Thermodynamic Computing – Model Systems

Todd Hylton

UC San Diego

CCC Thermodynamic Computing Workshop

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Motivation

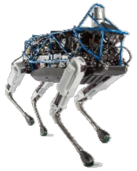
Technology Landscape

- Sensing
- Display
- Wireless communication & internet
- Computing at the edge

Mobile Phones

Dynamic, Online, Real World

- IoT
- Robotics
- Industrial Internet
- Self-driving Cars
- Smart Grid
- Secure Autonomous Networks
- Real-time Data-to-Decision



Intelligent Adaptive Systems "ROBOTS"

Program **Learn**

- Personal Computing
- Wired Internet

Desktop / Workstation

- Data Integration
- Large scale storage
- Large scale computing

Data Center / Cloud

Static, Offline, Virtual World

Conceptual Landscape

Dynamic, Online, Real World

Dynamic Modeling
- Calculus
- Systems of Differential Equations
- Lagrangian, Hamiltonian physics

Experiential Learning & Inference
- Non-equilibrium thermodynamics
- Predictive learning
- Evolution

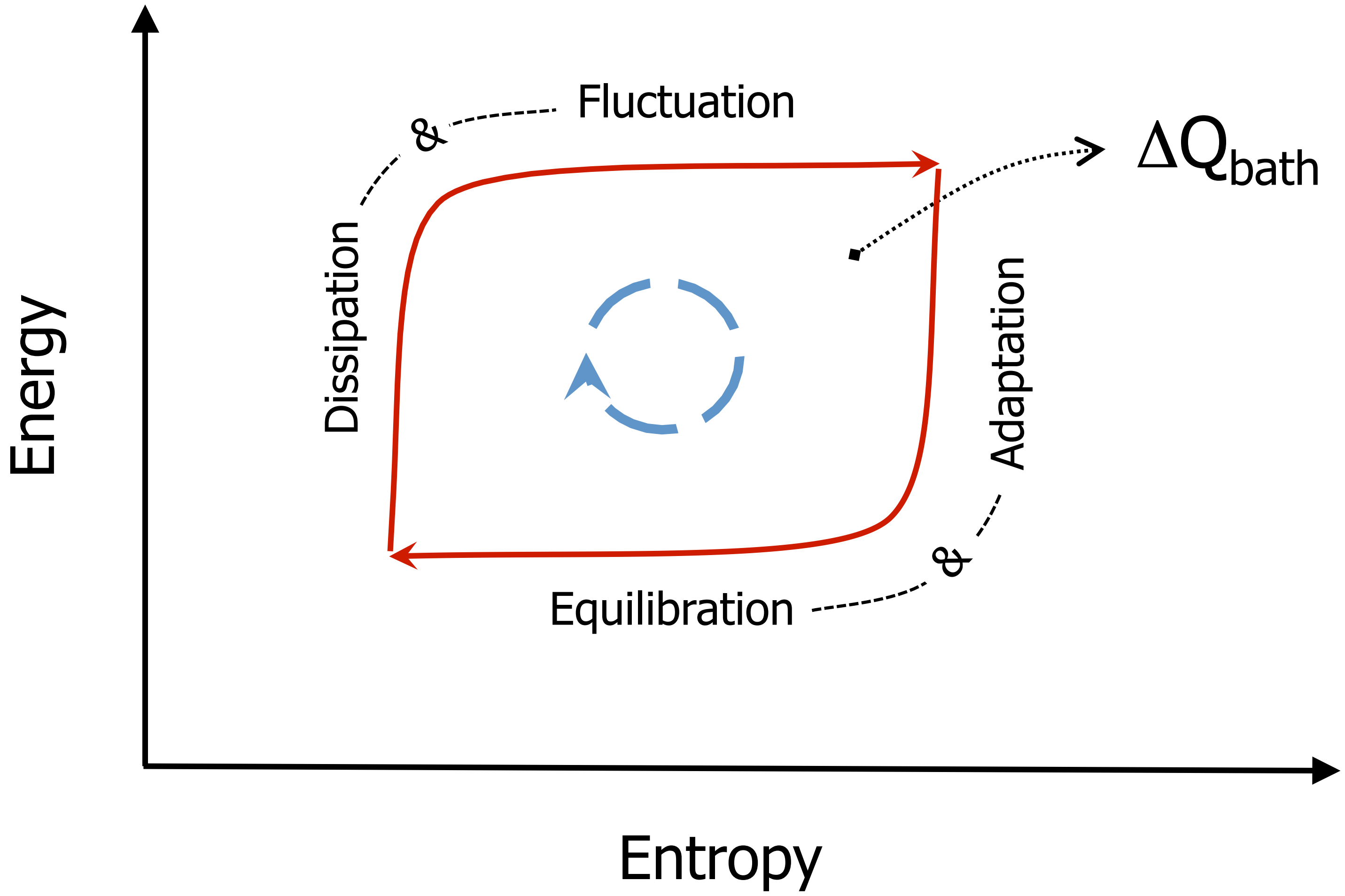
Program ⟷ **Learn**

Static Modeling
- Arithmetic
- Algebra
- Searching
- Sorting

Statistical Learning & Inference
- Probability and Statistics
- Equilibrium thermodynamics
- Deep learning

