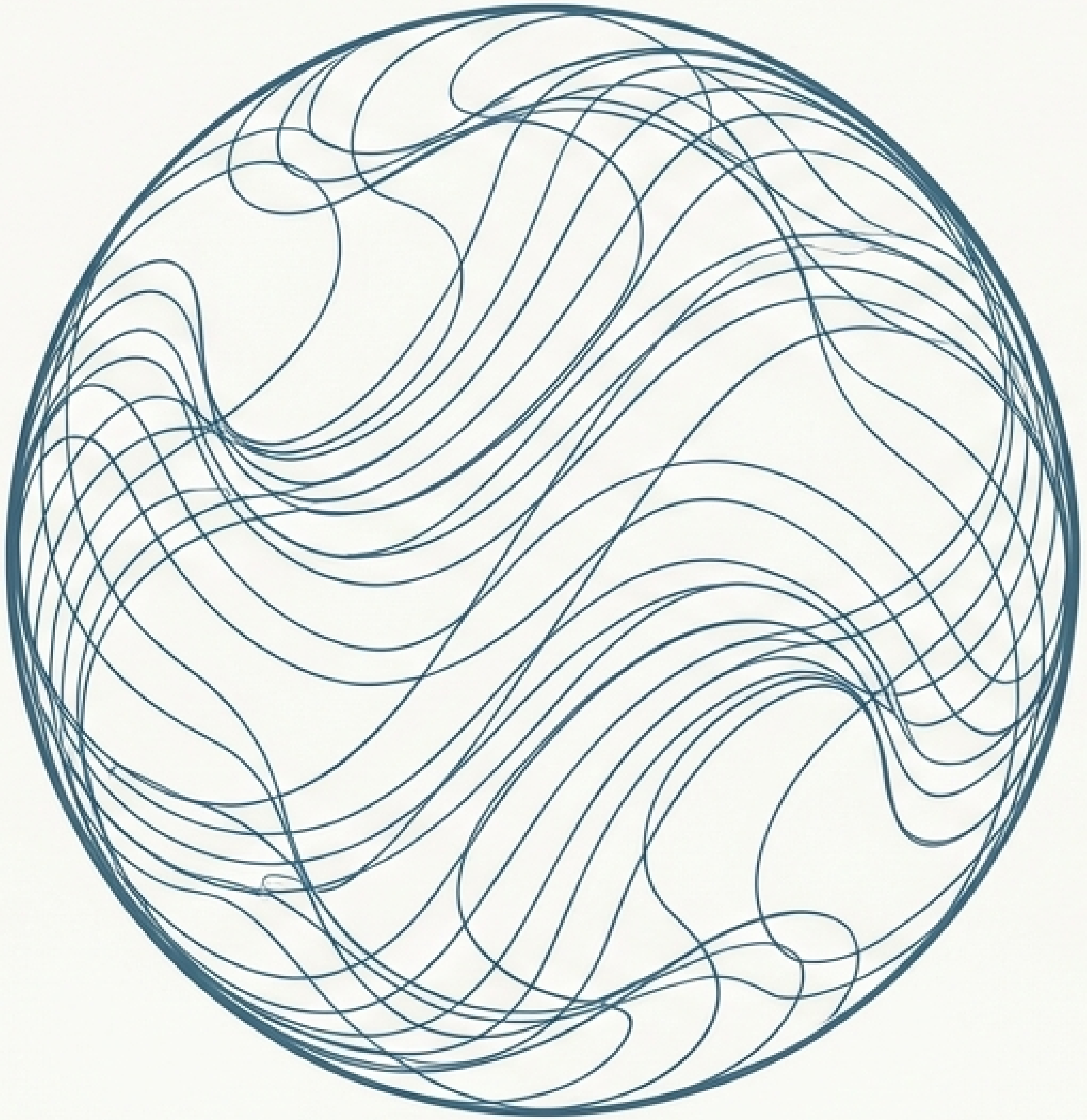
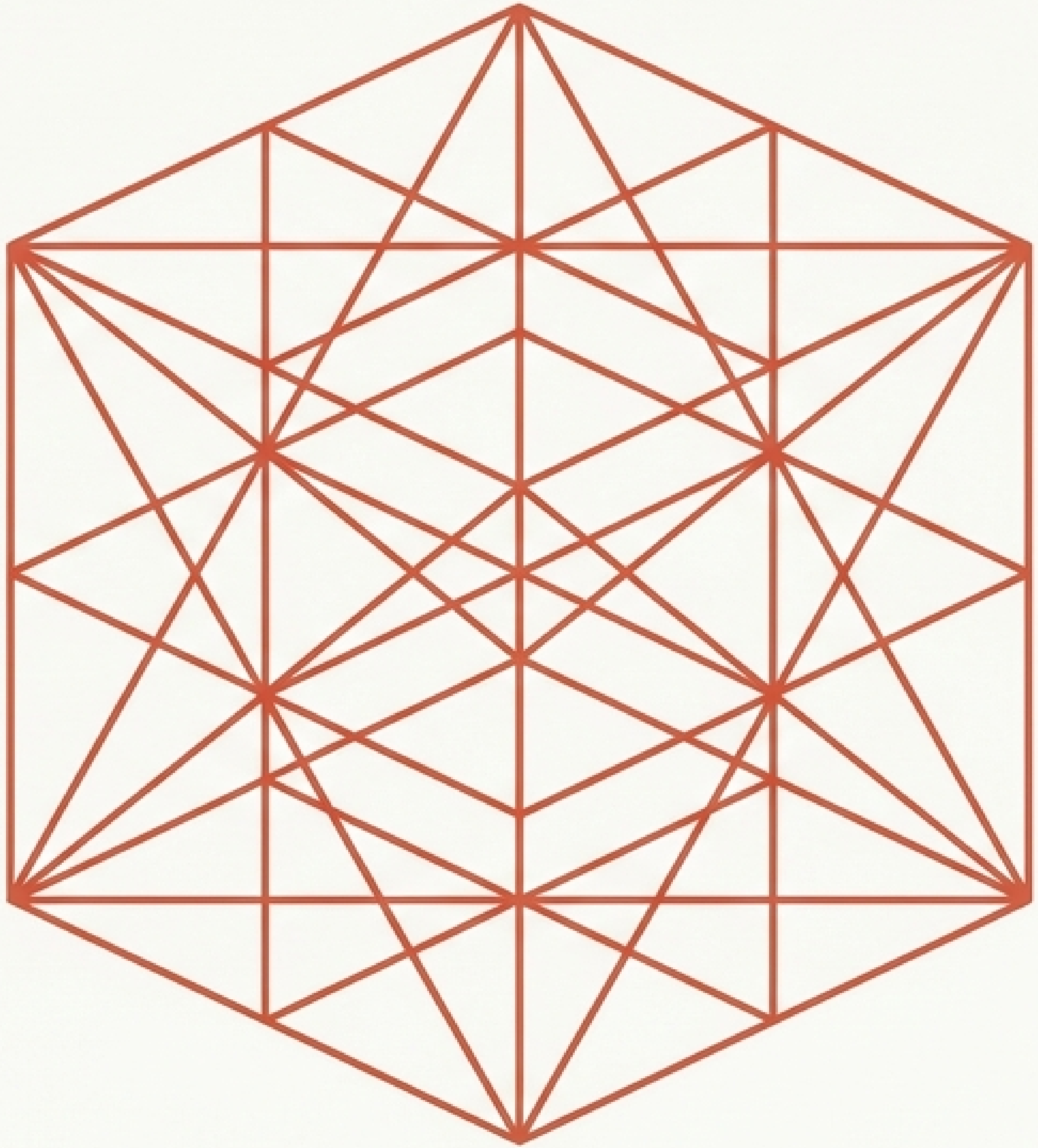
Can a Single Computational Model Truly Dream *and* Count?

