember the 100 step rule)

Constraint Satisfaction

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- These problems can be recast more generally as constraint satisfaction problems:

Constraint Satisfaction

– Simultaneously satisfy many interdependent relationships, or "constraints"
(e.g., matches between sensory cues, or sensory input and memory representations)

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(e.g., matches between sensory cues, or sensory input and memory representations)

Constraint Satisfaction

– There may be no perfect solution, so…

Constraint Satisfaction

– Look for the best "fit" — one that satisfies as many of the constraints as possible

Constraint Satisfaction

– Some constraints may be more common or important than others

Constraint Satisfaction

- Connectionist models lend themselves naturally to the solution of such problems...

Constraint Satisfaction

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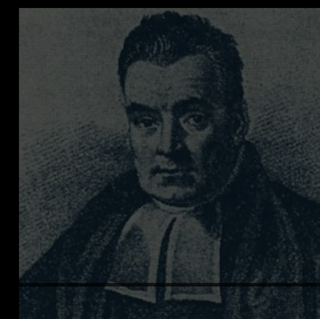

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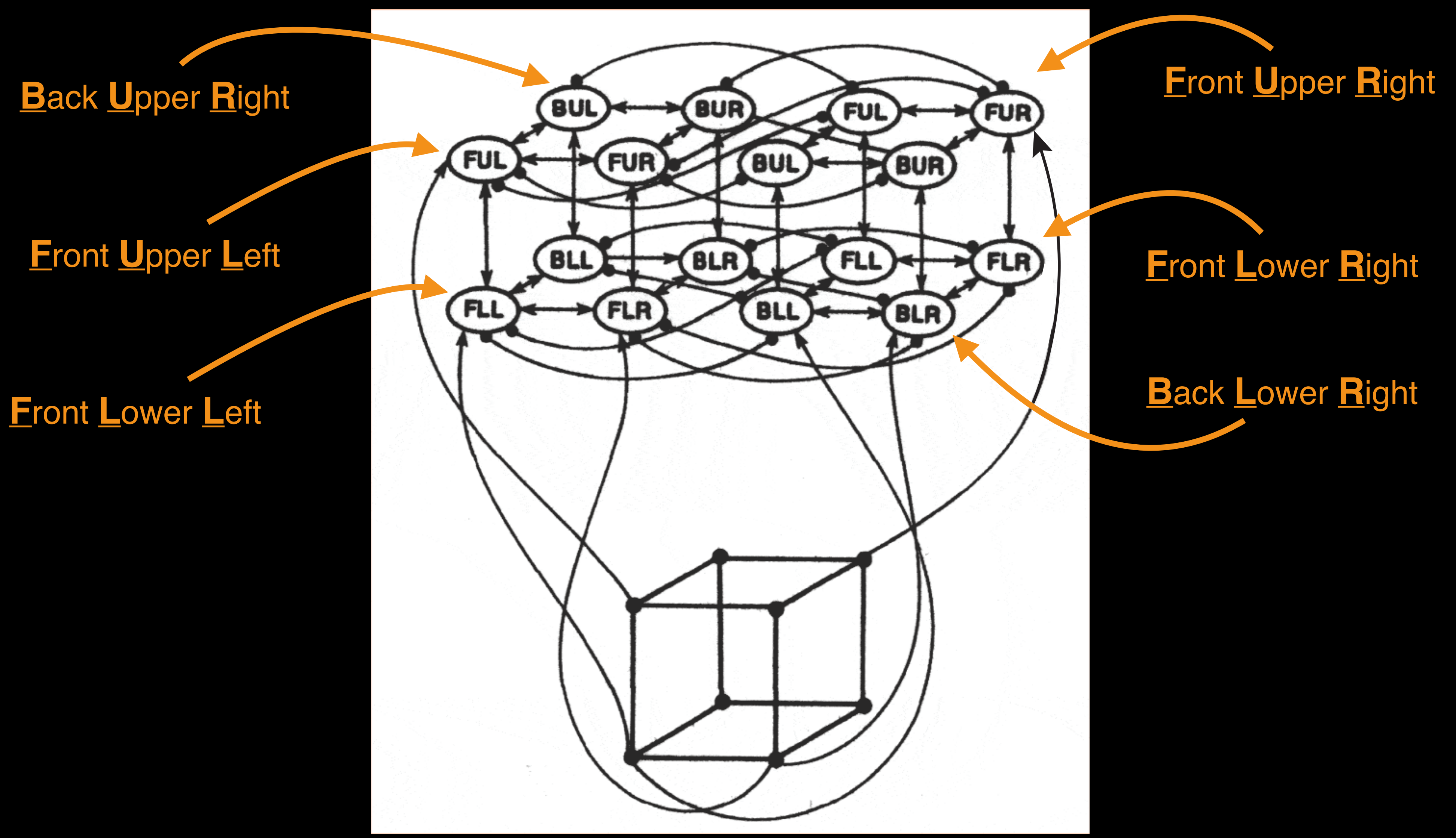
- How can this be applied to psychological phenomena?

Constraint Satisfaction Network



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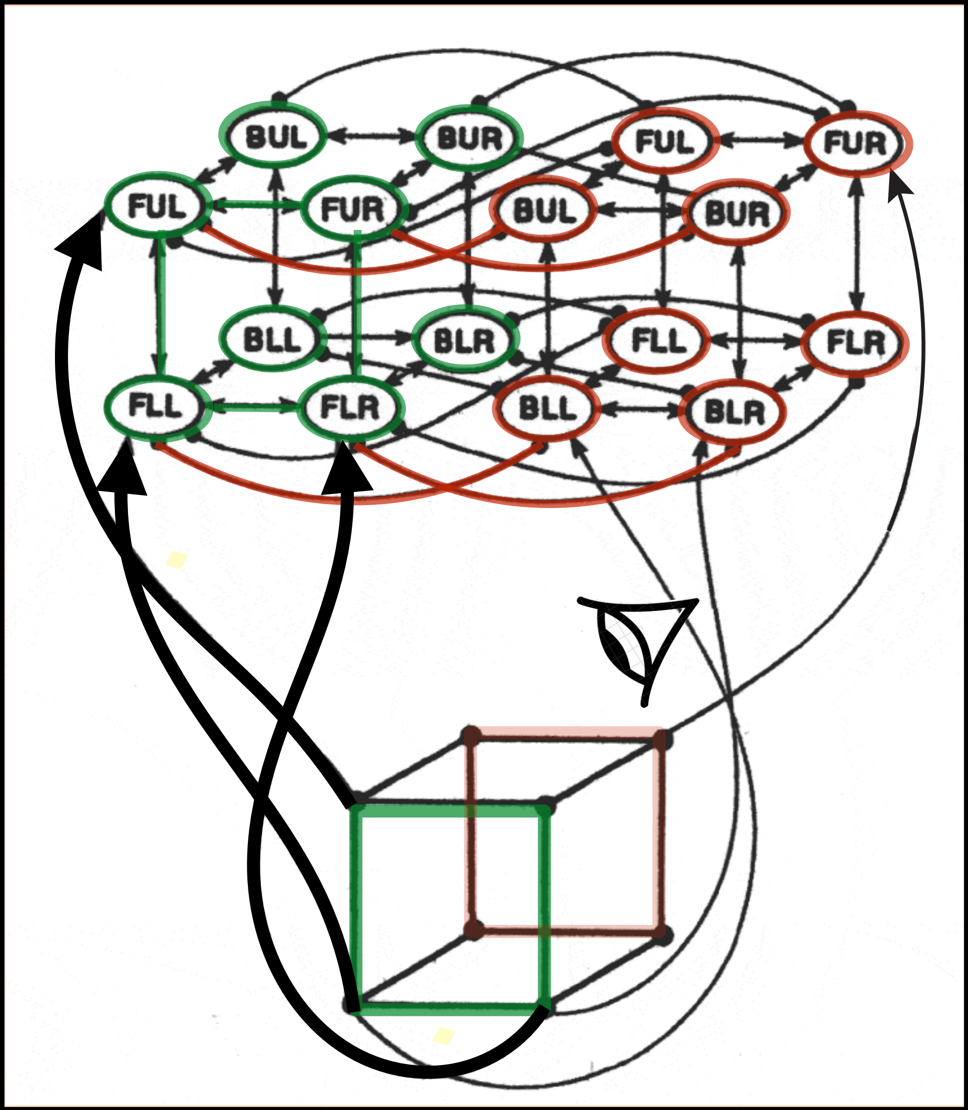

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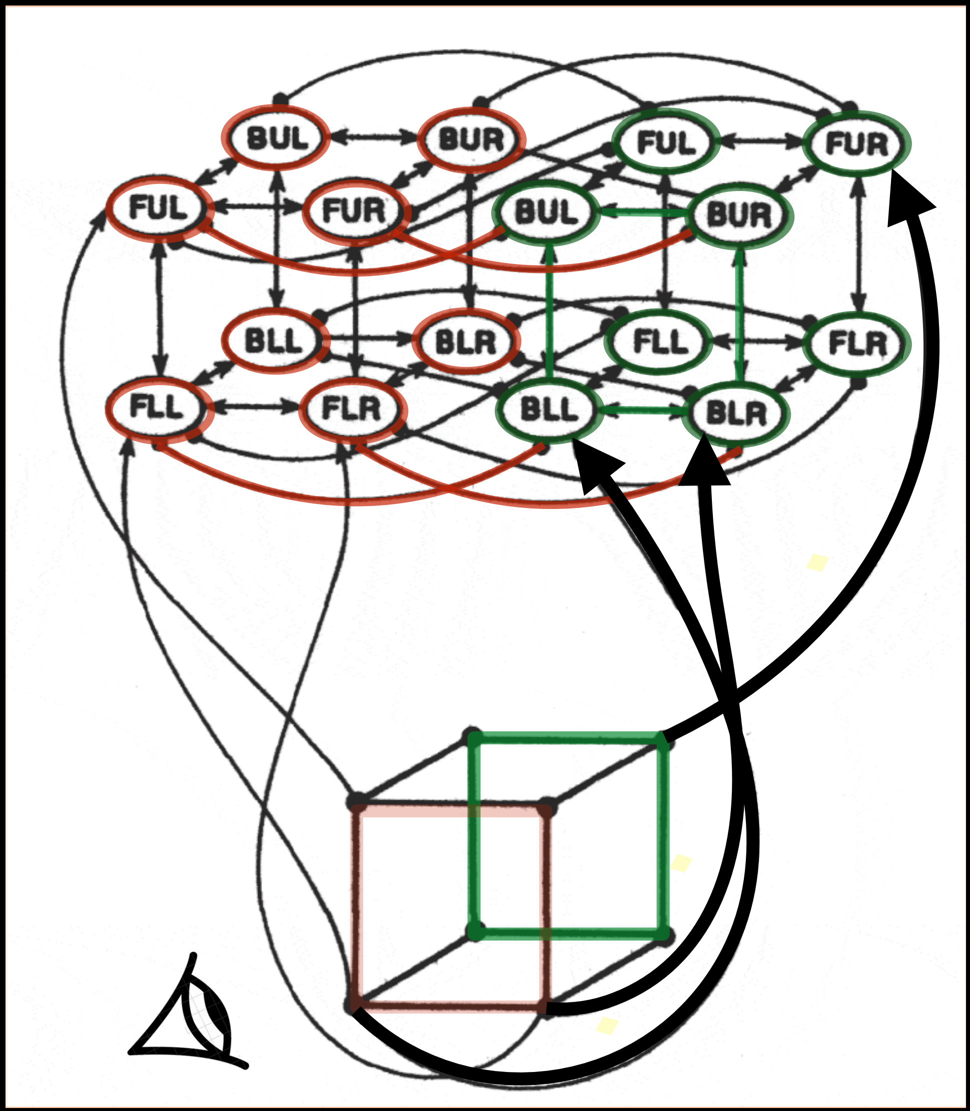