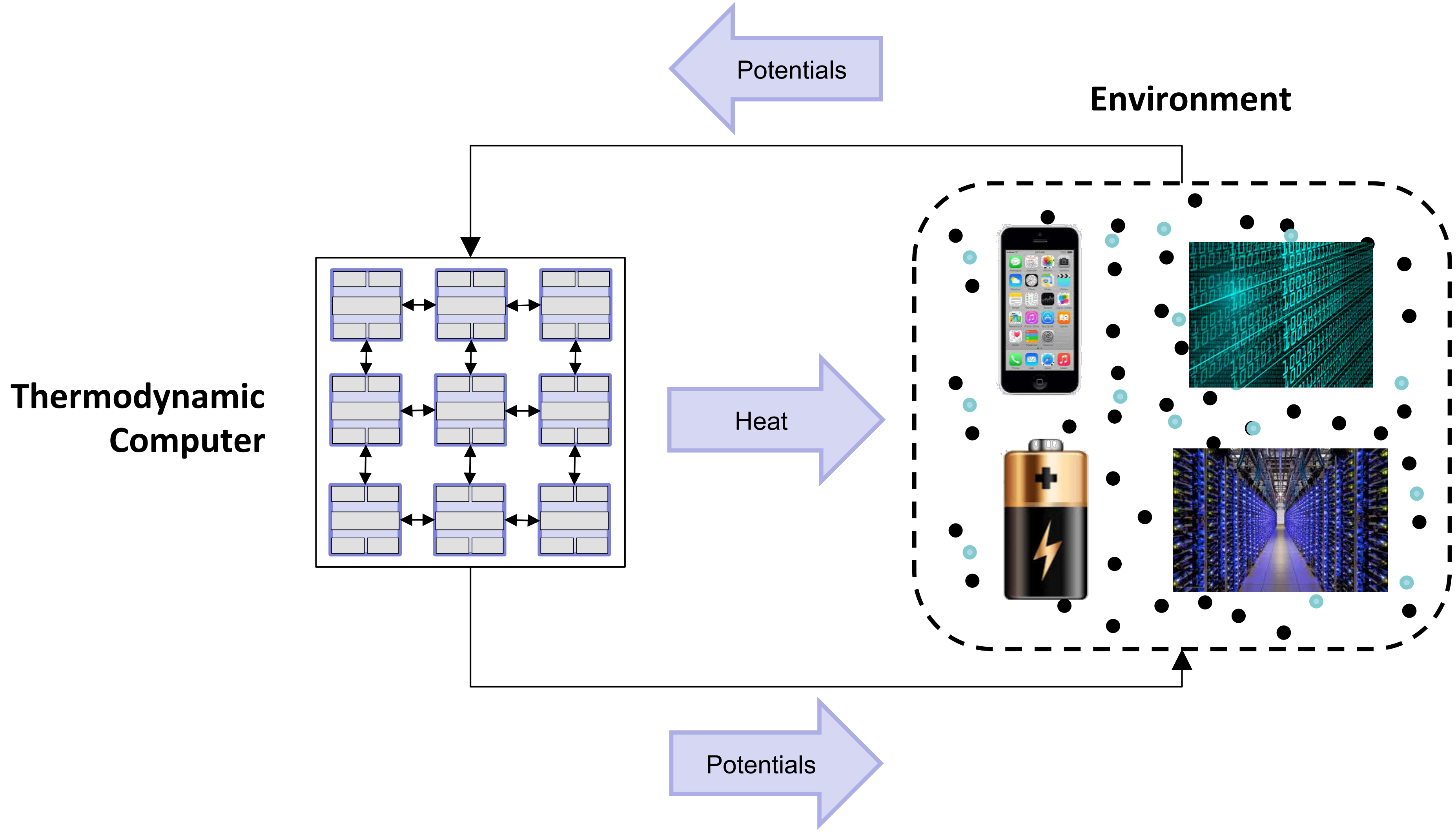
Static, Offline, Virtual World

Thermodynamic Evolution



Thermodynamic Computing Vision

Thermodynamic Computing – System Concept



Thermodynamic Computers are open thermodynamic systems embedded in an environment of electrical and information potential.

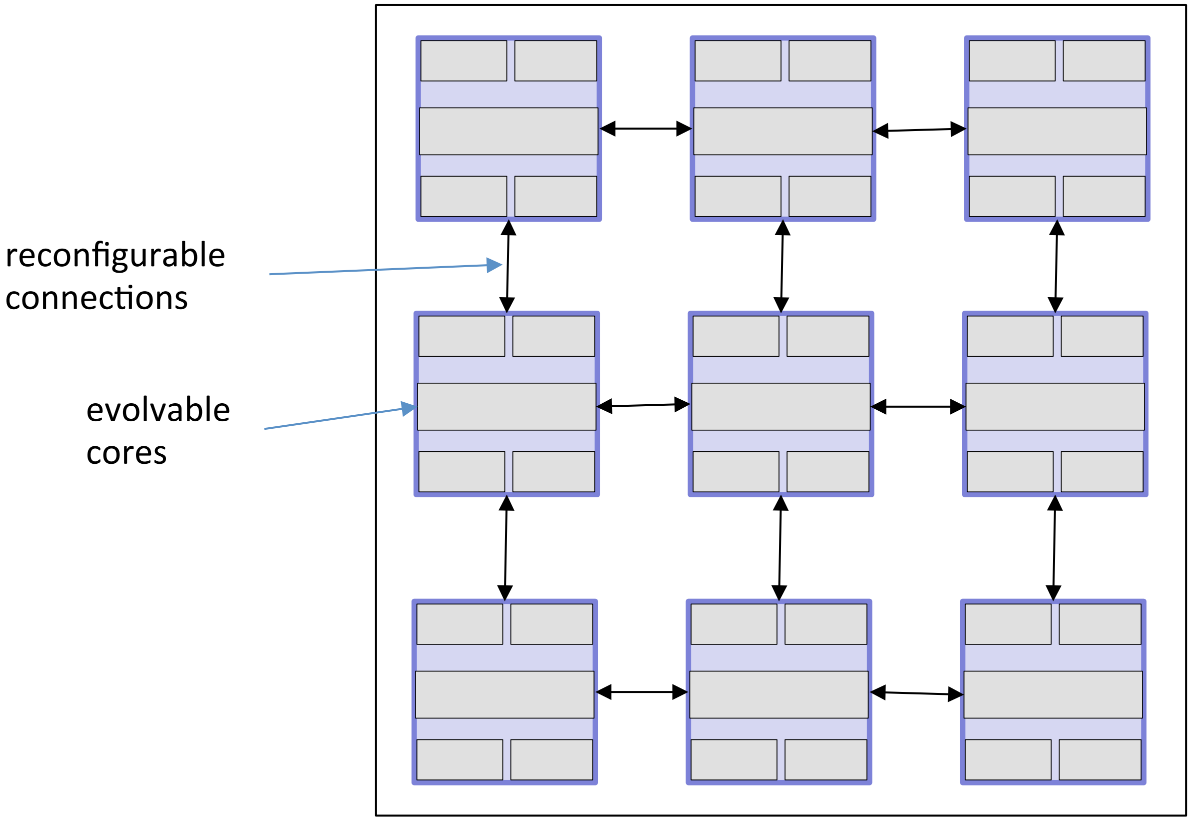
Thermodynamic Computing - Basic Concept

- A generic fabric of thermodynamically *evolvable elements or cores* embedded in a network of *reconfigurable* connections.