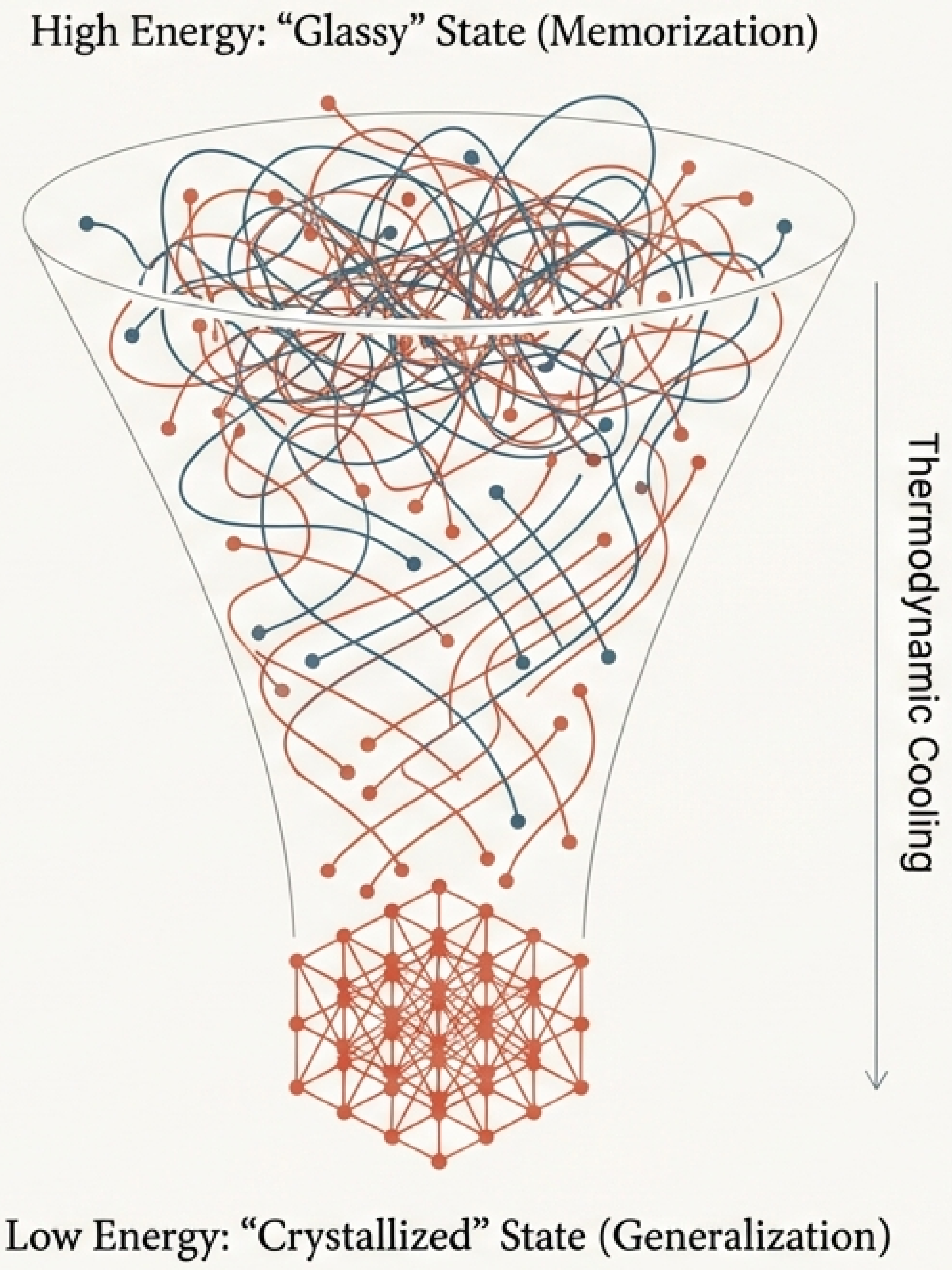
The landscape of computation is fractured. In physics, we see the schism between General Relativity’s smooth spacetime and Quantum Mechanics’ discrete states. In AI, this divide separates the intuitive, continuous “dreaming’ of neural networks from the rigorous, symbolic ‘counting’ of logic engines. This presentation introduces a model born from a theory that unifies them.