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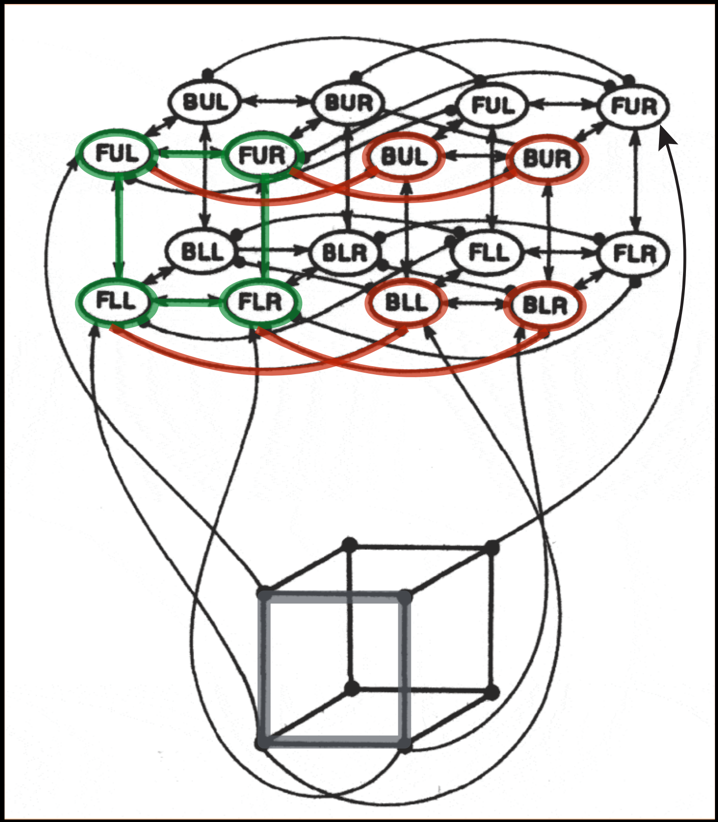
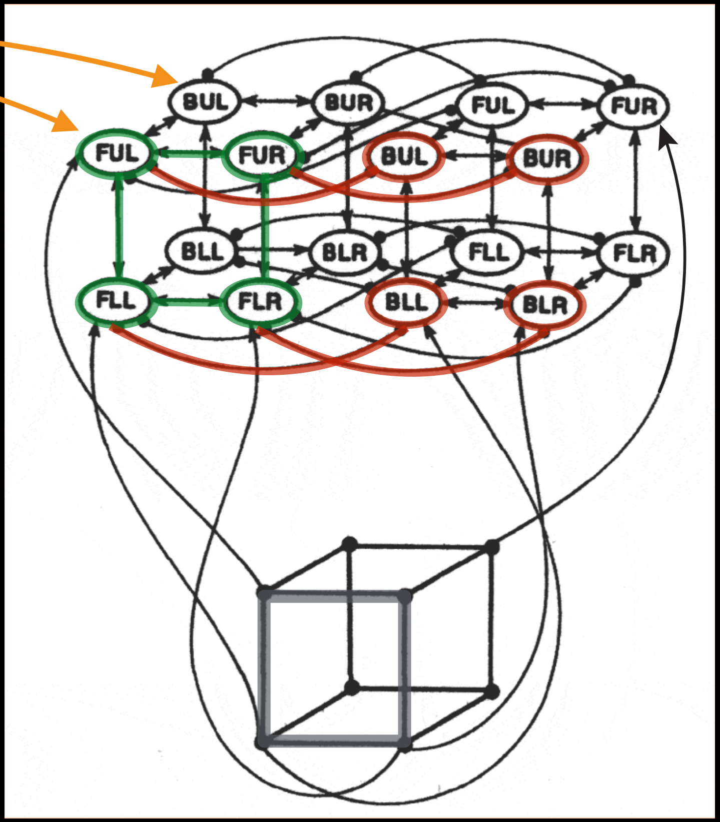