- External *potentials* drive the flow of *currents* through the network.

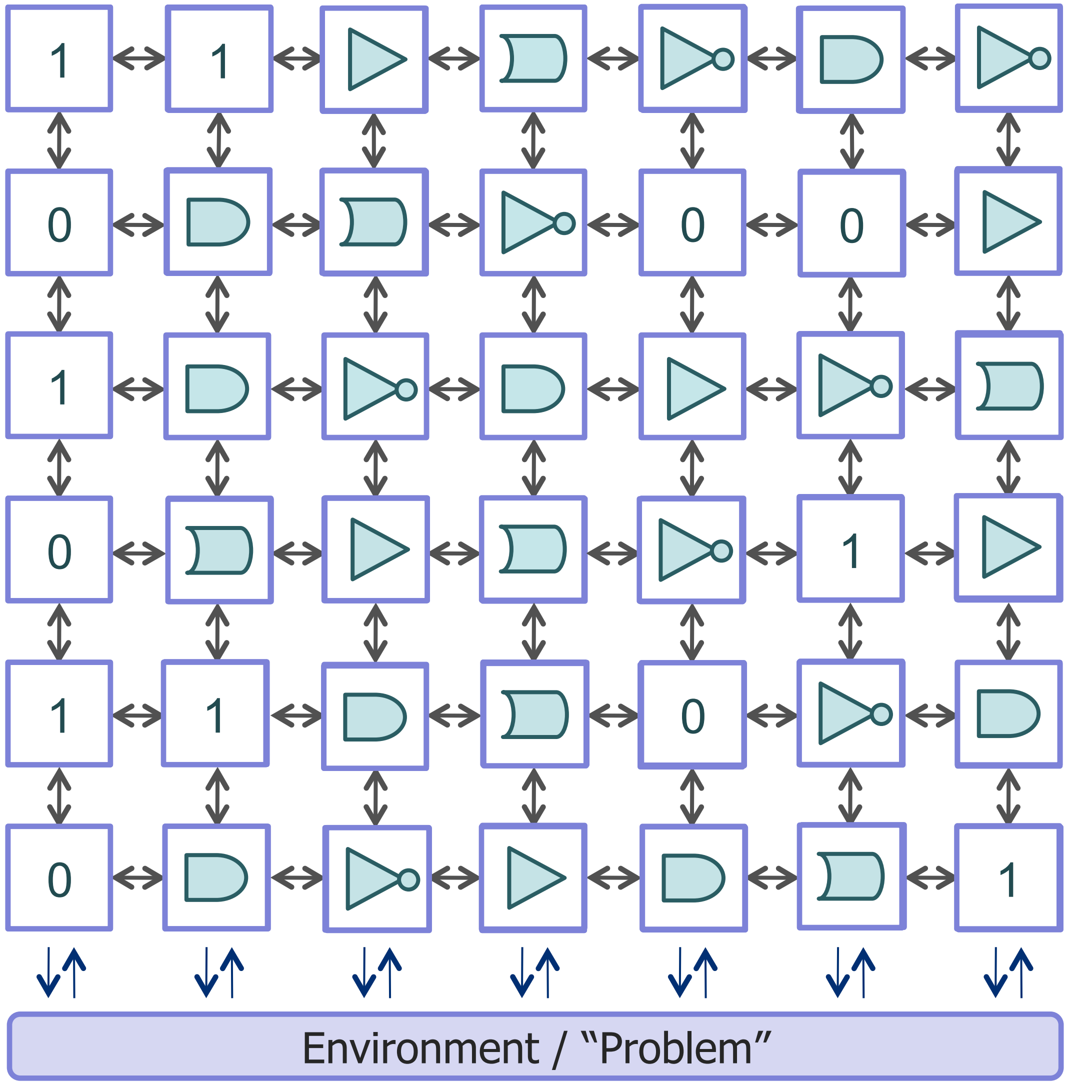
- Energy dissipation creates fluctuations that stabilize adaptations that decrease dissipation as it equilibrates with a thermal bath.

- The system thermodynamically evolves to move current through the network with *minimal loss*.



Thermodynamic Computing - Conceptual Illustration

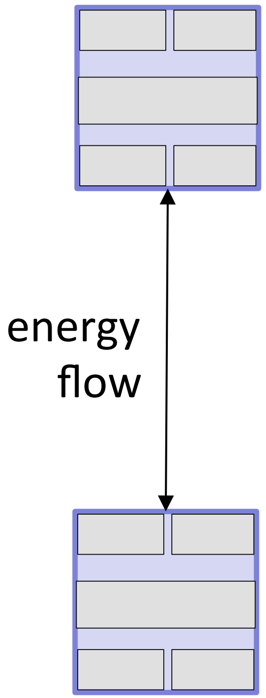
- Networks of simple ECs form a larger Thermo-Dynamic Computer (TDC)
- The "problem" is defined by the energy / information potential in the environment.
- Programmers can fix some of the ECs to define constraints / algorithms that are known to be of value.
- Dissipation within the network creates fluctuations over many length and time scales and thereby "search" for solutions over a very large state space.
- Structure precipitates out of the fluctuating state and entropy production increases in the environment as energy flows through the network and dissipation decreases