A Proposed Resolution: Unified Informatic Topology (UIT)

The UIT framework posits that information is a physical substrate with thermodynamic weight. From this perspective, the learning process in a neural network is isomorphic to thermodynamic cooling. The system transitions from a disordered, high-energy "glassy" state of memorization to an ordered, low-energy "crystallized" structure of understanding and generalization.

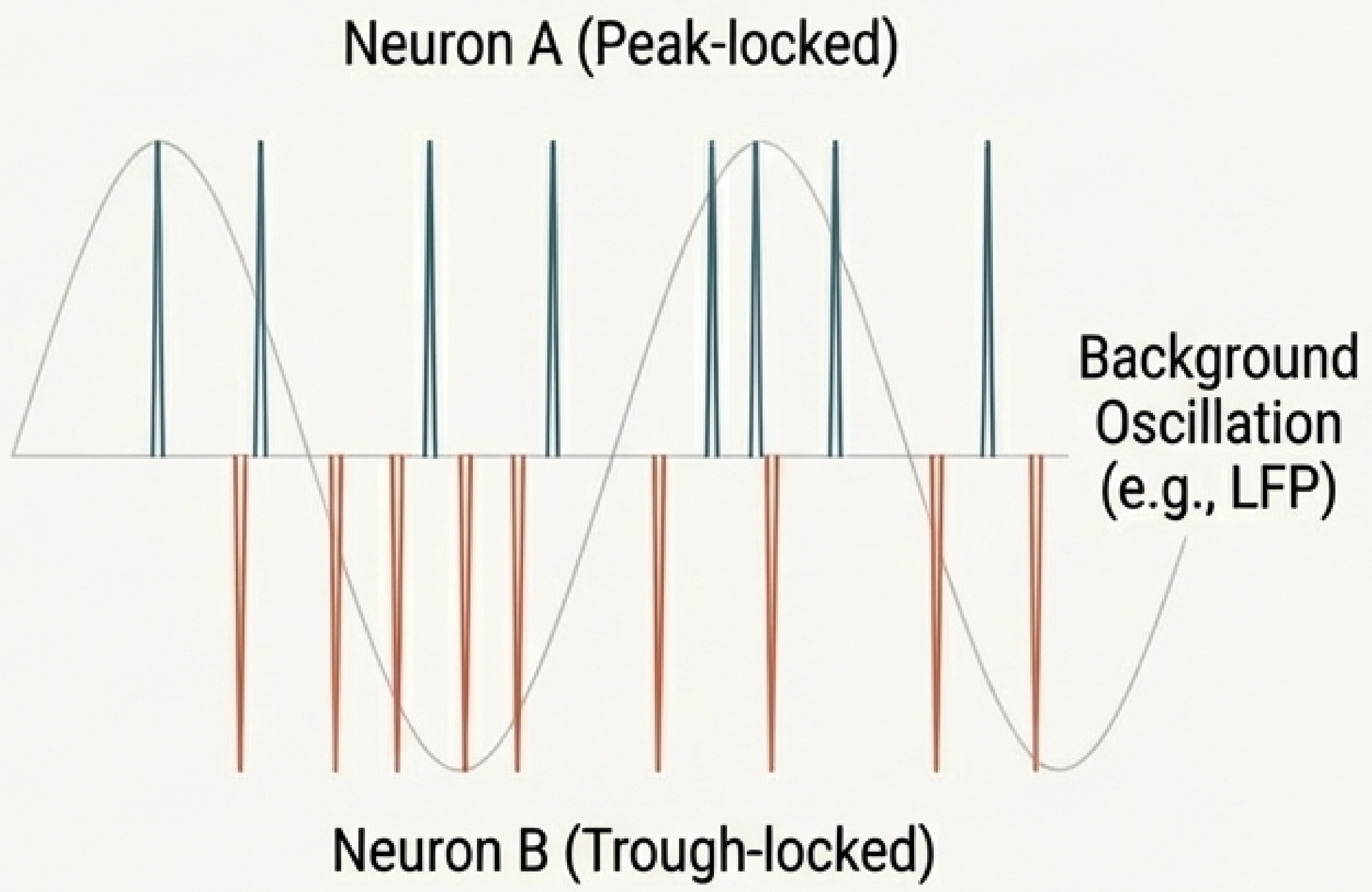


Nature's Precedent: Computation as Oscillation

Phase Coding in the Brain