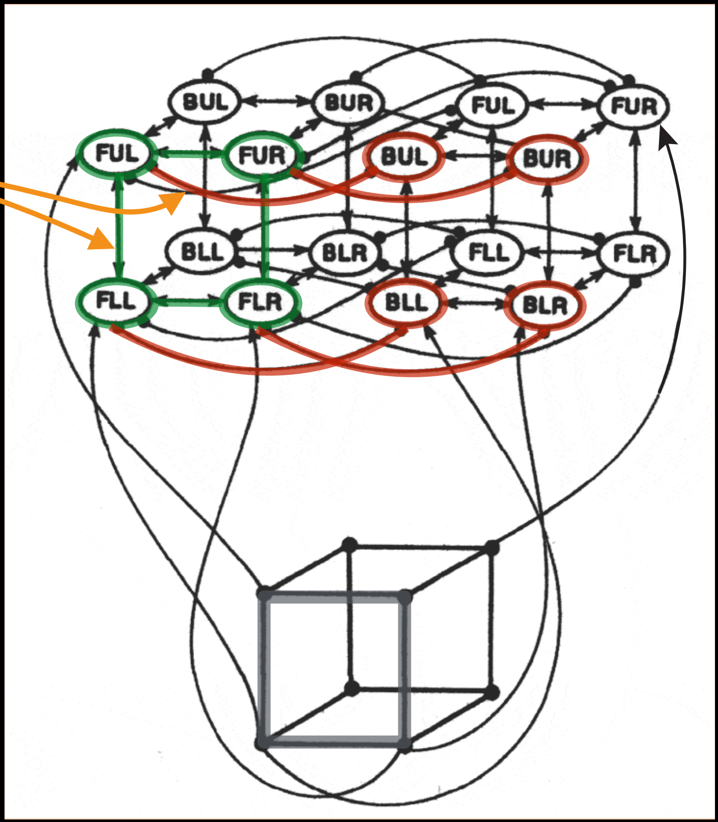
Constraint Satisfaction Network

- ***Hypotheses*** = unit activity values



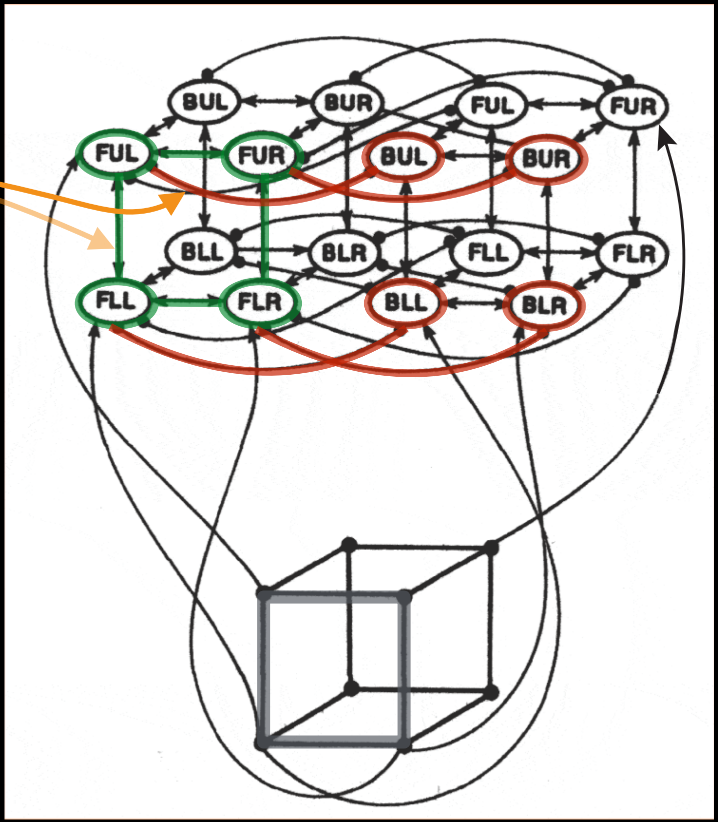
Constraint Satisfaction Network

- ***Constraints*** = connections between units



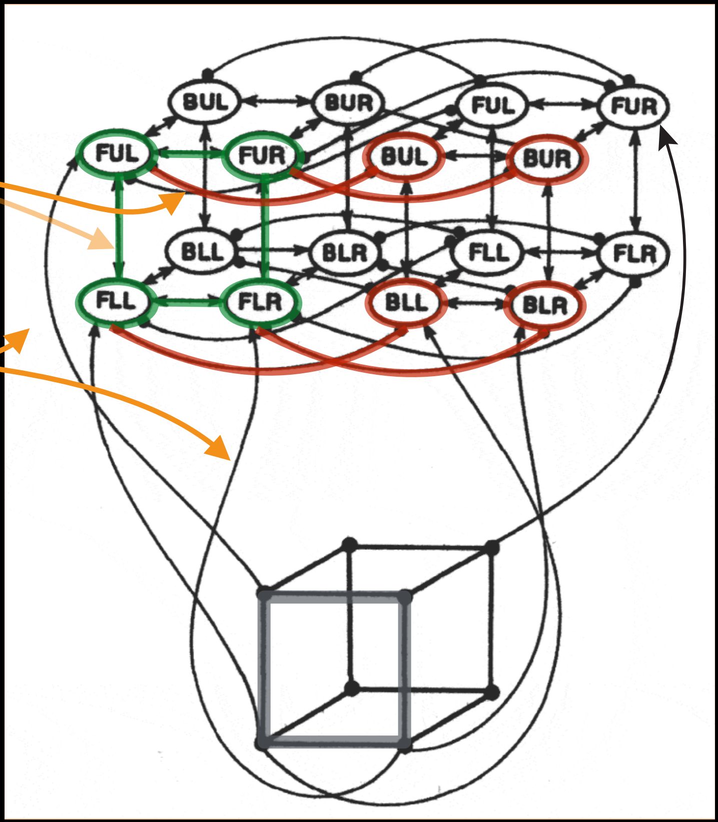
Constraint Satisfaction Network

- ***Importance of constraint*** = weight of connection



Constraint Satisfaction Network

- ***Evidence*** (for a given hypothesis) = external input



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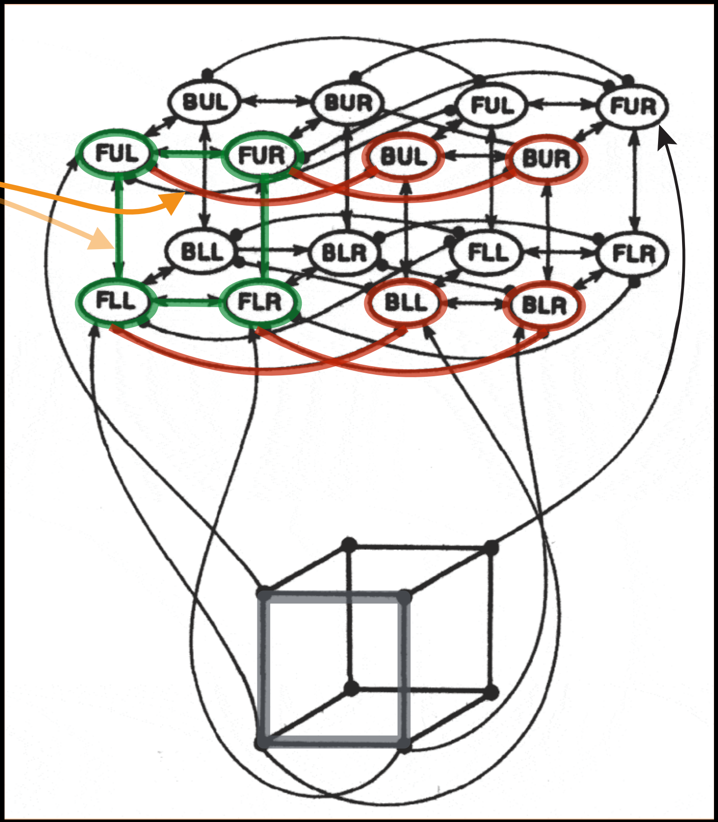
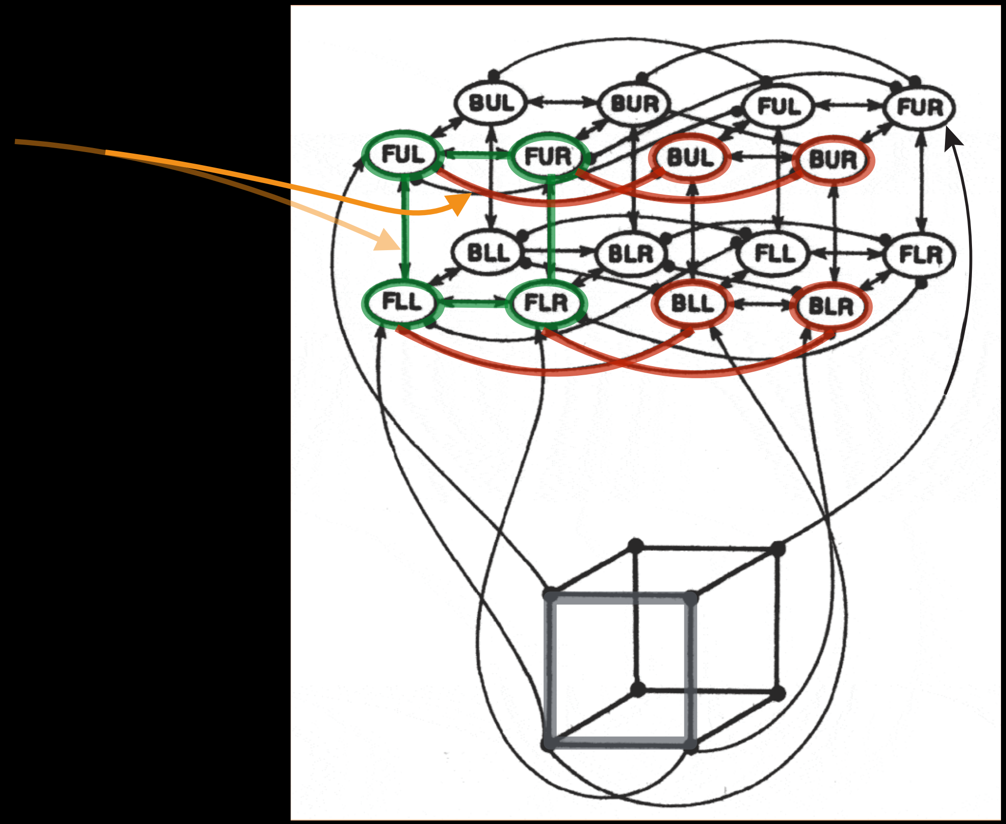


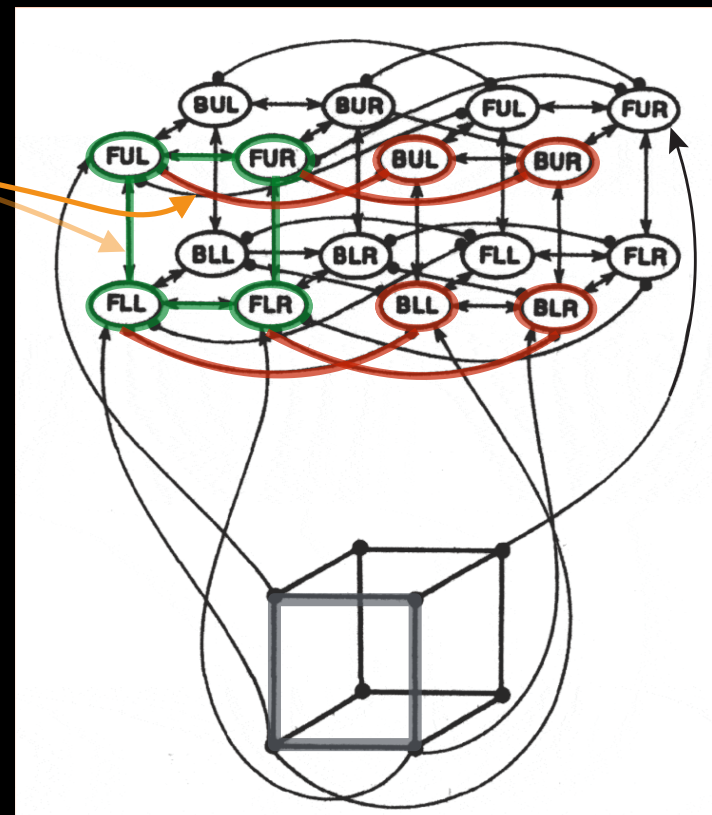
- ***A priori probability*** (for a given hypothesis) = biases

Constraint Satisfaction Network



- ***Inference*** = settling process

Constraint Satisfaction Network



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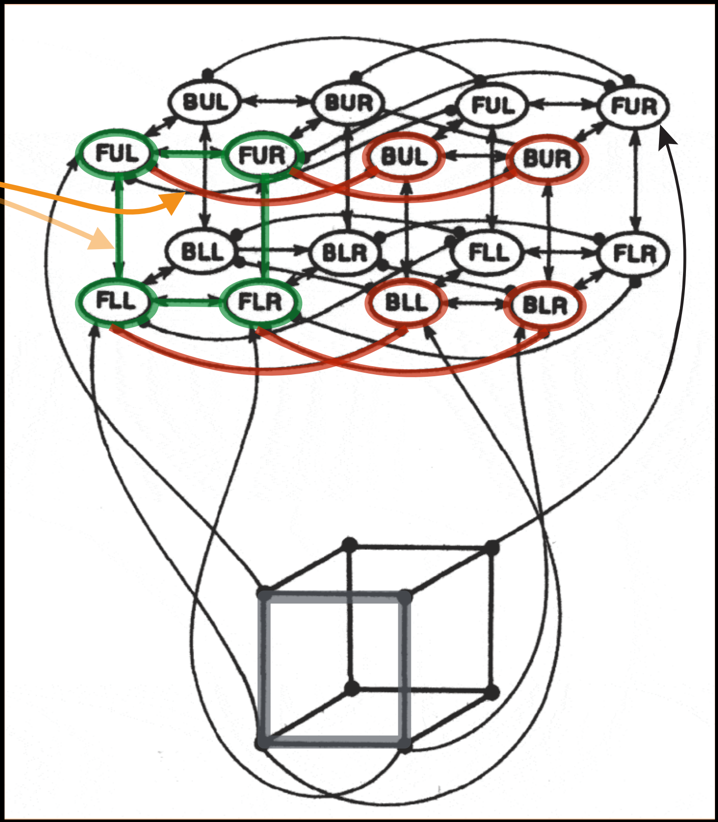


- ***Success*** = goodness of fit

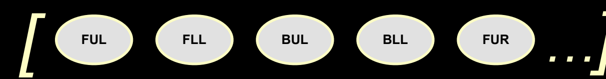
- **How can we formalize this?**

Hopfield Networks, Energy & "State Space" Dynamics

Hopfield Networks, Energy & "State Space" Dynamics

- **State: vector of unit activation values**

  (state space = range of all possible vector values)



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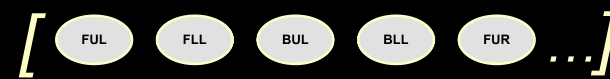
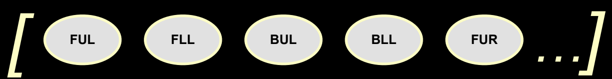


- **Energy of each state:** $E = -\dfrac{\Sigma_{ij} w_{ij} a_i a_j}{2}$

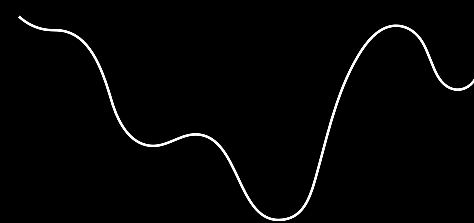
  (opposite of Goodness)

Hopfield Networks, Energy & "State Space" Dynamics



$$E = -\frac{\Sigma_{ij} w_{ij} a_i a_j}{2}$$

- **Energy surface:** **plot of energy for every state**



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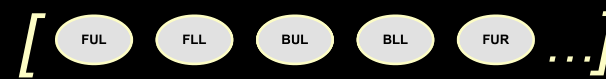

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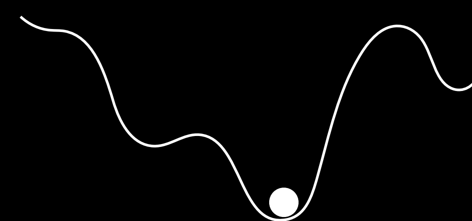
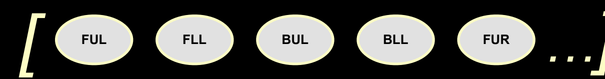


- **Dynamics:** traversal of energy surface

Hopfield Networks, Energy & "State Space" Dynamics



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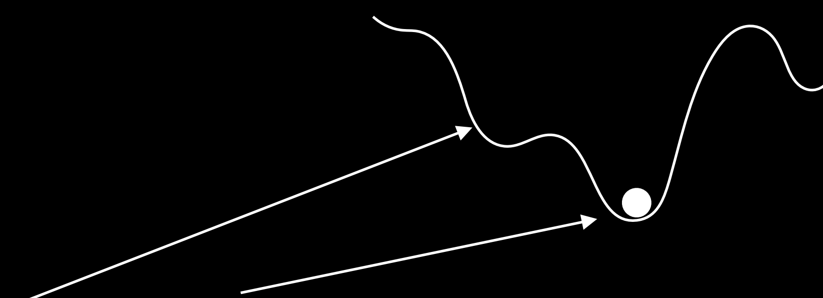
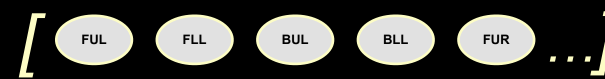


- **Minima:** points of lowest energy (local & global)