Role of Representations

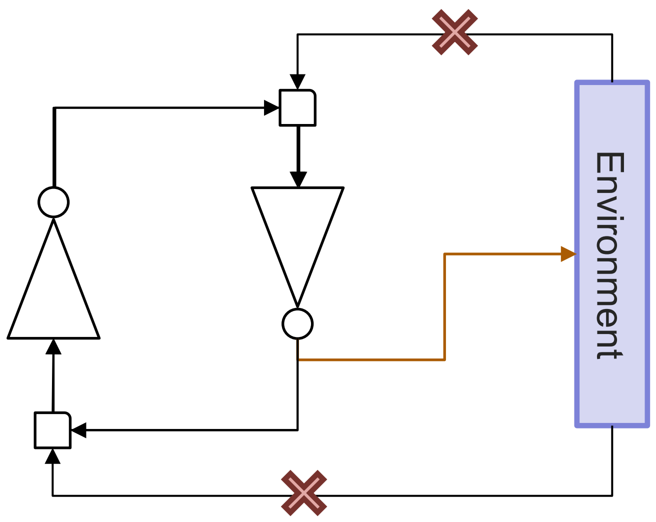
- Explicit representations – e.g. analog signals / pulses
  - naturally distribute energy and satisfy conservation laws (for energy, charge, etc.)
  - suffer from resistive losses in the network
  - probably impractical for the large networks

- Implicit representations – e.g. “spikes” or “messages” or “numbers”
  - require coding (energy → message) and decoding (message → energy) at the cores
  - do not suffer resistive losses
  - require an accounting system to satisfy conservation laws
    - analogous to money in economic systems

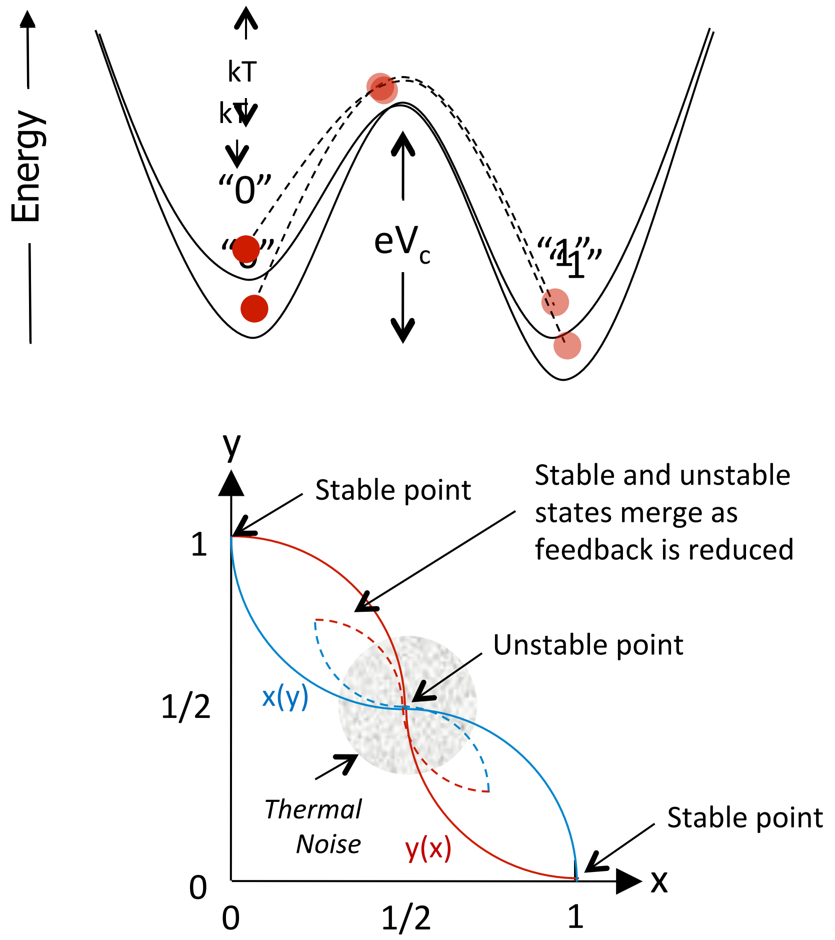


Thermodynamic "Bit"