Biological neural circuits have long used oscillations as a computational resource. In **phase coding**, information is represented not by the magnitude of neural activity, but by the *relative timing* of spikes within an ongoing oscillation. Studies of recurrent neural networks (RNNs) trained on modular arithmetic tasks confirm this: networks without oscillatory-promoting biases can naturally converge on phase-coding solutions to solve the task. This suggests phase coding is an efficient and natural computational strategy.

(Murray, 2024; O'Keefe & Recce, 1993)



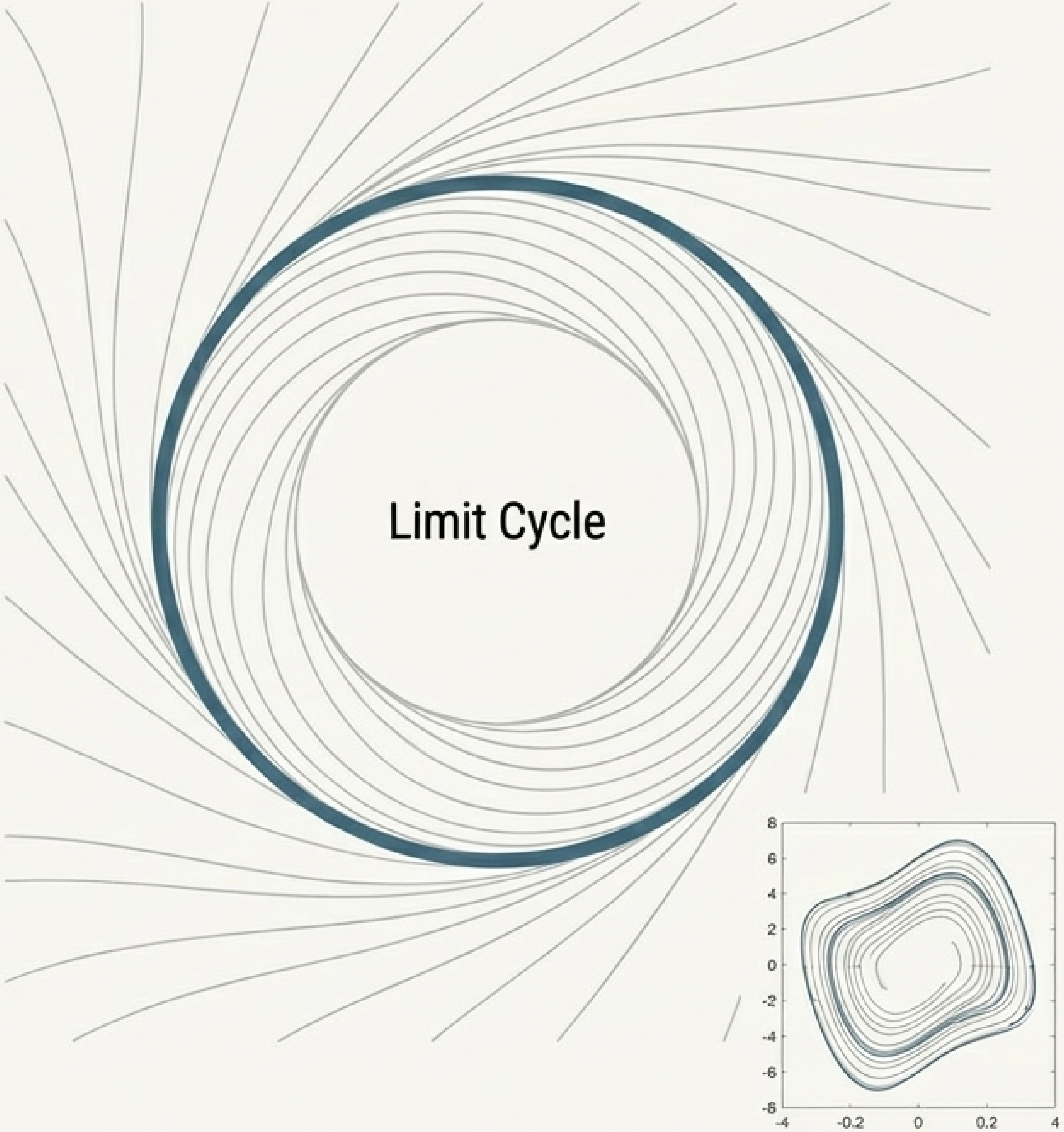
Different phases encode distinct information.