Hopfield Networks, Energy & "State Space" Dynamics



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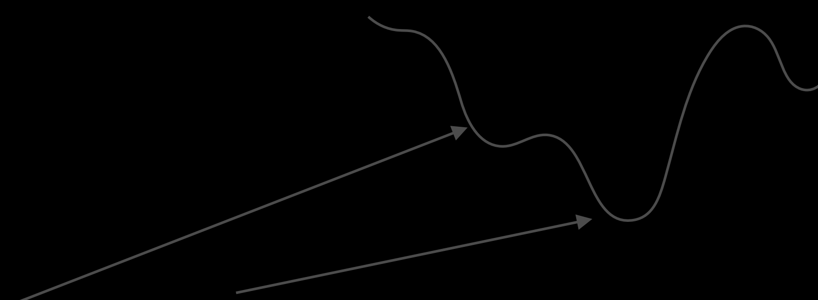
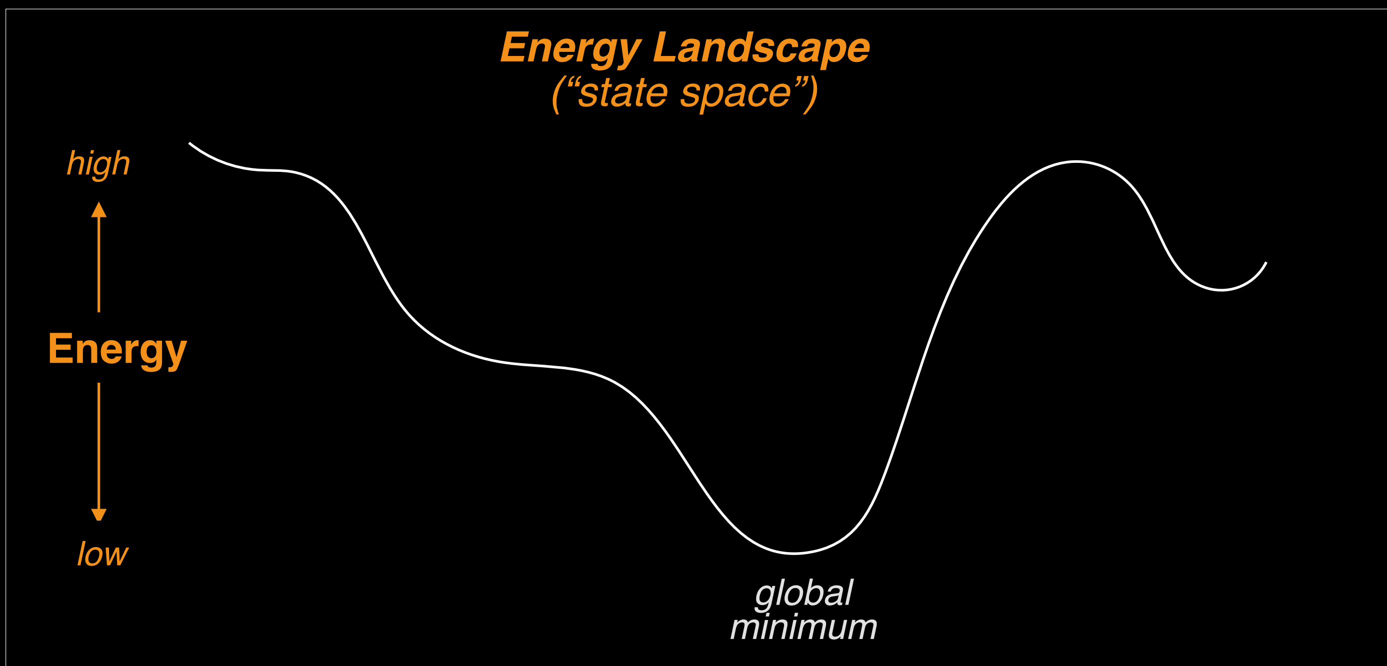
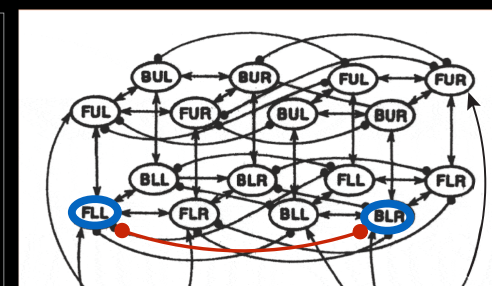
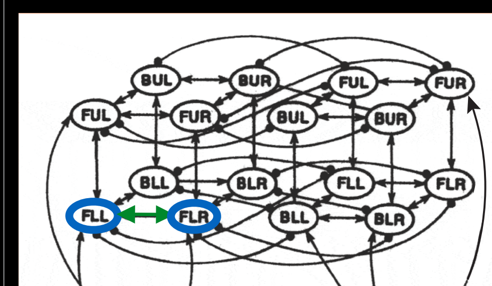


- Under proper assumptions, can prove that system will flow down hill

Engergy Landscape







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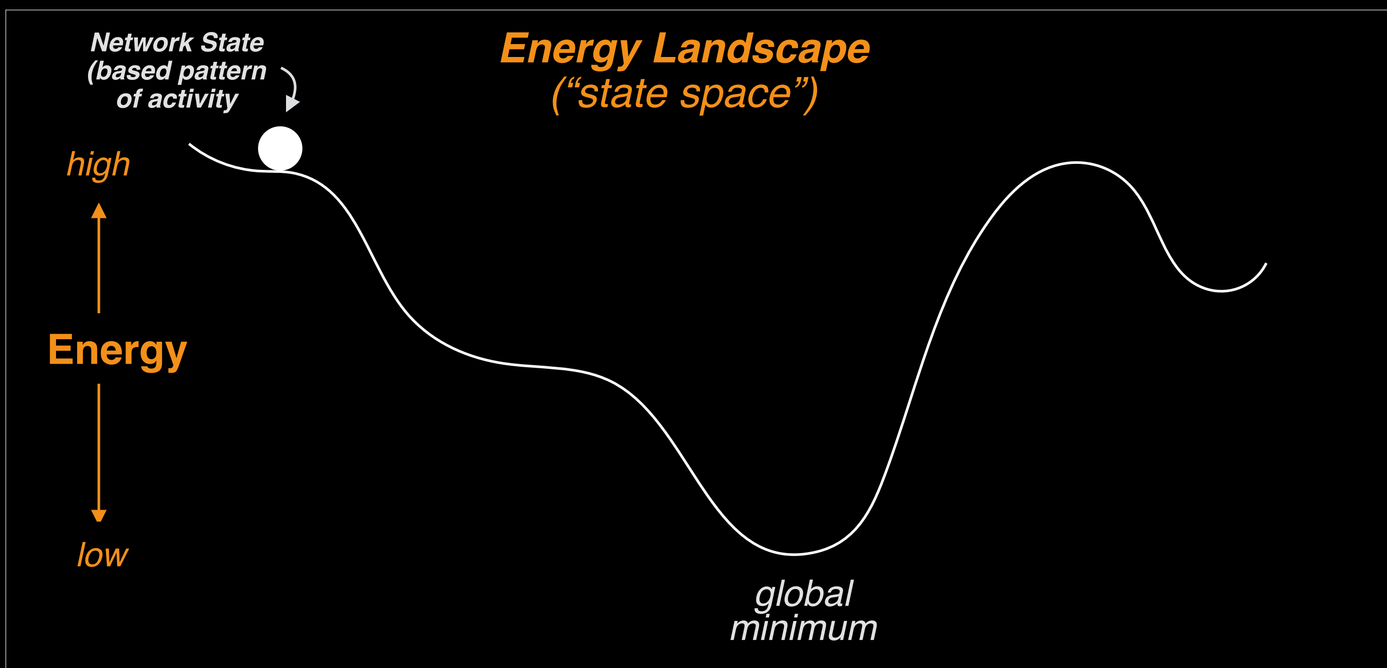

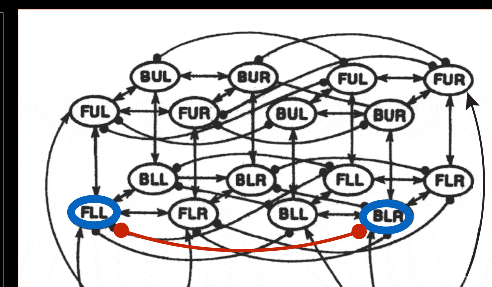

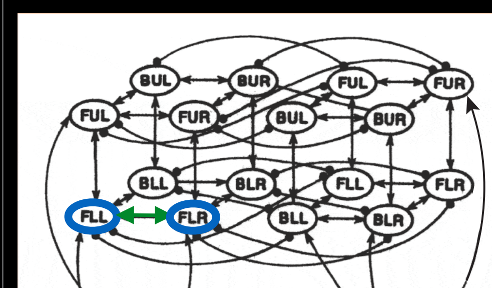

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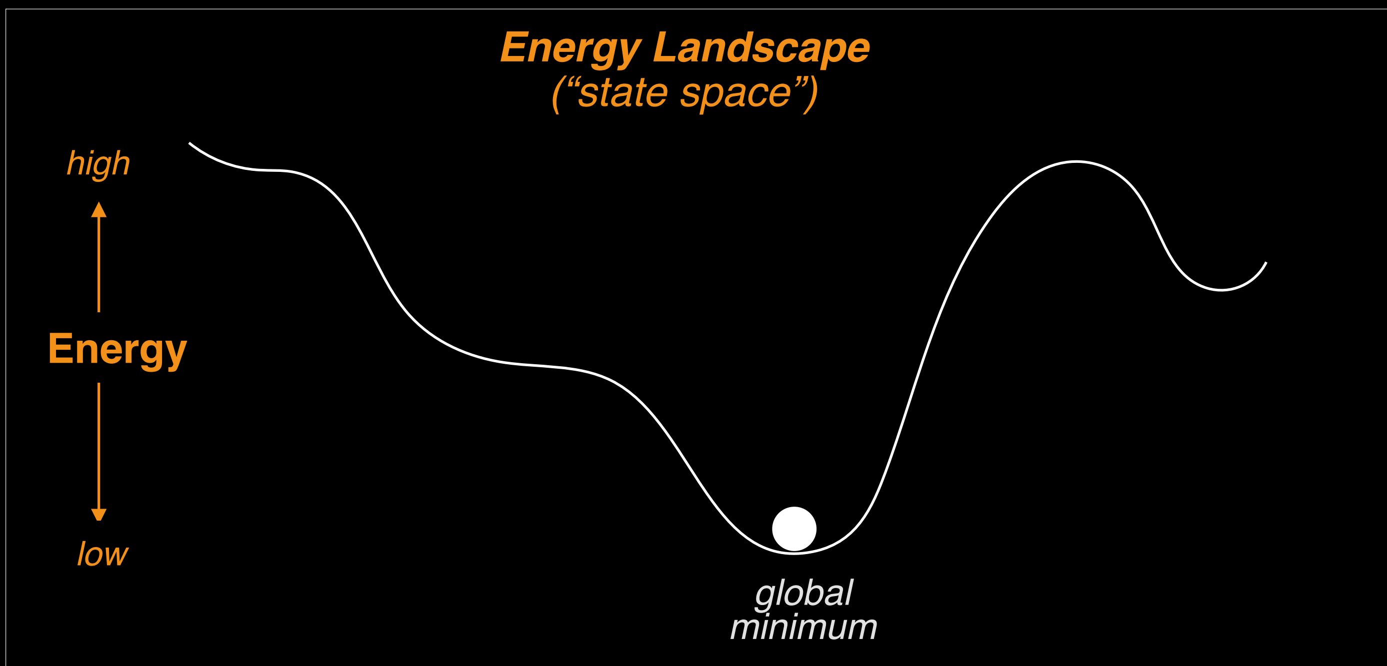
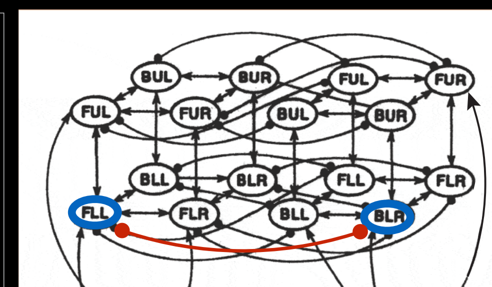
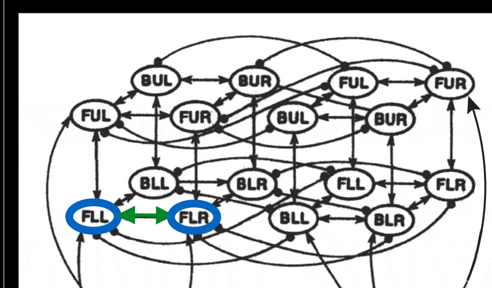