Circuit Concept



Thermodynamics

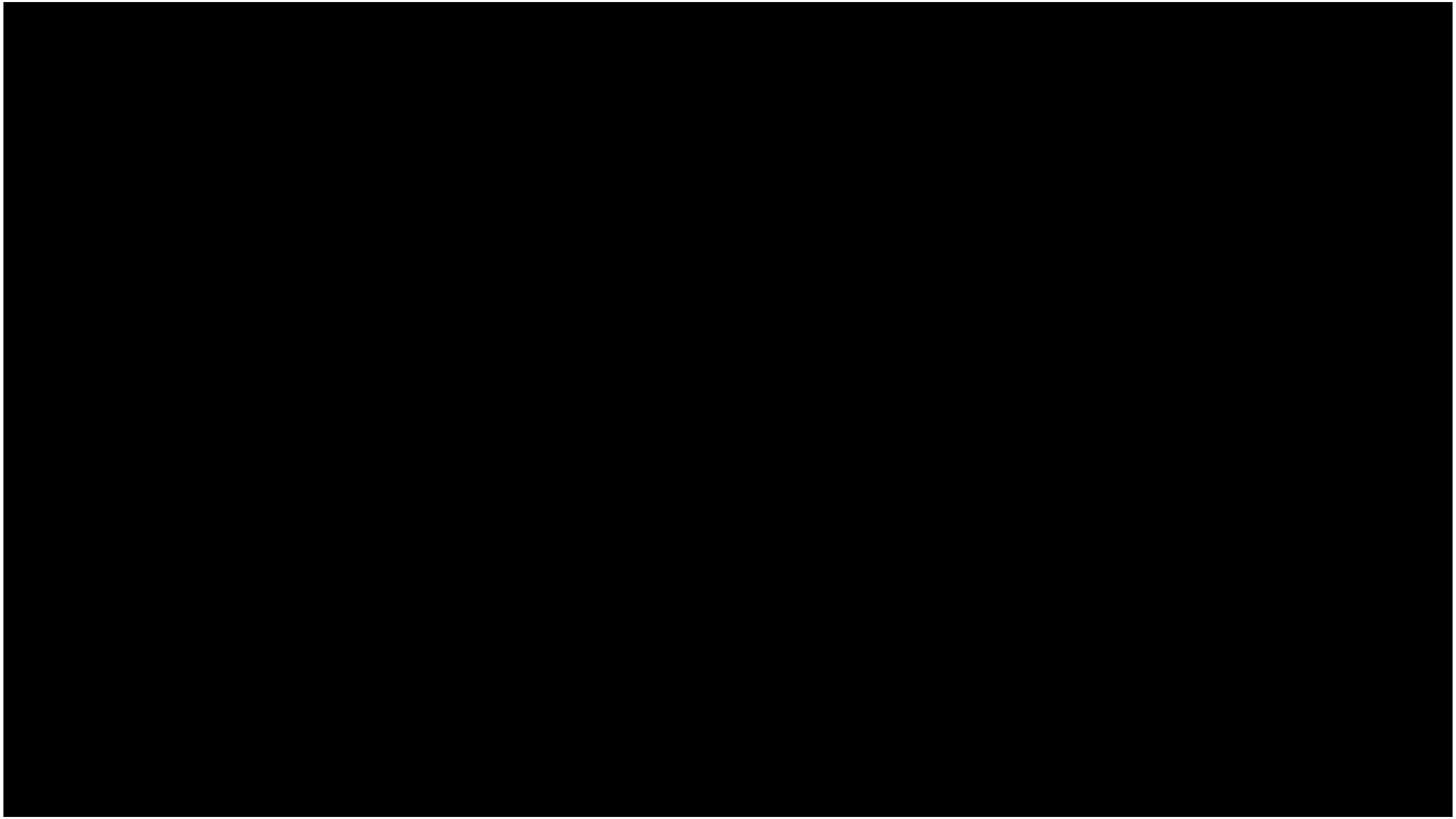


- Unstable state / inherent variations
- Environment influences variation / selection
- Selected state feeds back to the environment
- Weighting changes relative influence

The Thermodynamic Bit is a simple evolvable element.

Thermodynamic Neural Network Model

Arbortron Demos – Stanford Complexity Group



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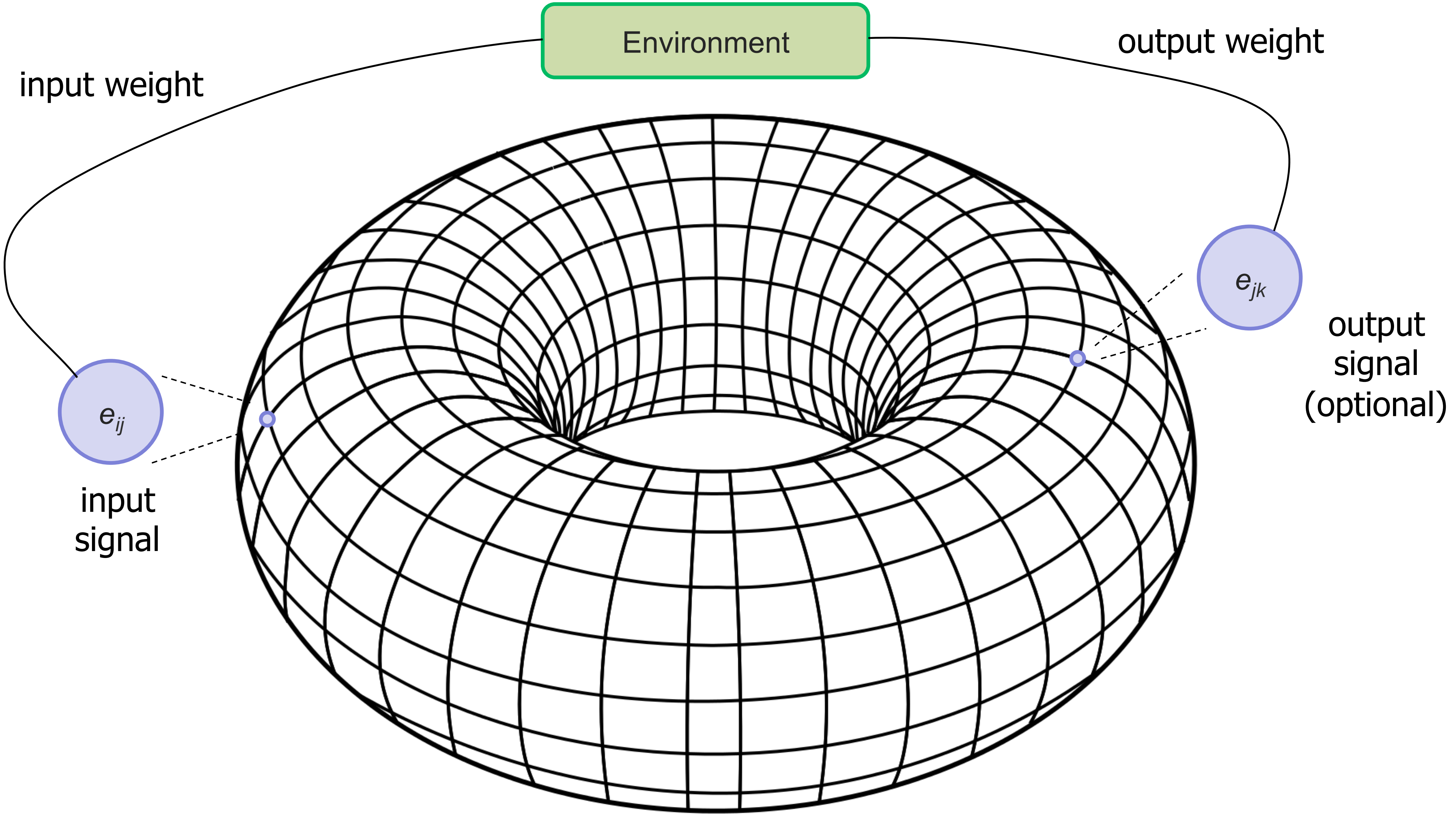
Thermodynamic Neural Network Model