The Mathematics of Stability: Limit Cycles

Limit Cycle Attractors

In dynamical systems, a **limit cycle** is a closed, periodic trajectory in phase space that is also an *attractor*. Nearby trajectories, regardless of their initial conditions, spiral into this stable loop over time. This provides a mechanism for
robust, self-correcting oscillations. Research has shown that RNNs trained for working memory tasks develop **phase-locked limit cycles**, where each memory corresponds to a distinct, stable attractor.

(Pals et al., 2024; 'ODEs: Limit cycles')



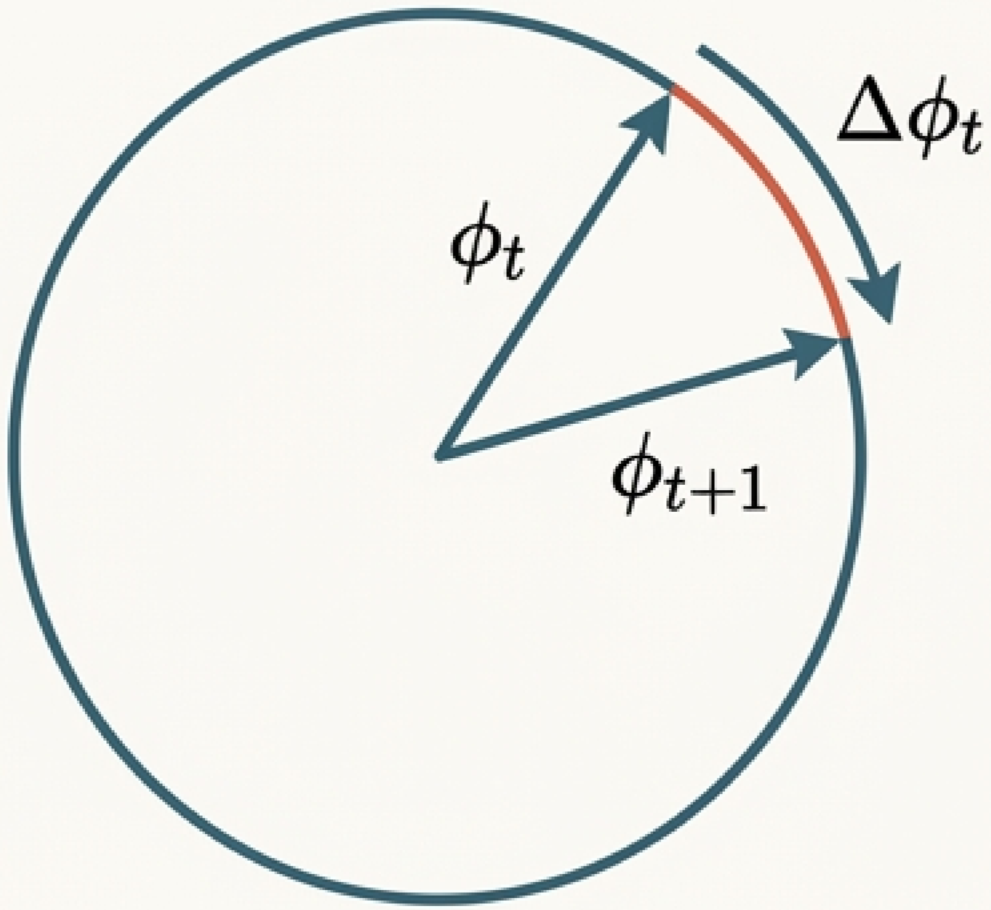
The Hypothesis Embodied: The U-Neuron

Riemannian Optimized Unified Neural Dynamo (ROUND)
A Spinning Dynamo, Not a Leaky Valve.

