AMPM 2021

Self-optimization for transdisciplinary intervention

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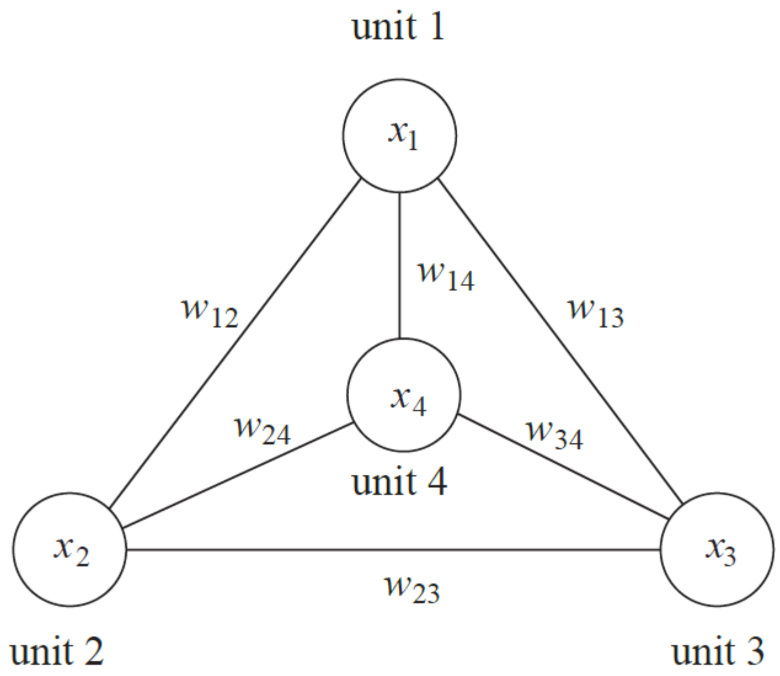
Public policy making

Complex adaptive systems

Hopfield networks

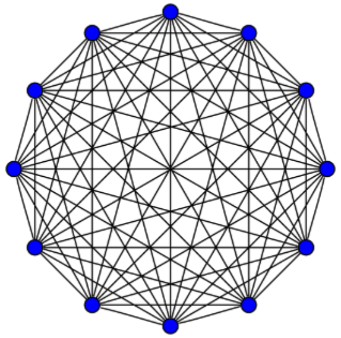
Hopfield networks



- Recurrent neural networks
- Neurons with two values of activity (-1 and 1)
- Optimization, associative memory

Little (1974), Hopfield (1982)