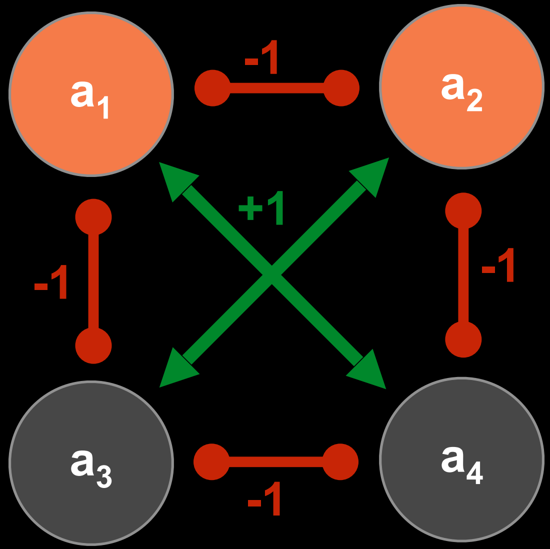




An Example

$$E = -\frac{\Sigma_{ij} w_{ij} a_i a_j}{2}$$

Update	a_1	a_2	a_3	a_4	Energy
Initial State	1	1	0	0	+0.5



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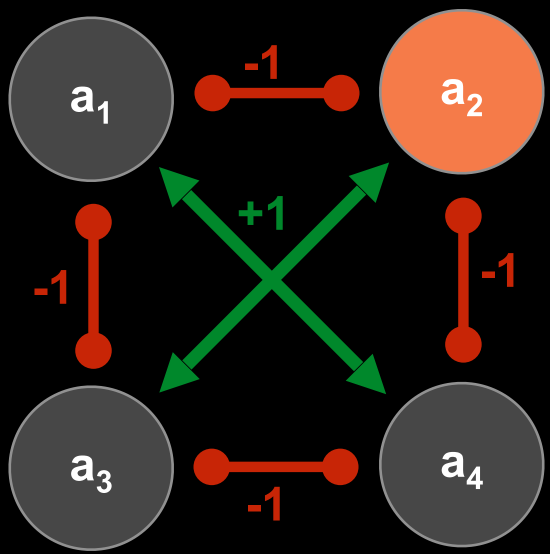

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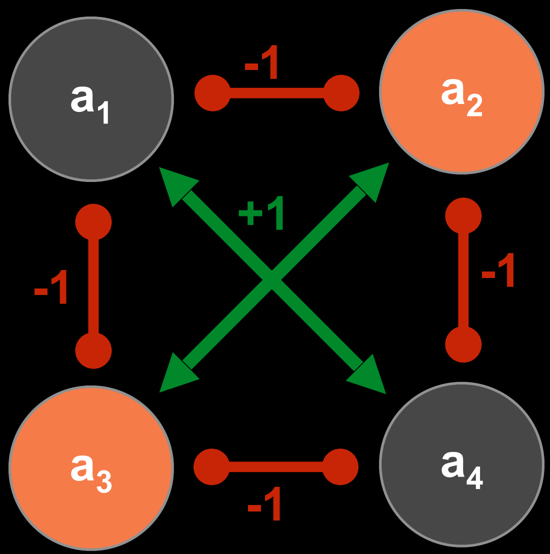

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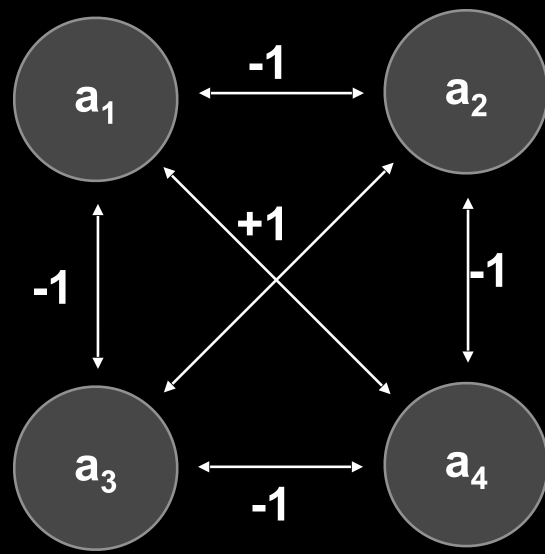
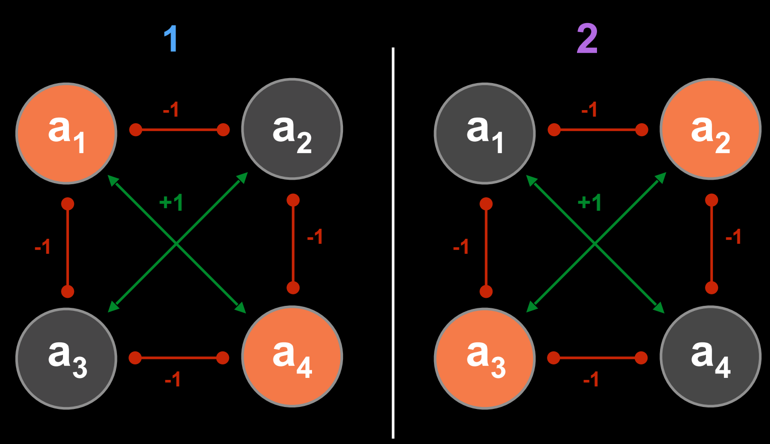


Two stable states — percepts *(or memories)*

State	a_1	a_2	a_3	a_4	Energy
1	1	0	0	1	-0.5
2	0	1	1	0	-0.5



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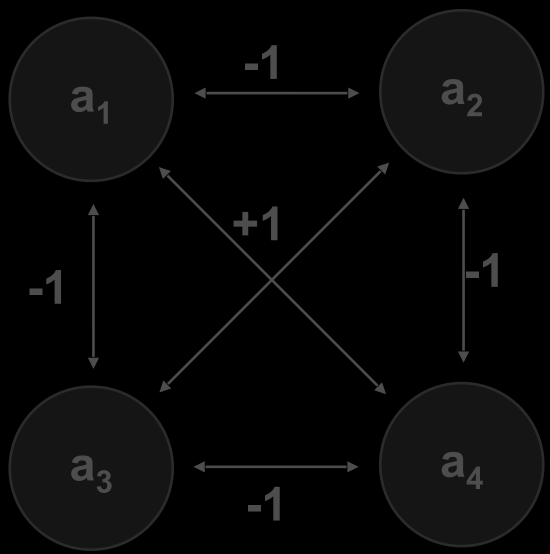

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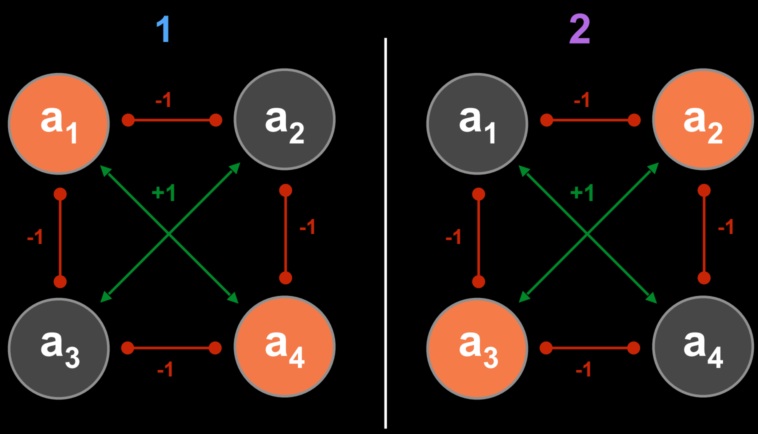


Energy Landscapes

Energy Landscapes

- A surface that is the energy of the network as a function of the activity of its units

Energy Landscapes

- The state of the system is a point on this surface

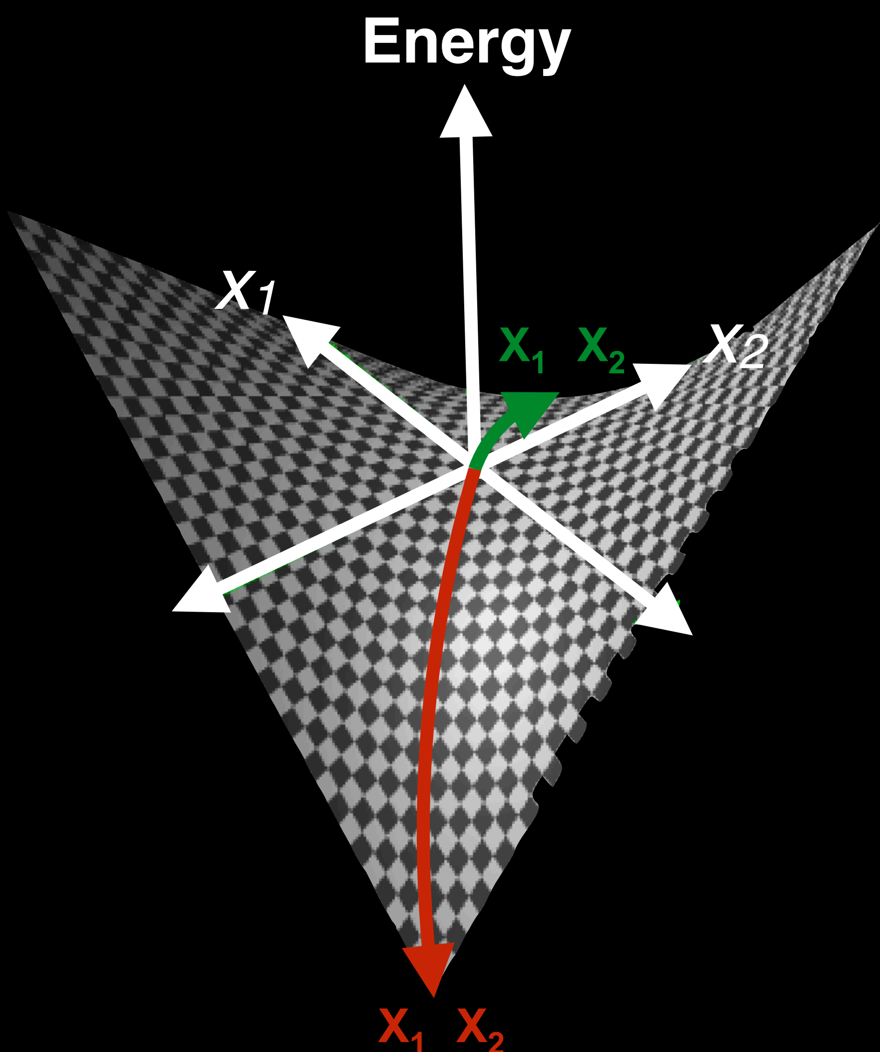
Energy Landscapes

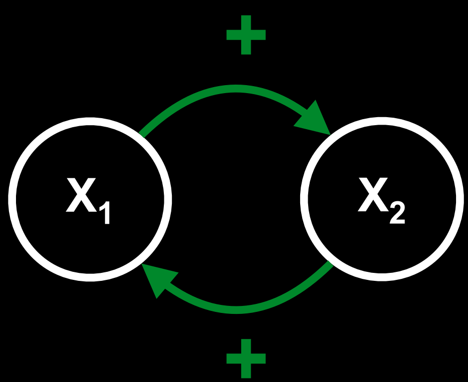
- The settling process of the network is the downhill trajectory of this network along this surface