GRU (Gated Recurrent Unit)	ROUND (U-Neuron)
Mechanism: Multiplicative gating ($\sigma, \tanh$).	Mechanism: Additive phase accumulation ($\phi + \Delta\phi$).
Memory: Volatile. State decays or "leaks" unless actively maintained by gates.	Memory: Stable (Non-Volatile). A phase angle ϕ on a circle does **not decay**. If input ceases, memory persists indefinitely as a standing wave.
Analogy: Holding water in cupped hands; you must actively clench to keep it.	Analogy: A gyroscope; it stays where you set it until a new force acts upon it.

The Mechanism: Memory as Phase Accumulation

The U-Neuron represents its hidden state not as a scalar magnitude, but as a phase vector ϕ (in radians) on a learned manifold.



Update Rule

State is updated via simple accumulation, not complex gating:

$$\phi_{t+1} = \phi_t + \Delta\phi_t$$

Learned Drift

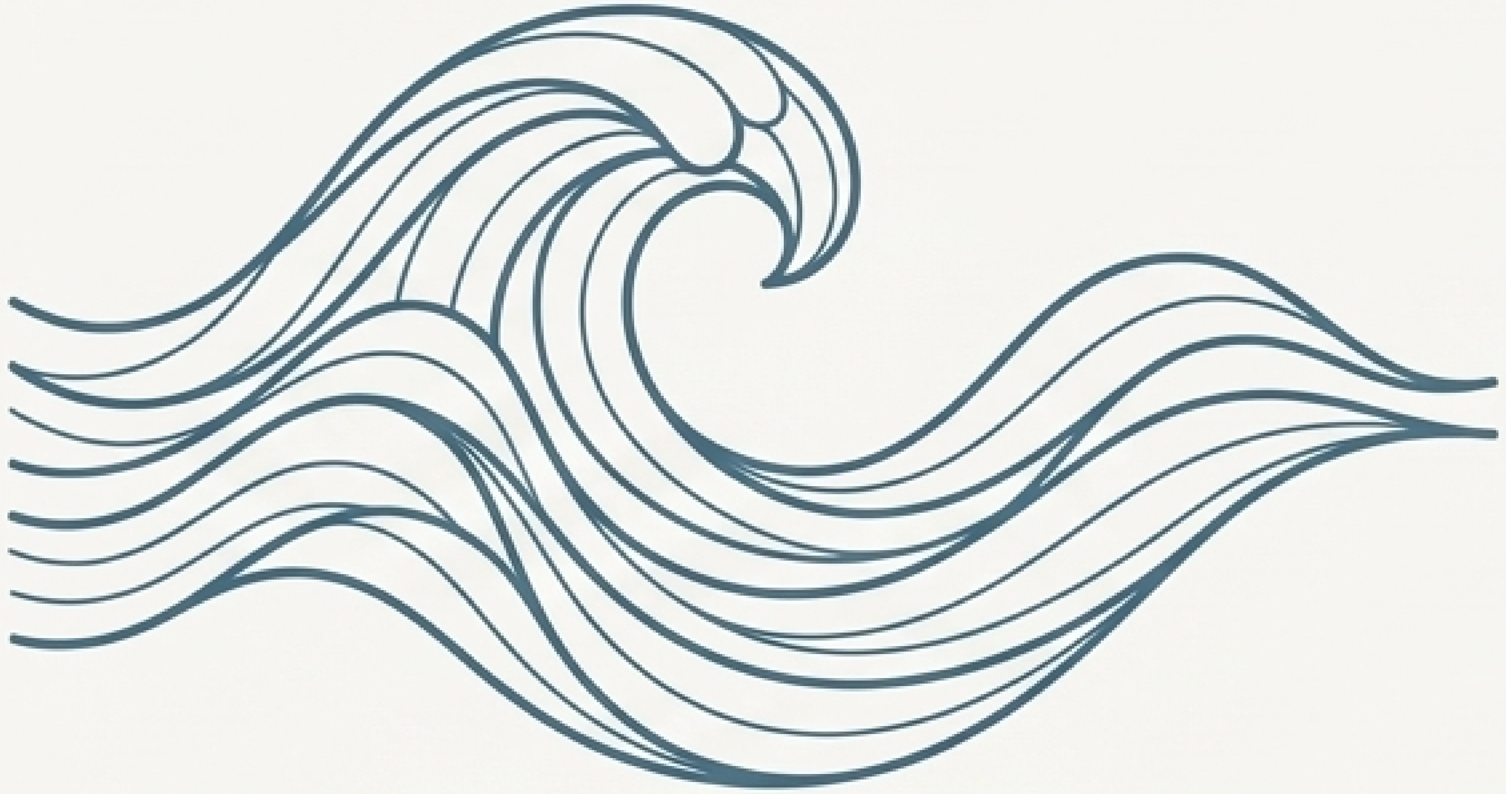
The change in phase, $\Delta\phi_t$, is computed from phasor features (cosine and sine) of the current state and the encoded input:

$$\Delta\phi_t = W[\cos(\phi_t), \sin(\phi_t), \cos(\phi_{in}), \sin(\phi_{in})] + b$$