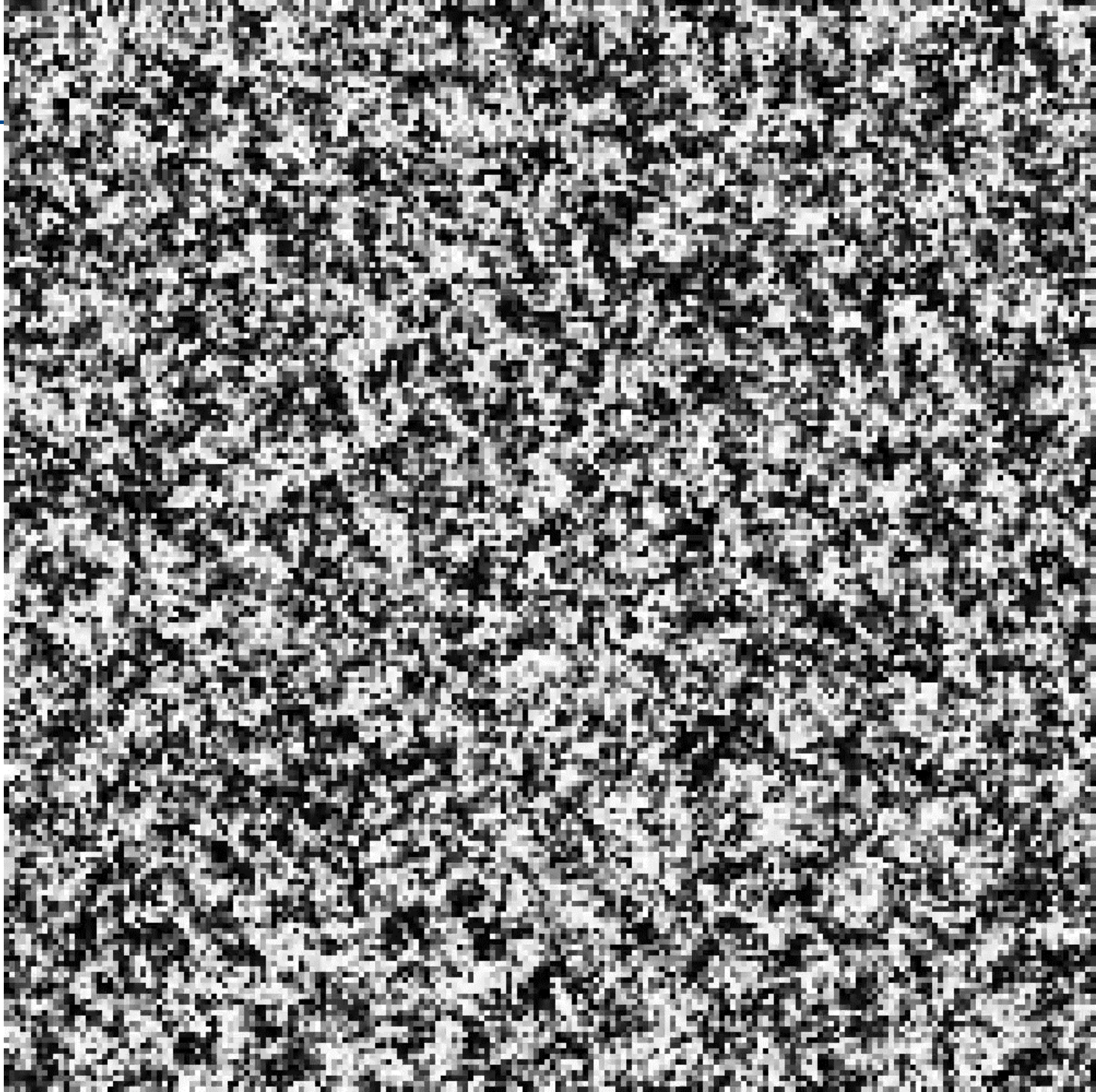


Core Ideas

- A network of internal nodes (“neurons”) is connected by bi-directional, weighted edges (“synapses”) and driven by a collection of “external” nodes that bias the network with potential and charge.
- Internal nodes assume states (“potential”) on the interval [-1, 1].
- Weights are real numbers describing the capacity to transport “charge” between the nodes. Charge is the product of the node state and edge weight.
- Network nodes optimize the transfer of charge from / to edges through selection of state.
- Charge is conserved via a detailed accounting system.
- Externally imposed potentials diffuse through the network to connect their corresponding external sources and sinks of charge. Network weights increase to facilitate this charge transport.
- Node state selection is determined by network-scale relaxation to a thermal bath using Boltzmann statistics.
- Residual charge remaining on the nodes after state selection, which is the source of “loss” in the system, adapts edge weights by relaxation to a thermal bath according to Boltzmann statistics.
- Many network topologies are possible – naturally recurrent. There is no need to impose a hierarchy or “layers” upon the network.
- No back-propagation, no learning / decay rates, no drop-out…