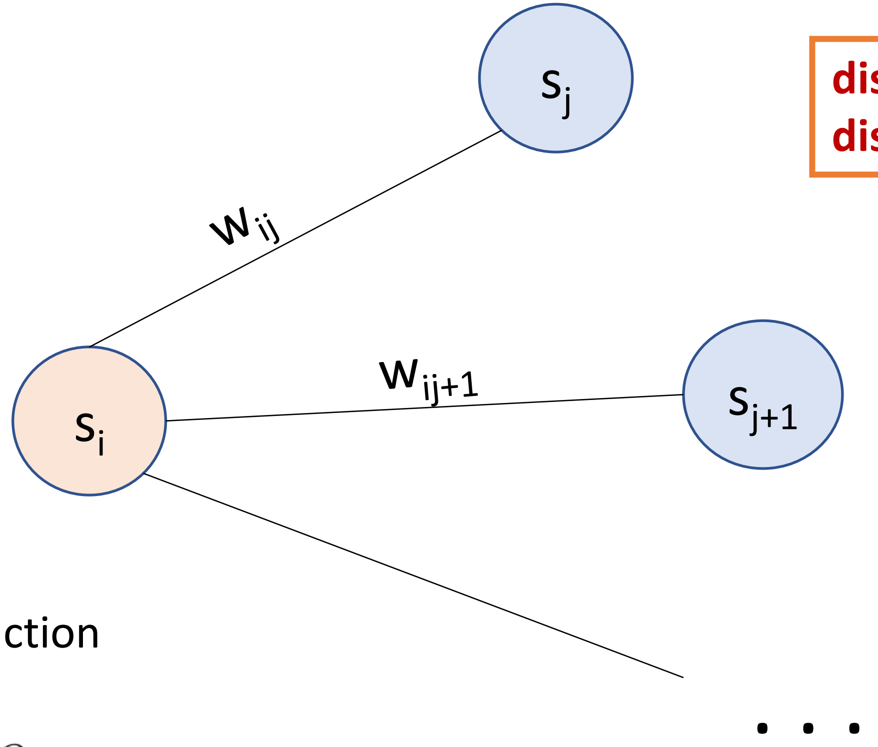
Self-optimization on Hopfield networks



- Asynchronous state updates

$$s_i(t+1) = \theta\left[\sum_{j}^{N} w_{ij} s_j(t)\right]$$

$$s_i = \pm 1 \qquad w_{ij} > 0$$



discrete-time
discrete-state

- Constraint satisfaction

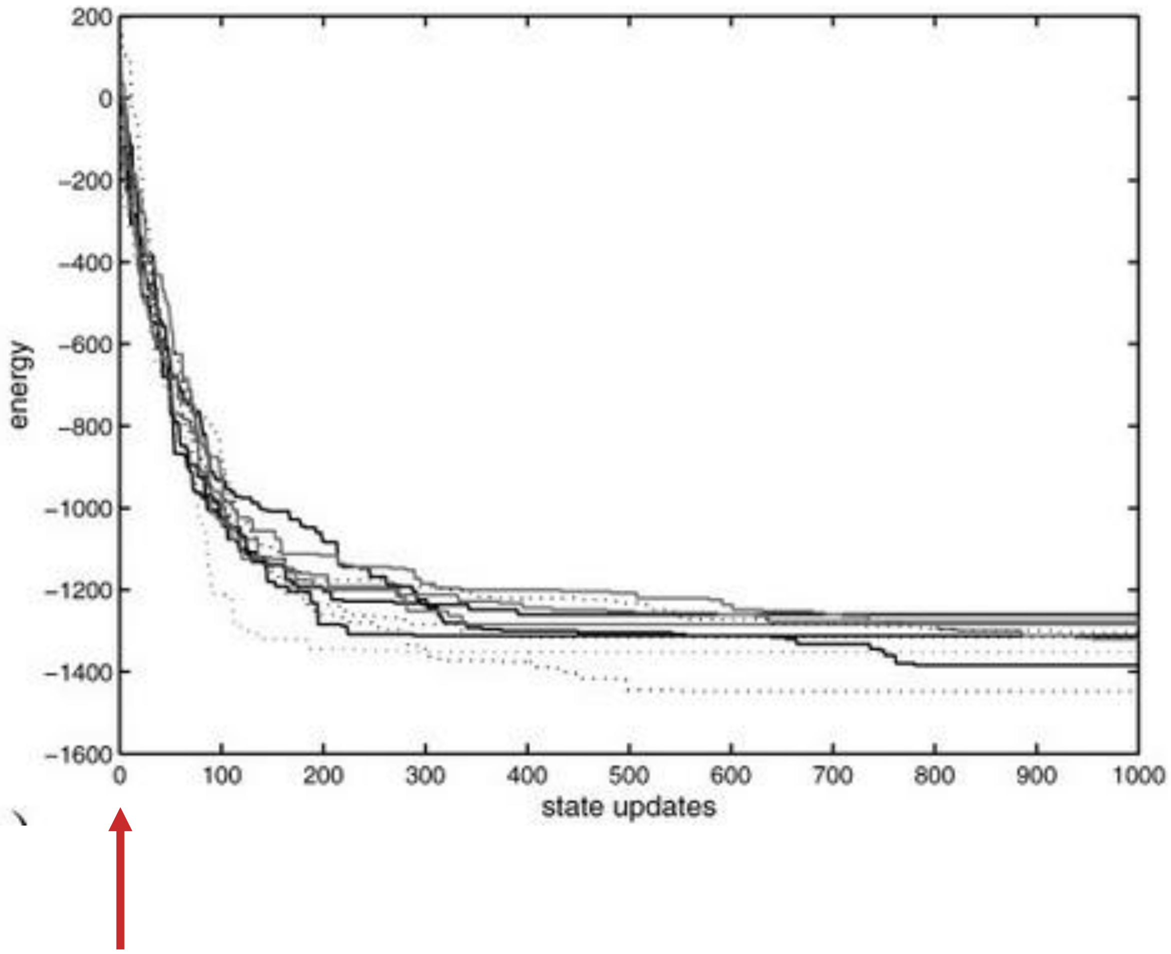
Energy function

$$s_i s_j w_{ij} > 0 \quad \Rightarrow \quad E = -\sum_{ij}^{N} w_{ij}^{O}(t) s_i(t) s_j(t)$$

Watson, R. A., Buckley, C. L., and Mills, R. (2011).

Self-optimization on Hopfield networks

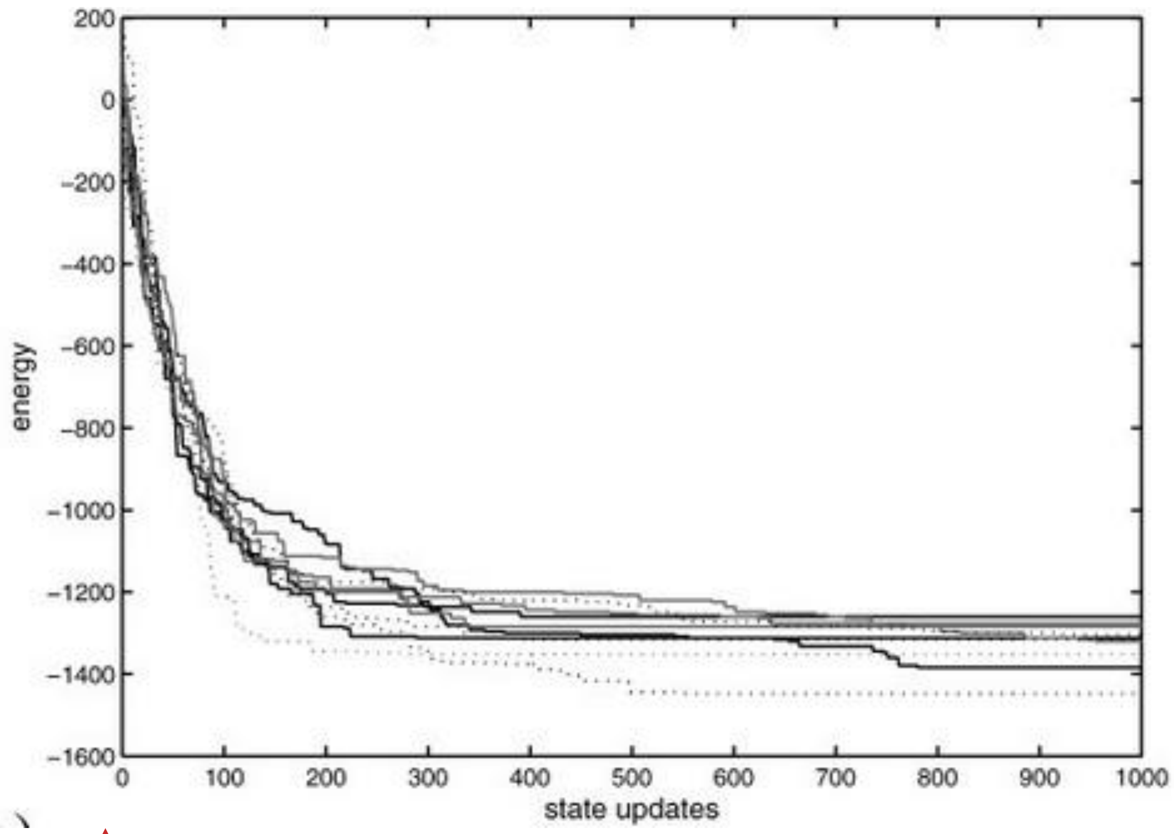
1. Neuron states are randomized.