Energy Landscapes

- Hard to visualize in high dimensions, so stick to 2.5-D…

Energy Landscapes





Mutually Excitatory units

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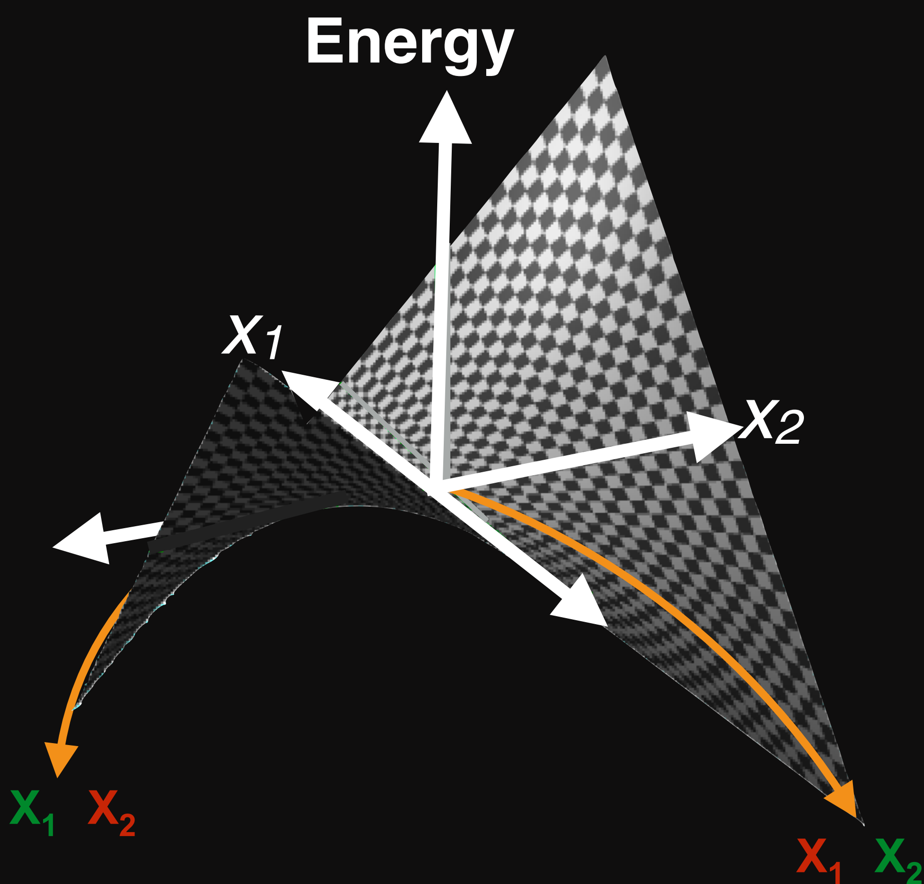

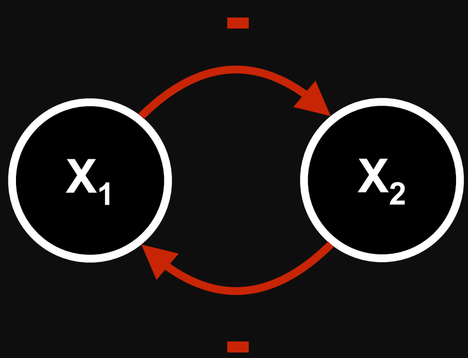

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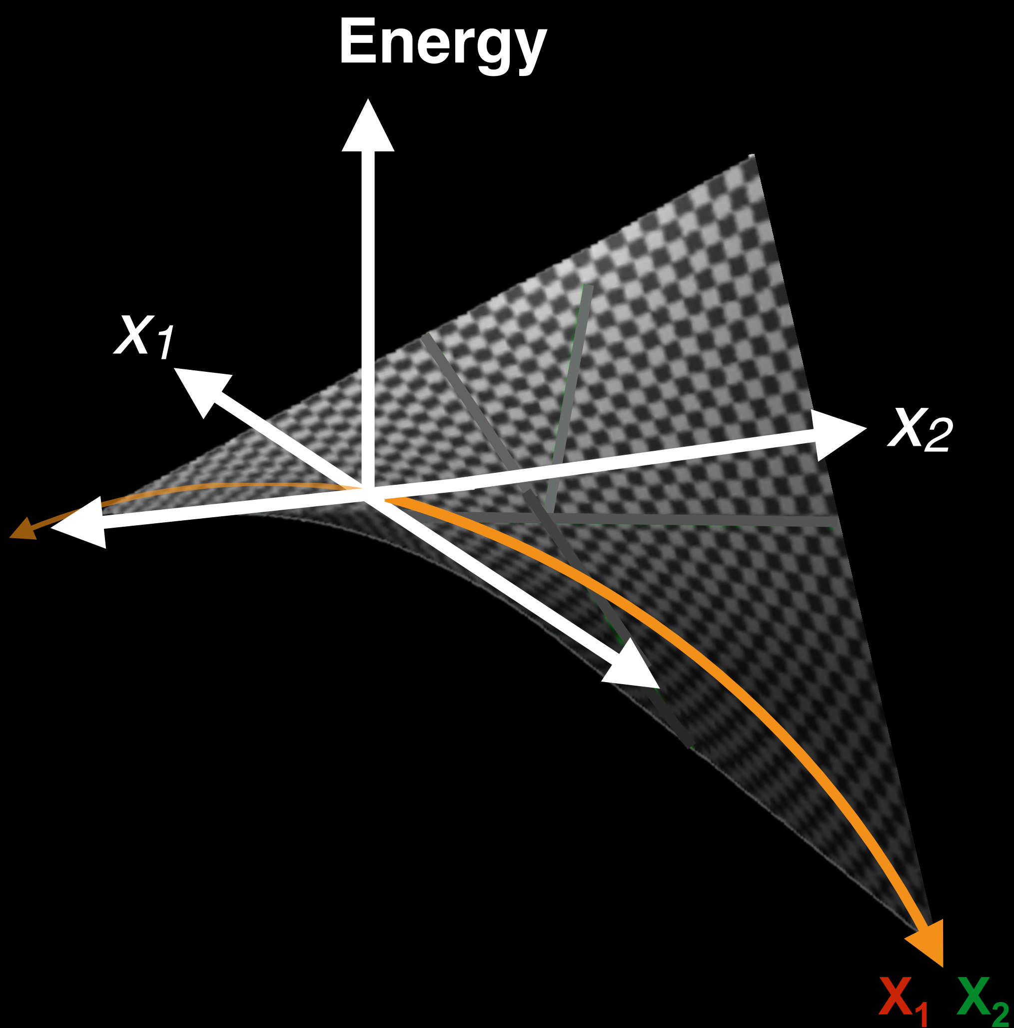

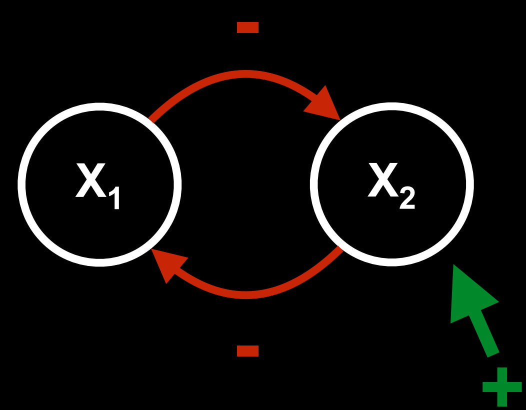

Mutually Inhibitory units
and strong input to x_2

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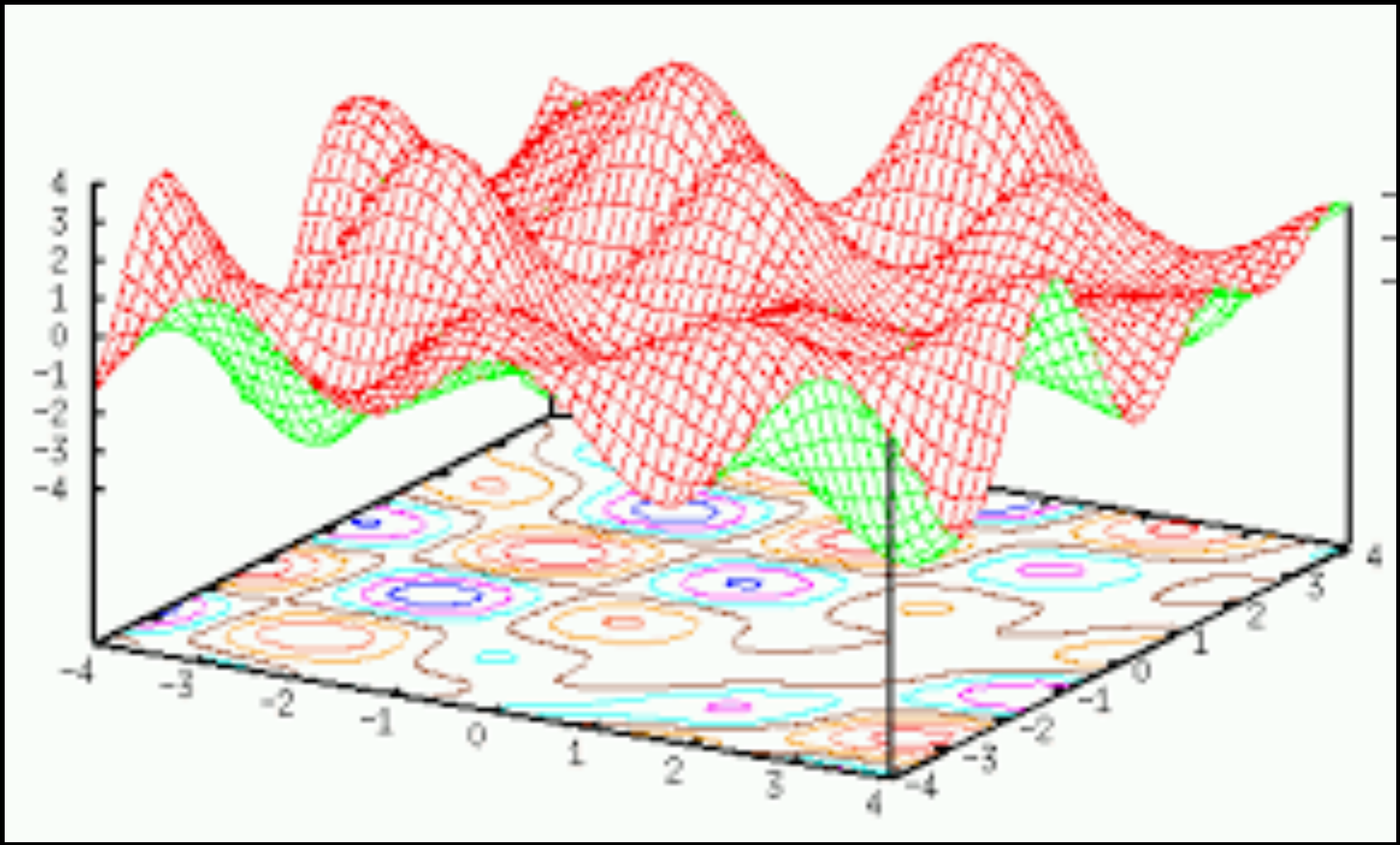