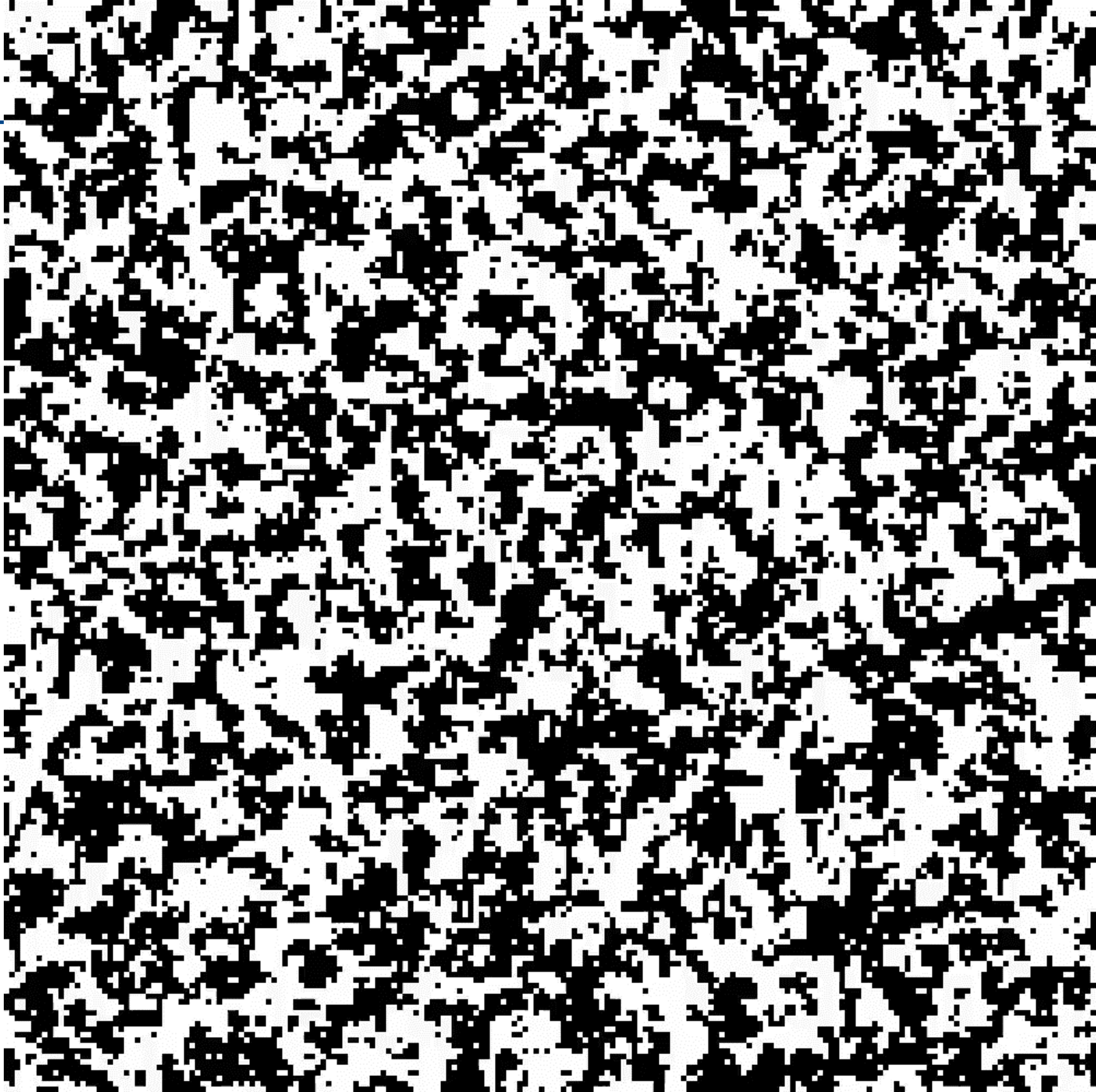
Thermodynamic Neural Network

- Nearest neighbor 2D grid with periodic boundary conditions
- 40,000 nodes
- 4 connections / node
- 101 Node states on [-1,1]
- 10 MCMC cycles to adapt nodes states before weight updates
- Energy scales selected to create “fluid” state



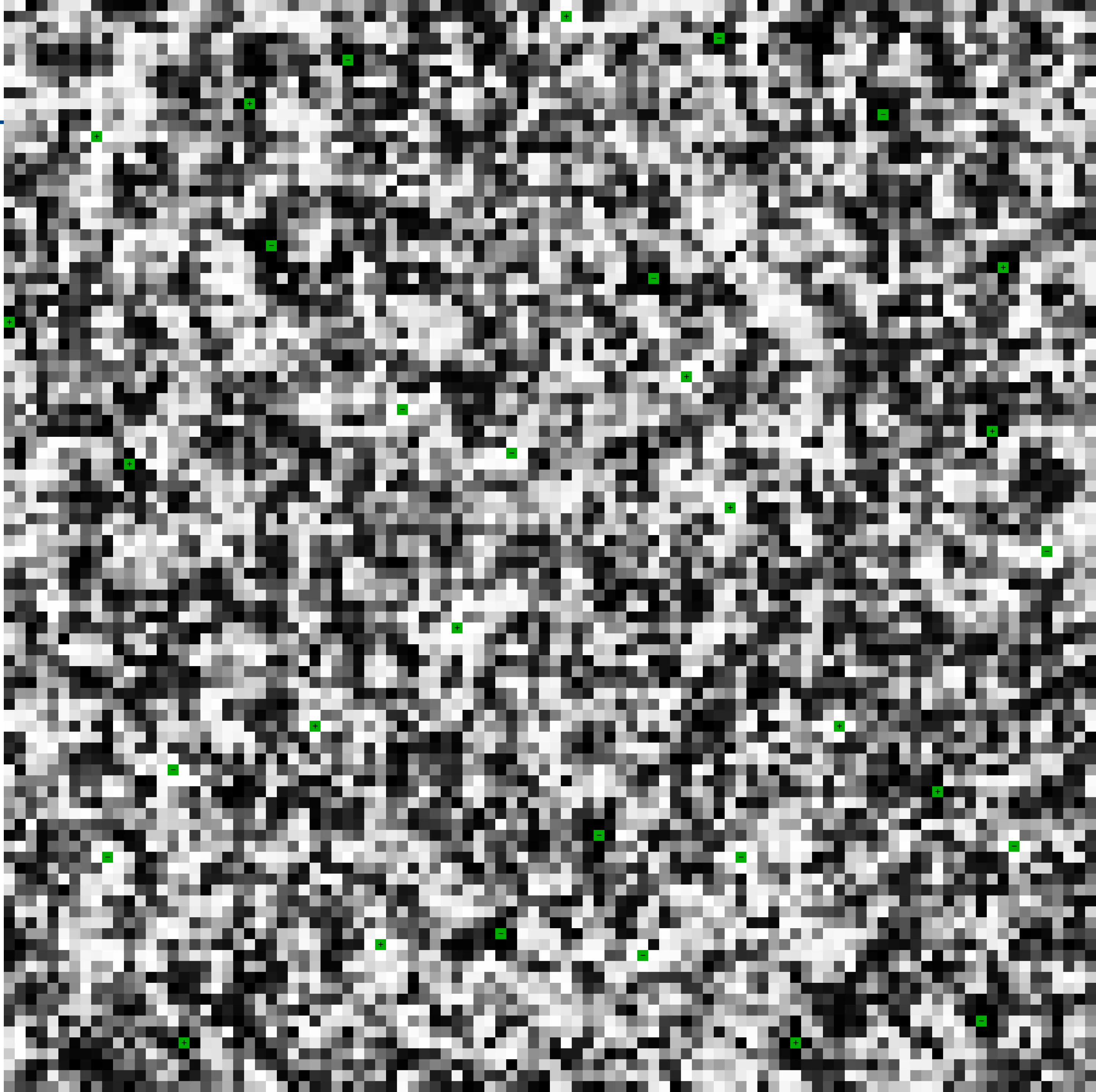
Thermodynamic Neural Network

- Nearest neighbor 2D grid with periodic boundary conditions
- 40,000 nodes
- 4 connections / node
- 2 Node states on [-1,1]
- 10 MCMC cycles to adapt nodes states before weight updates
- Energy scales selected to create "fluid" state