Self-optimization on Hopfield networks

1. Neuron states are randomized.

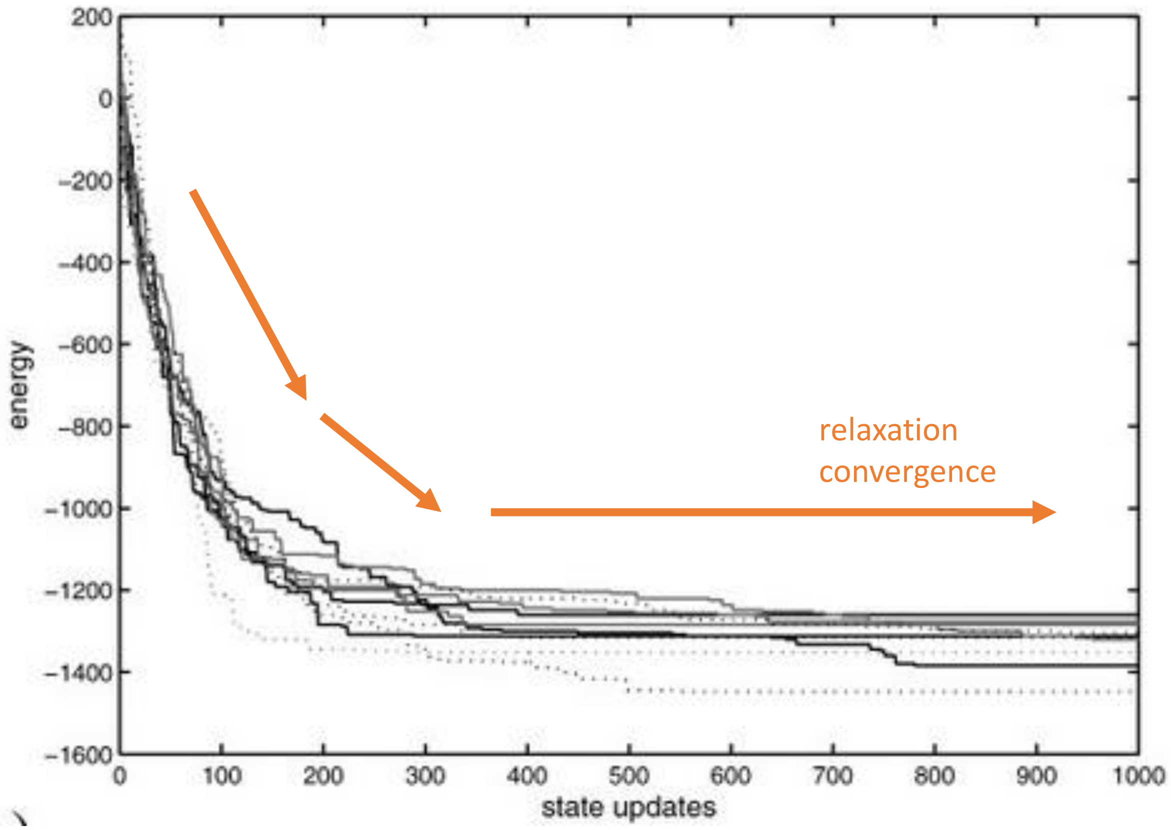
Keep this for later



Self-optimization on Hopfield networks

1. Neuron states are randomized.

2. The network is allowed to converge from this random state configuration to an attractor of the network and lasts t time steps.



Self-optimization on Hopfield networks

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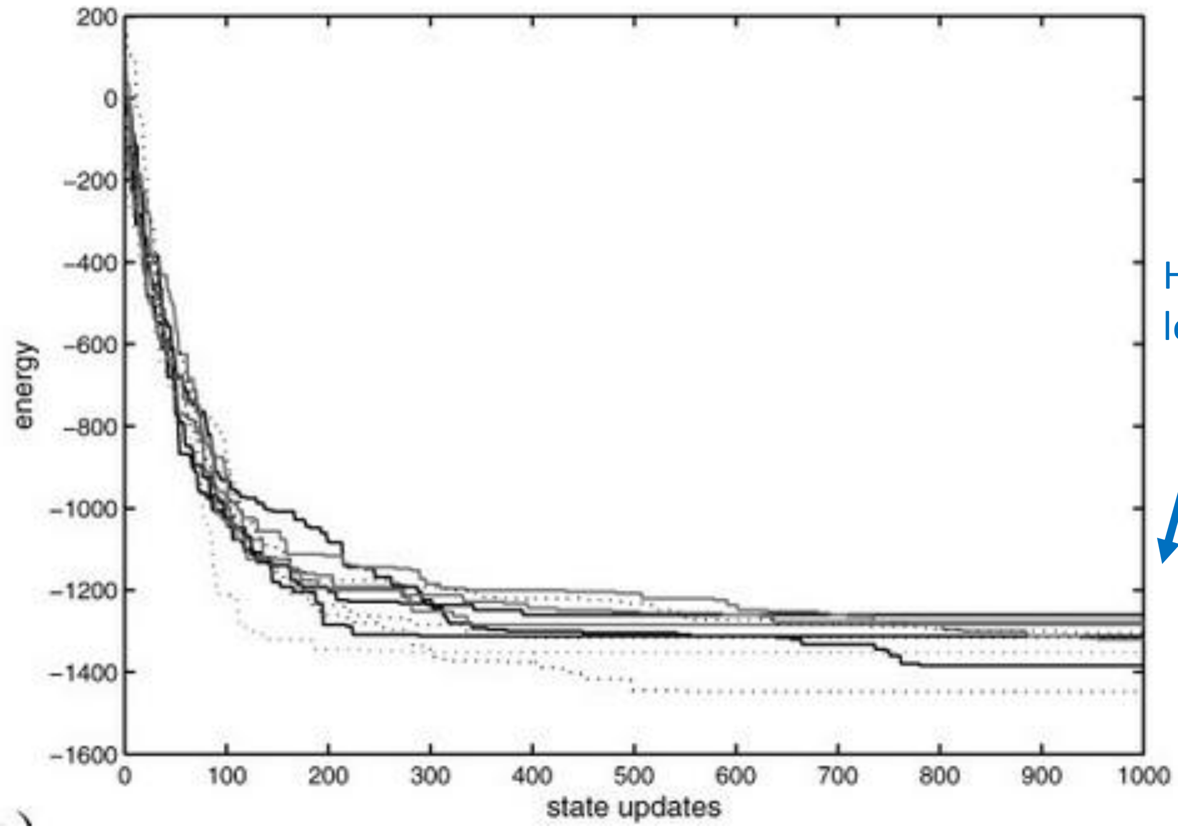
3. Application of Hebbian learning.