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- No guarantee that nearest minimum is the best: local minima
  - ball can get stuck in a shallow well before finding deepest one…

Local Minima

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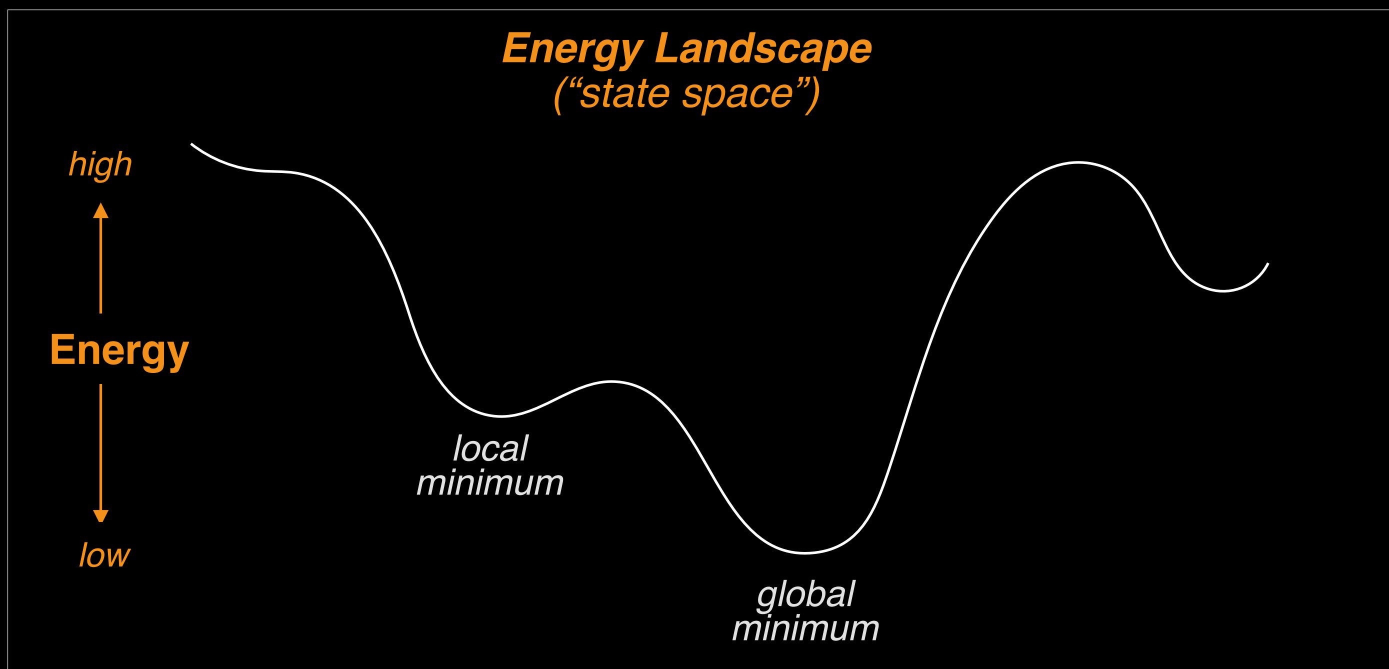

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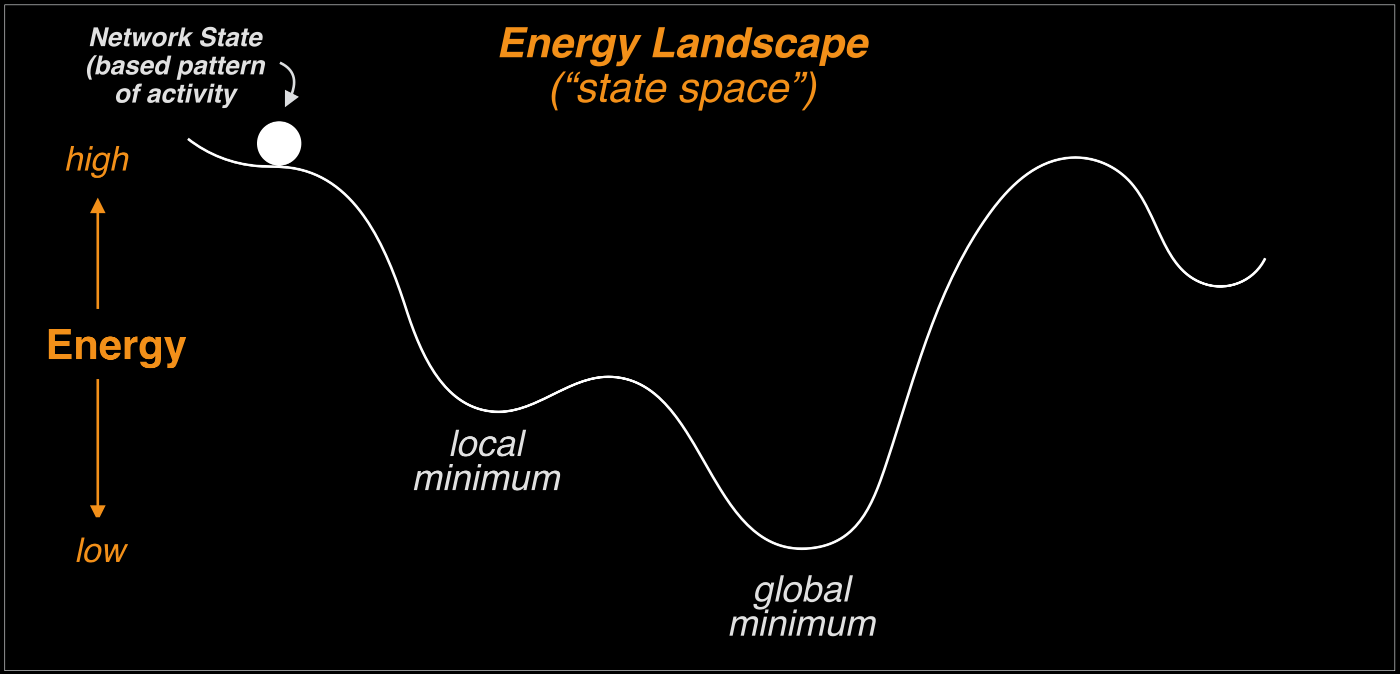

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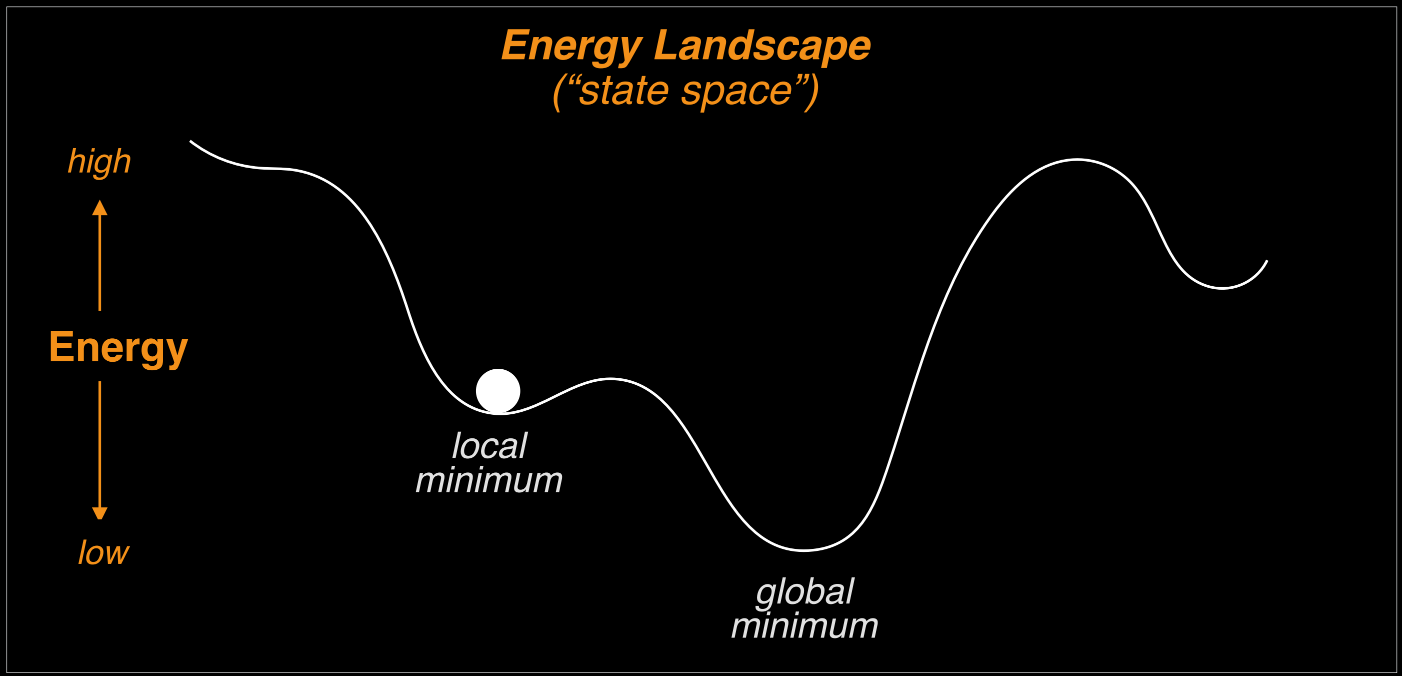

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  - **Temperature modulates the effects of both…**

Effects of Temperature

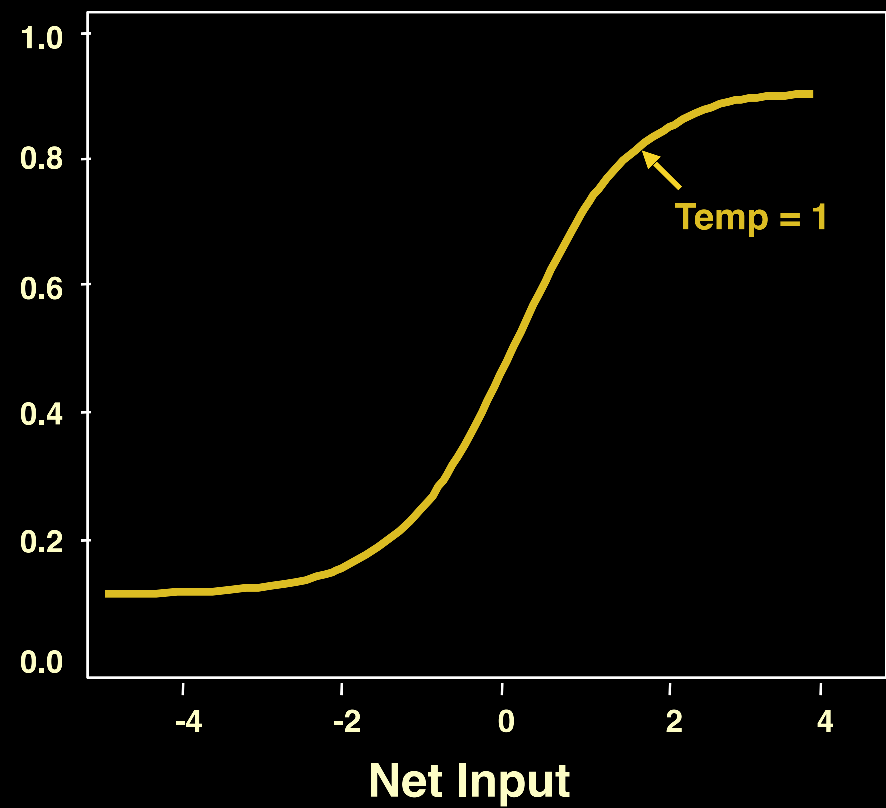
$$\frac{1}{1 + e^{-\frac{net\ input}{Temp}}}$$