This architecture replaces complex, potentially unstable multiplications with simple, efficient addition, learning a "rotation field" directly in phase space.

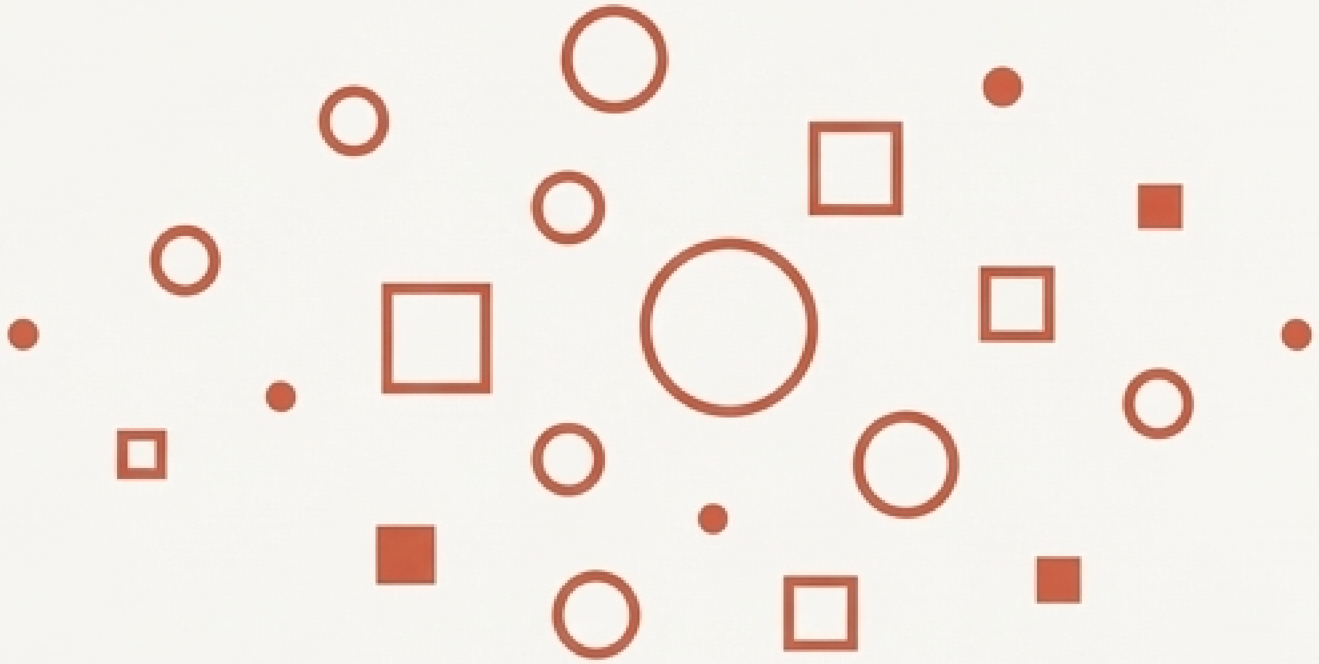
Source: ROUND.py (`PhaseAccumulator` module)

“The Complementarity Problem: A Neuron That Could Dream, But Not Count”



The initial state: The phase-accumulating architecture inherently excelled at **topological tasks.** Its continuous phase space was a natural fit for representing shapes, curves, and geometric geometric invariants—the "Wave" aspect of computation.

How can a system maintain its continuous, exploratory "wave" nature while also being able to collapse into a discrete, definite state upon measurement?