Hebbian learning

Self-optimization on Hopfield networks

1. Neuron states are randomized.
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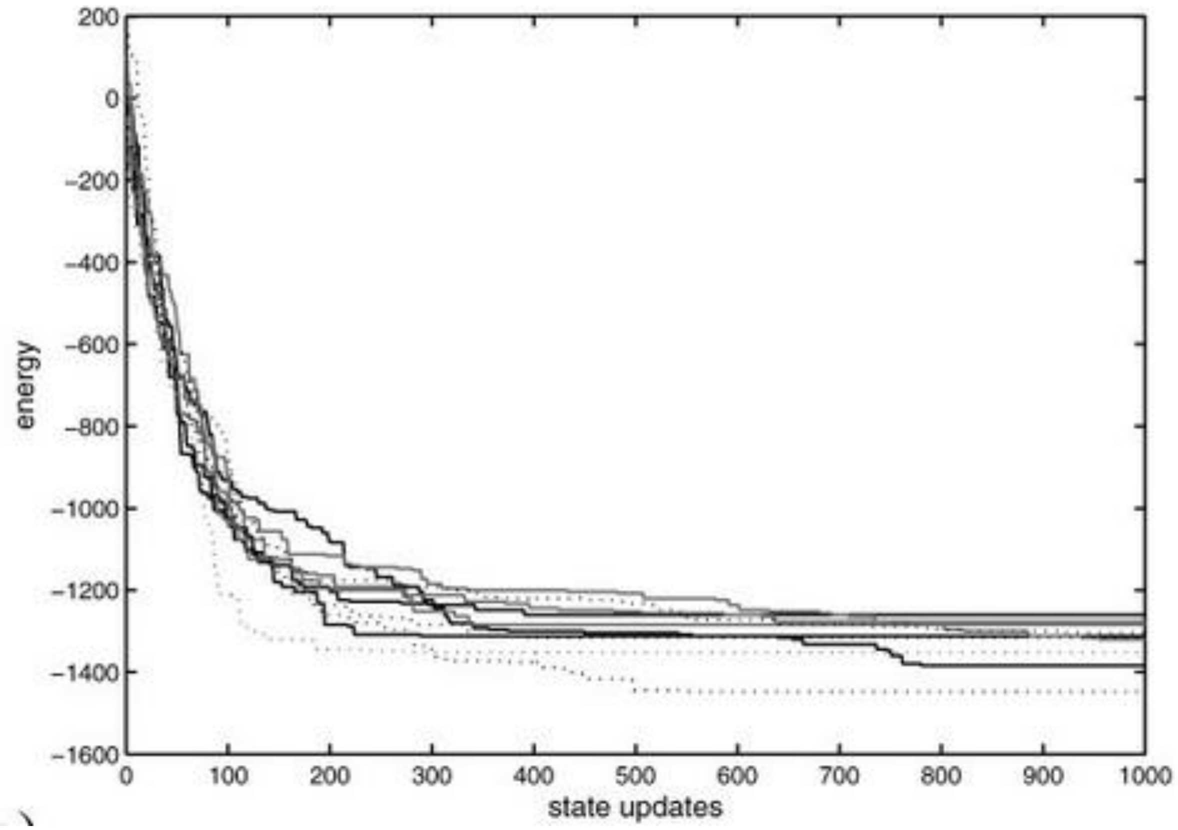
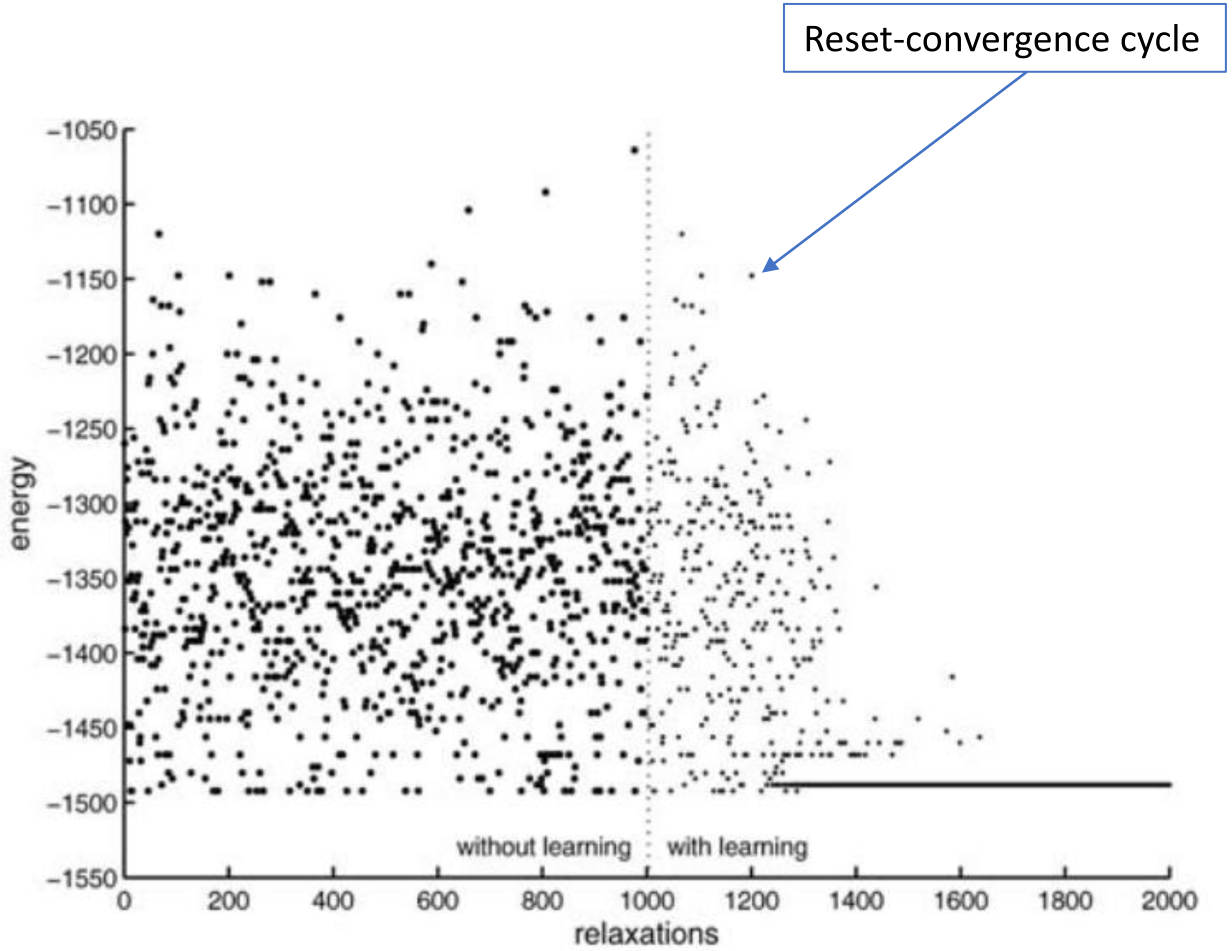
3. Application of Hebbian learning.

Reset-convergence cycle



Self-optimization on Hopfield networks

- Associative memory of its own state attractors
- Converge on optimal attractors
- Based on a simple form of unsupervised learning (Hebbian)

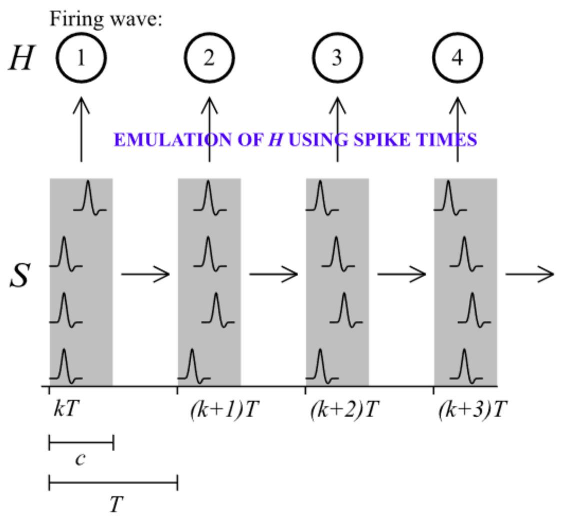


Watson, R. A., Buckley, C. L., and Mills, R. (2011).

Self-optimization on Hopfield networks

Different neural architectures

- Continuous activation functions (Zarco and Froese, 2018)
- Spiking neural networks (Woodward et al.,2015)

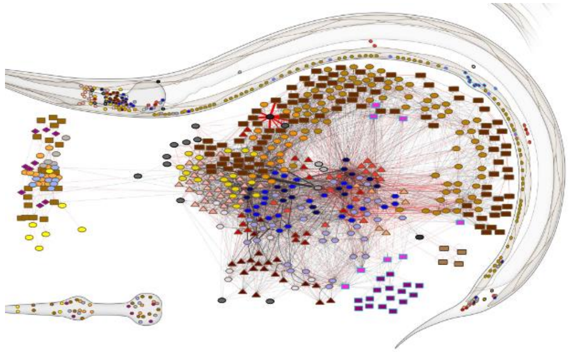


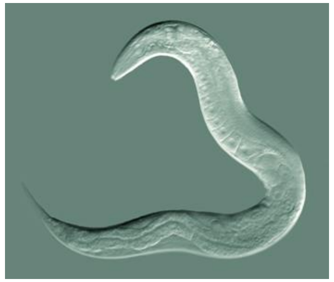
$$\tau_i \dot{s}_i = -s_i + \sum_{j=1}^{N} \omega_{ji} \sigma \left(g_j \left(s_j + \theta_j \right) \right)$$