Activity

(Hopfield Net, 1984)

Probability of firing

(Boltzmann Machine)



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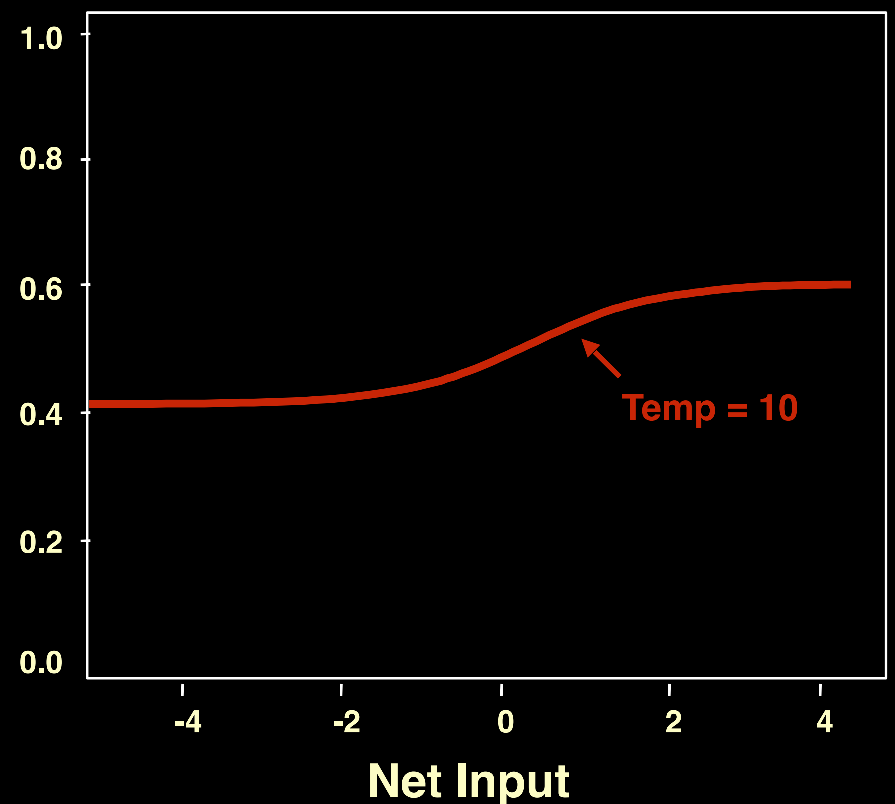

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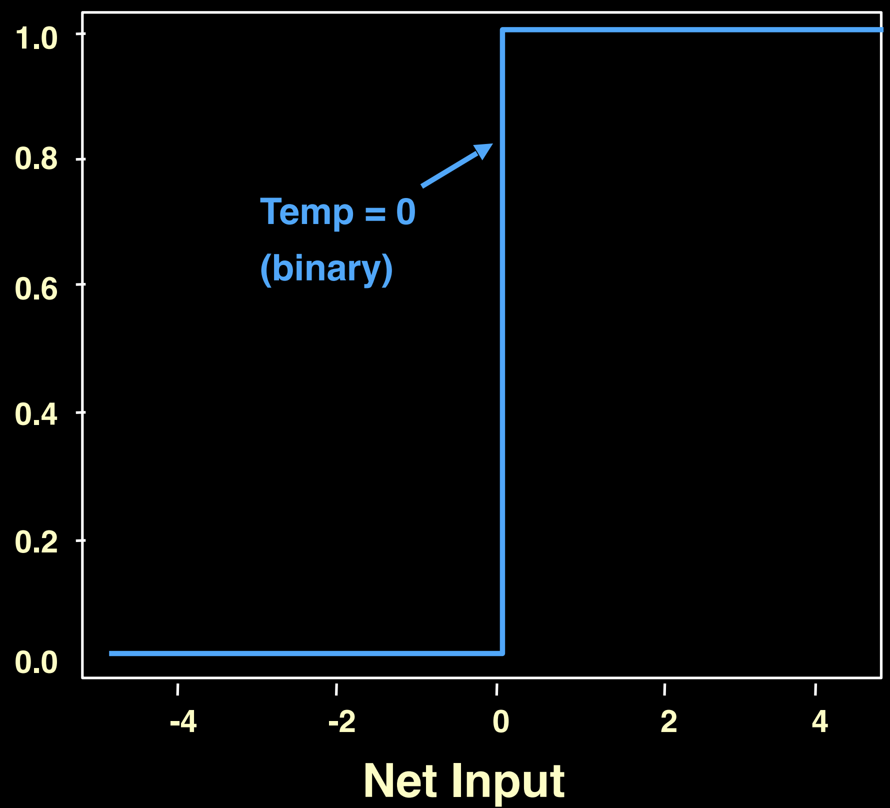

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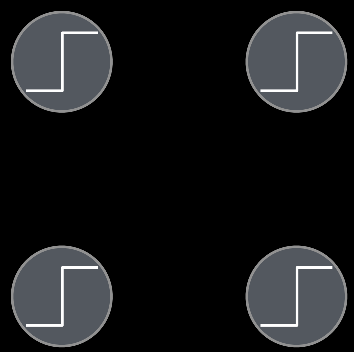

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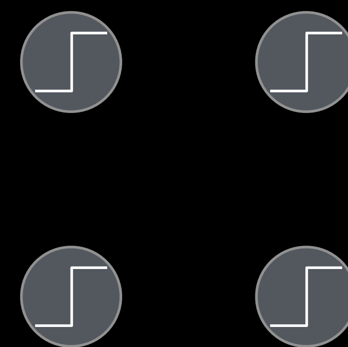

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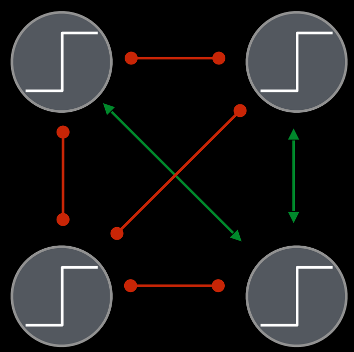

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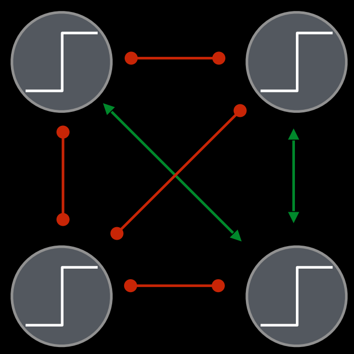

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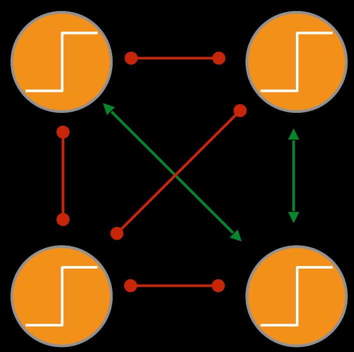

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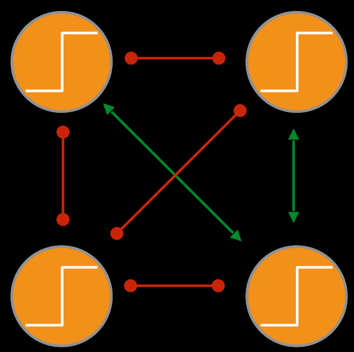

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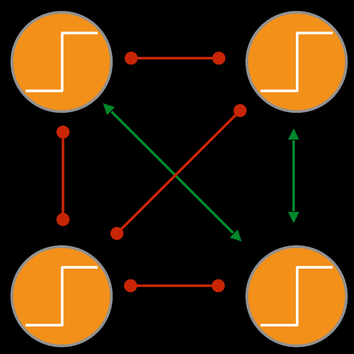

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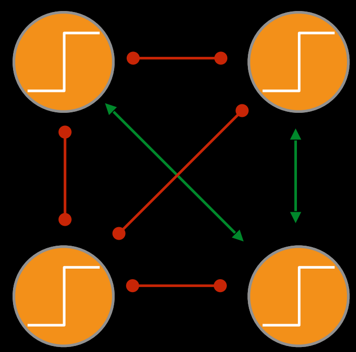

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Comparison of Models

Model	Activation	Updating	Connections
Hopfield (1982)	Binary	Deterministic	Symmetric
Hopfield (1984)	Continuous	Deterministic	Symmetric
Bolzmann Machine	Binary	Stochastic	Asymmetric
Interactive Activation and Competition (IAC)	Continuous	Deterministic	Symmetric
Leaky Competing Accumulator (LCA)	Continuous	Stochastic	Asymetric

Comparison of Models

- To what extent are setting dynamics psychologically/ neurally plausible?

Comparison of Models

- How can such models be used to account for empirical data...

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McClelland & Rumelhart, 1981

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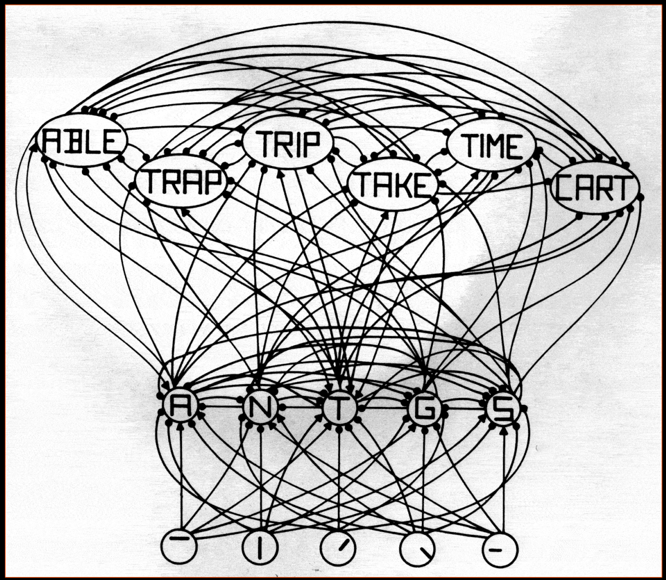

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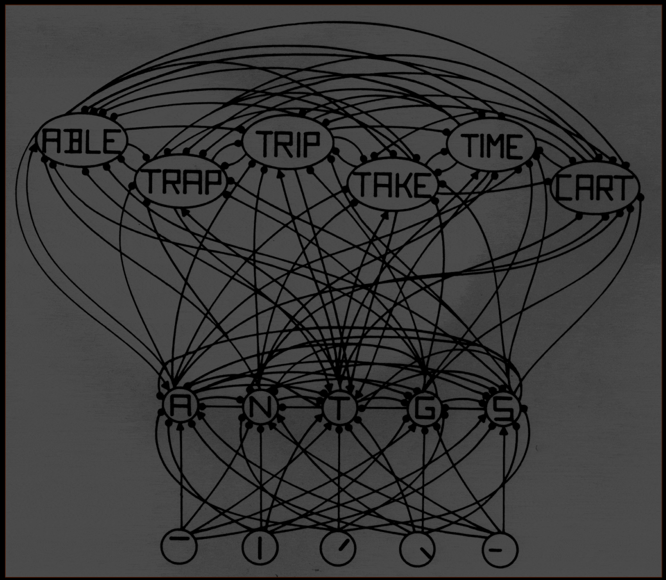

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- Will come back to this under section on language