Thermodynamic Neural Network

- Nearest neighbor 2D grid with periodic boundary conditions
- 10,000 total nodes
- 16 pairs of periodically changing potentials at different frequencies (in green)
- 4 connections / node
- 101 Node states on [-1,1]
- 10 MCMC cycles to adapt nodes states before weight updates, which are visualized in the videos
- Energy scales selected to create “fluid” state for unbiased network.

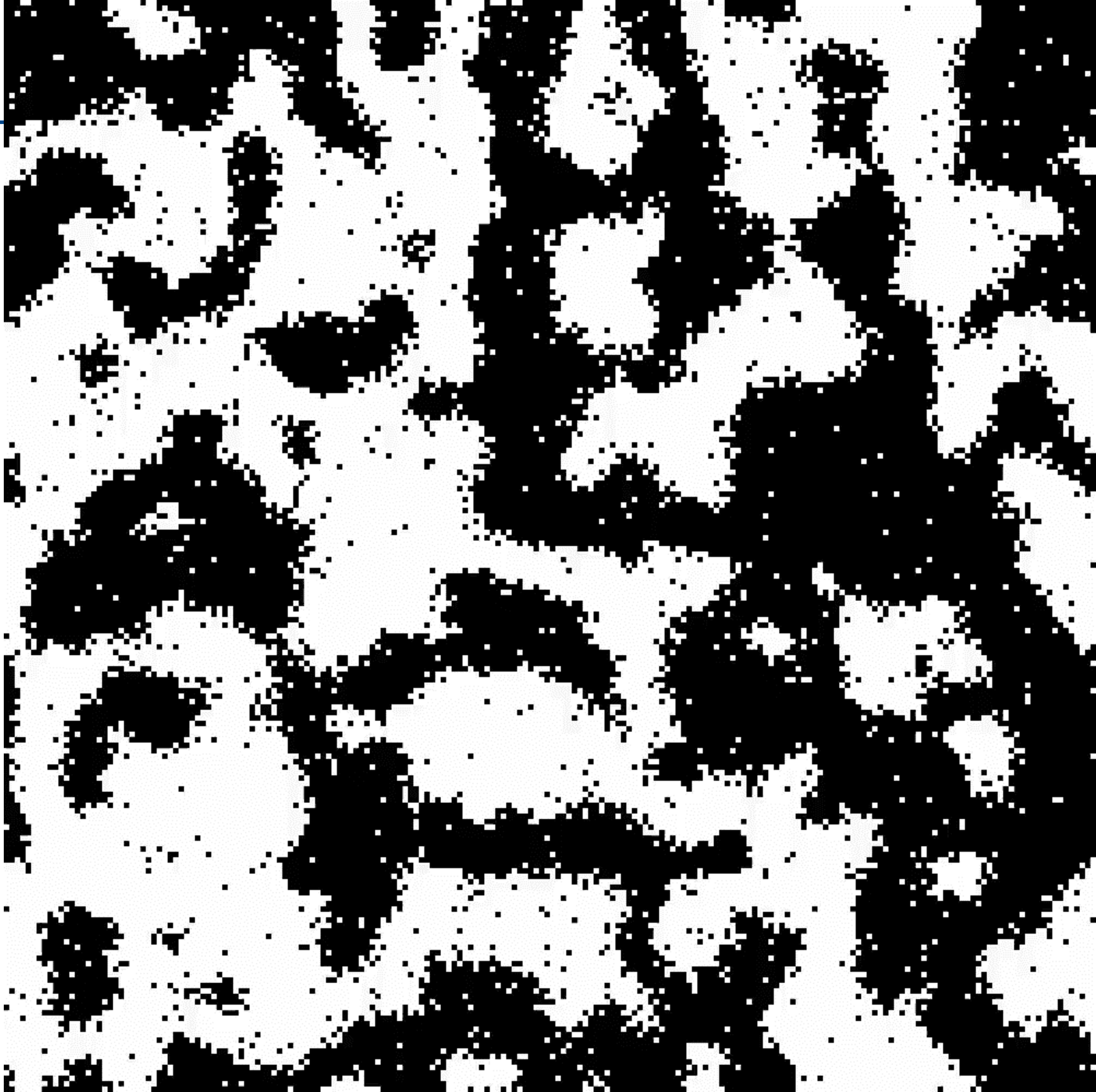


Thermodynamic Neural Network

- Random network
- 10,000 total nodes
- 16 pairs of periodically changing potentials at different frequencies (in green)
- 4 connections / node
- 101 Node states on [-1,1]
- 20 MCMC cycles to adapt nodes states before weight updates
- Energy scales selected to create "fluid" state for unbiased network.

Thermodynamic Neural Network

- Next nearest neighbor network on 2D grid with periodic boundary conditions
- 40,000 total nodes
- 16 connections / node
- 2 Node states on [-1,1]
- 10 MCMC cycles to adapt nodes states before weight updates
- Energy scales selected to create “fluid” state.



Observations

- Code analysis (Python)
  - 40% (~620 lines) - I/O, setup and overhead
  - 56% (~860 lines) – Model infrastructure and accounting
  - 4% (~60 lines) – Thermodynamics

- In natural systems we are similarly overwhelmed with the details of previously evolved organization

- In Thermodynamic Computing systems we should expect something similar
  - Large amount of engineered hardware and software infrastructure
  - An almost “invisible” thermodynamically evolving capacity

A Thermodynamic Computer Is...

- a network of nodes
- that globally selects node states to efficiently transport charge
- that locally adapts connectivity to improve transport efficiency
- as driven by external potentials
- as constrained by a designer
- as it equilibrates with a thermal bath