Self-optimization on Hopfield networks

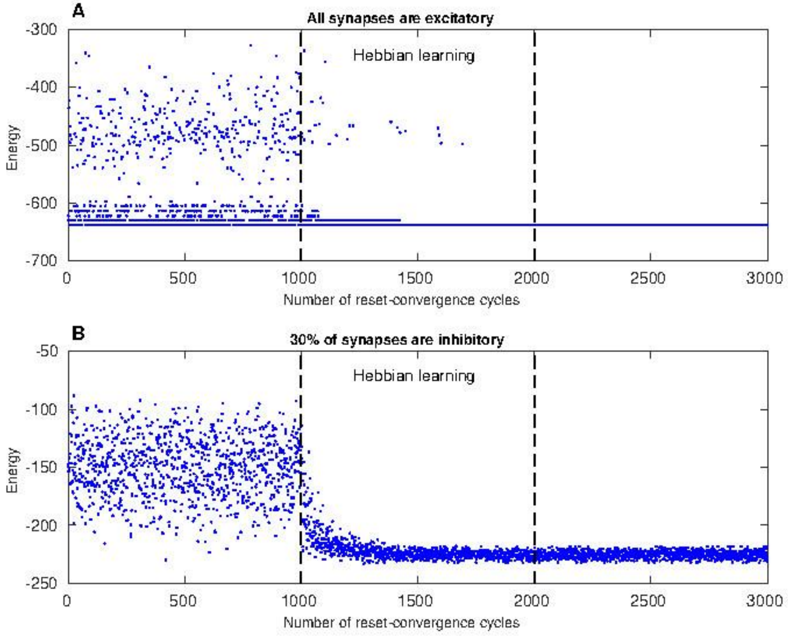
Different neural architectures

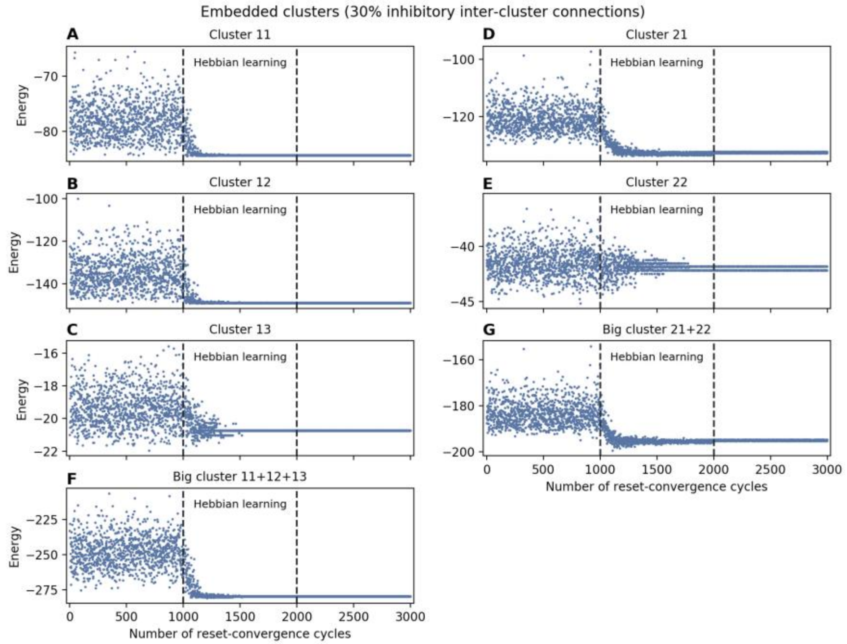
- Biological network architectures (Morales and Froese, 2019)



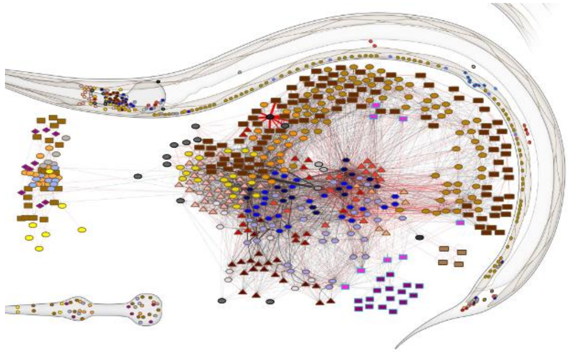


Caenorhabditis elegans





Self-optimization on Hopfield networks



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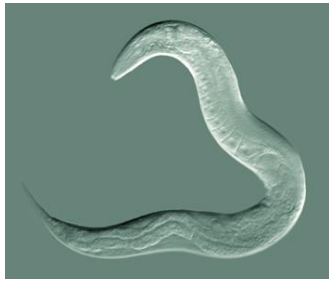
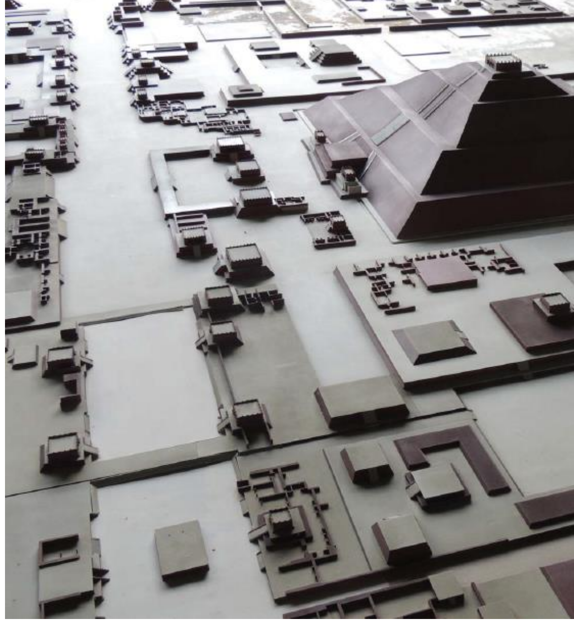


Caenorhabditis elegans

Remember....

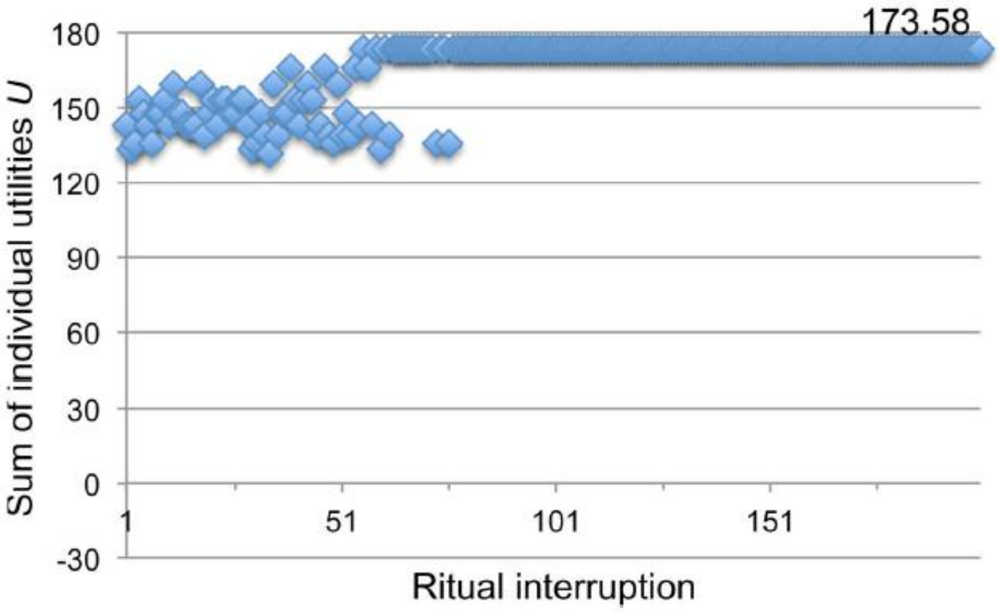
Randomization -> Sleep cycle

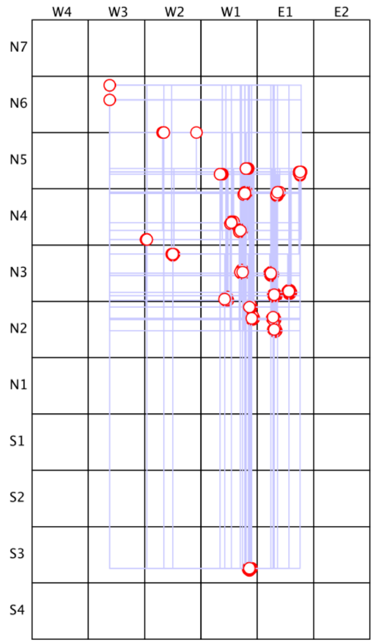
Self-optimization on Hopfield networks



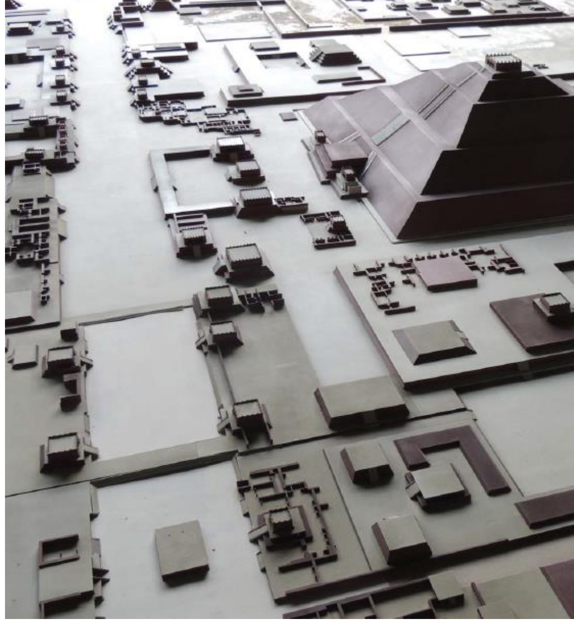
Social modeling

- Teotihuacan government (Froese, Gershenson, Manzanilla, 2018)





Self-optimization on Hopfield networks



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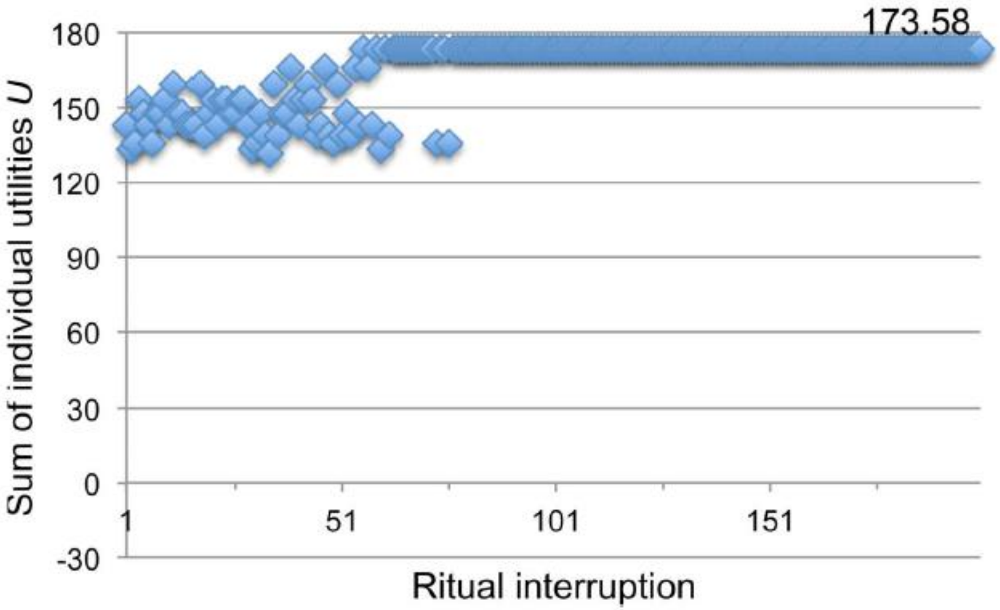
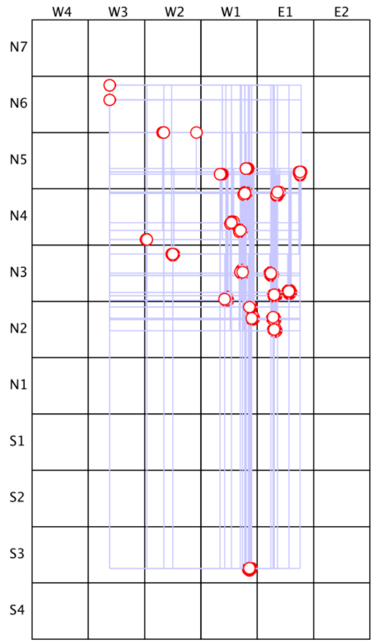
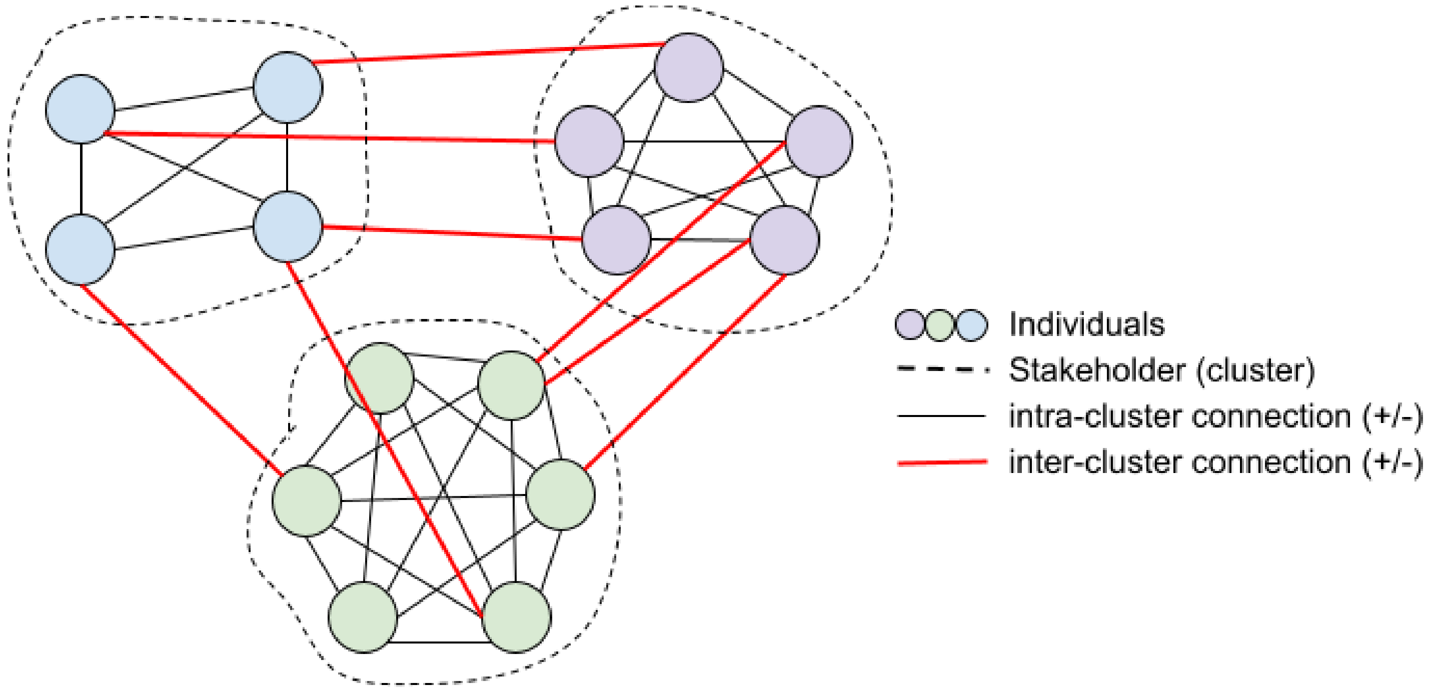
Randomization -> ritual interruption

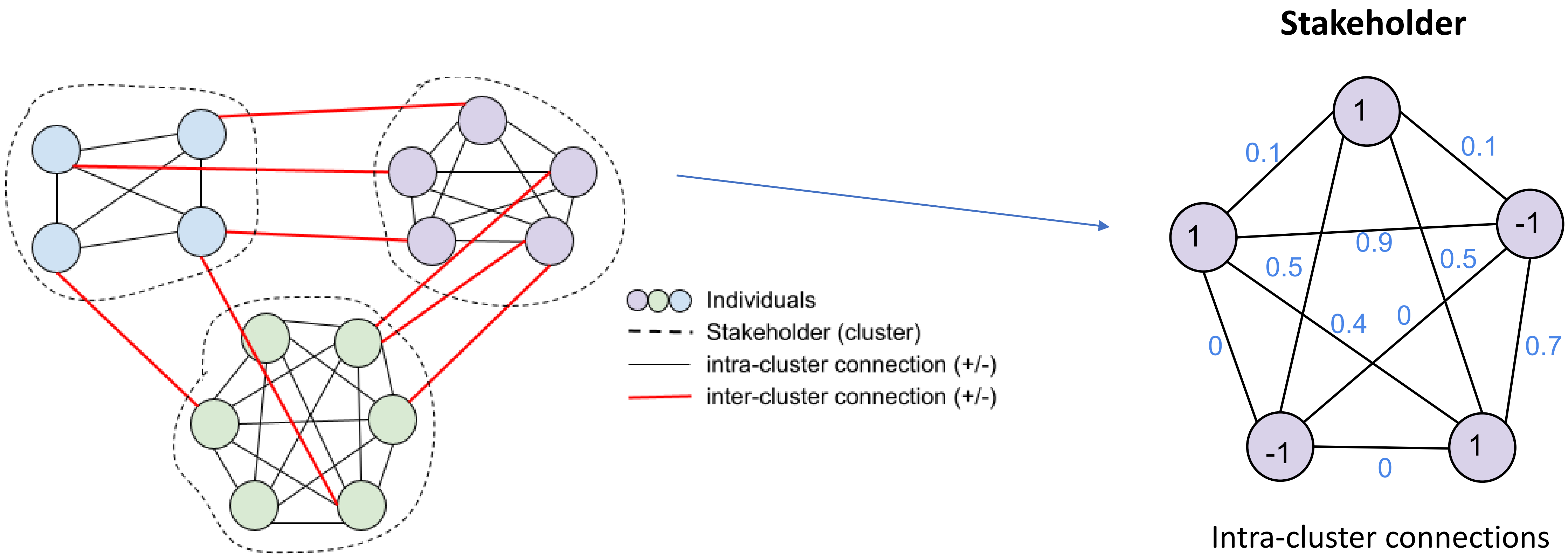




Self-optimization to policy making

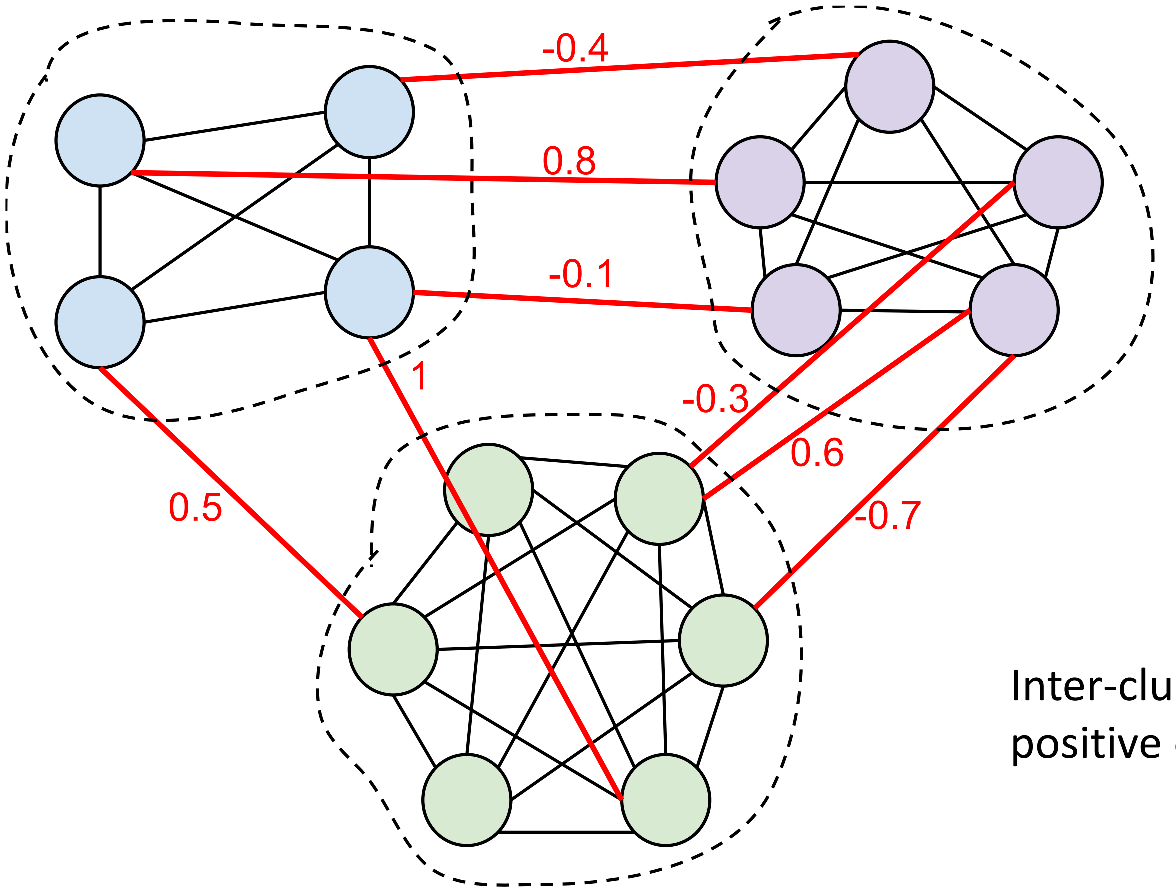


Self-optimization to policy making



Intra-cluster connections
(preferably positive)

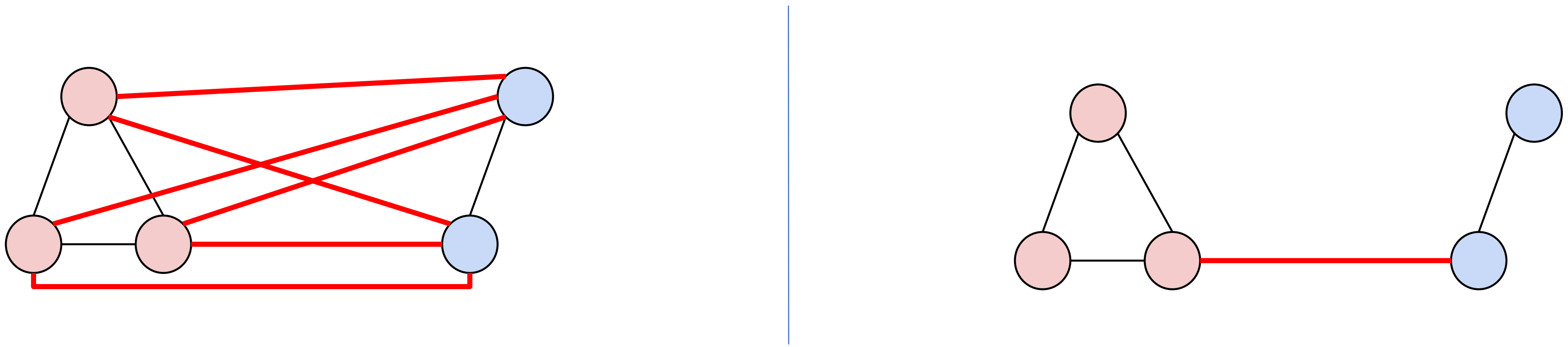
Self-optimization to policy making



Inter-cluster connections
positive or negative

Self-optimization to policy making

Affinity (between two stakeholders)



100%

16%

Affinity is a fixed parameter defined at the start

Self-optimization to policy making

- This model aims to simulate possible outcomes of a meeting (taking into account the affinity between individuals).
- In this case, randomizations represent "transdisciplinary interventions."
- The idea is that by applying the self-optimization algorithm, the network finds an optimal configuration of states that minimizes tensions and conflicts between stakeholders and thus be able to make a joint decision. However, this is not always possible.

Self-optimization to policy making

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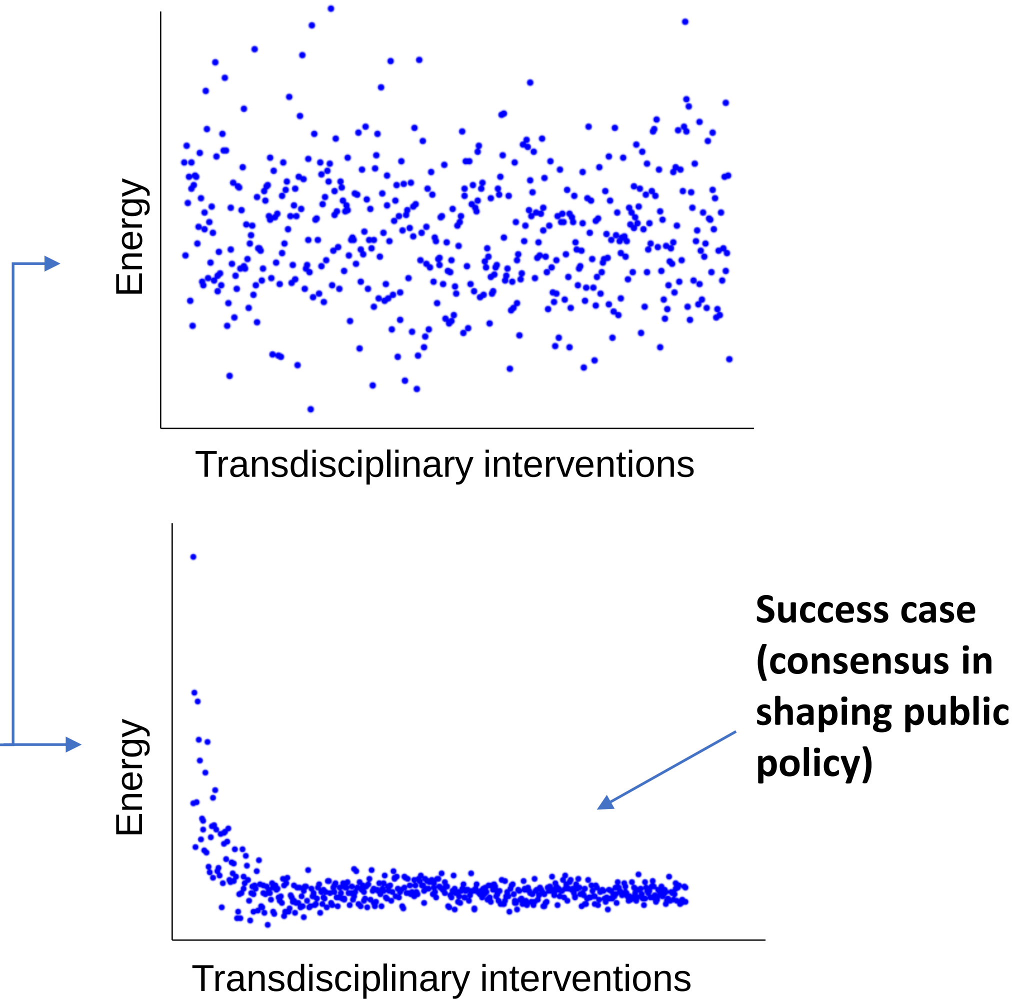

Conclusions

- **The model is limited, represents reality with a high level of abstraction.**
- **The use of Hopfield networks may have disadvantages compared to agent-based models with more parameters.**
- **Politics is present in these meetings, and it is pending how to represent it.**
- **It is still pending how to model multidimensional/hierarchical policies. The model only considers two behavioral states of agents.**

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References

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