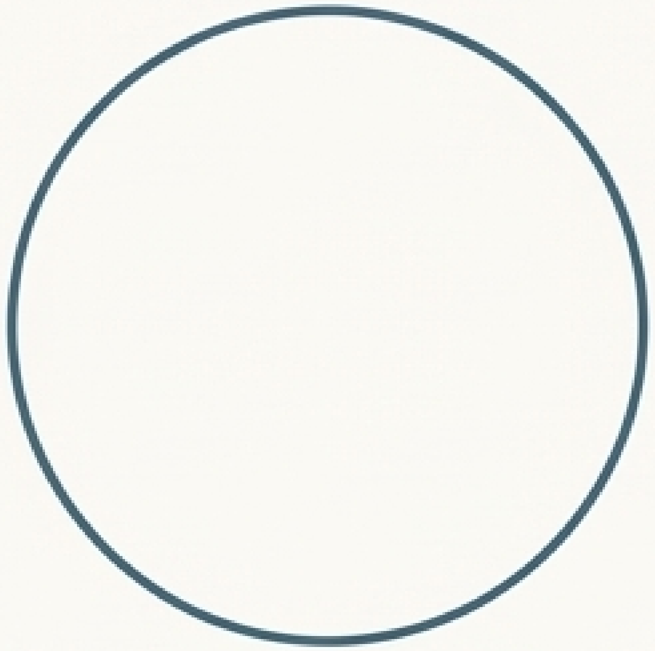


The core conflict: When tasked with **discrete logic** (e.g., parity, modular arithmetic), the initial design floundered. The continuous nature of its memory made it difficult to lock onto precise, symbolic states.

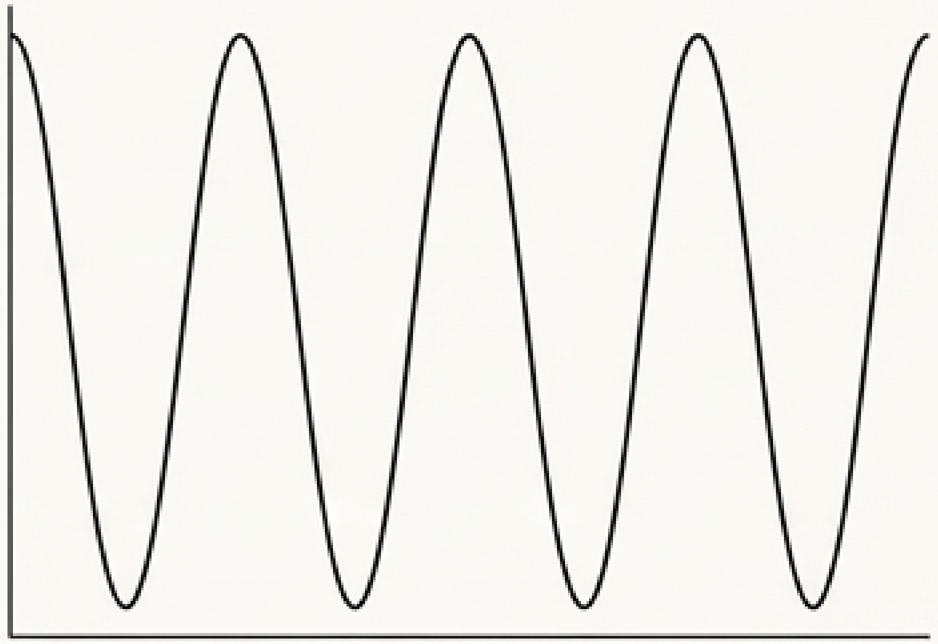
The Breakthrough: Harmonic Quantum Locking

The Solution: Impose a potential energy field onto the neuron's continuous phase space using a loss function composed of a harmonic spectrum of stability potentials:

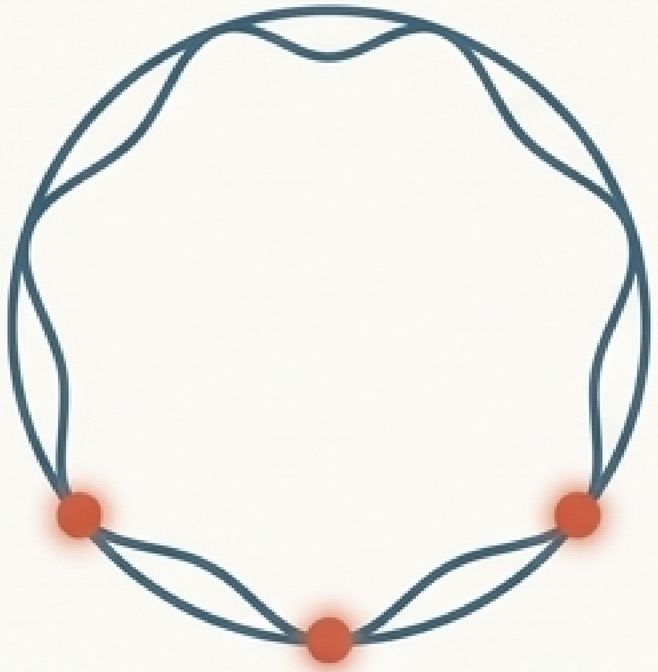
$$V = \sum \sin^2(h \cdot \phi)$$



The Wave: Continuous Phase Space



ϕ (from 0 to 2π)



The Particle: Quantized Resting Points

Key Innovation: Terminal-Only Locking: The locking potential is applied *only* to the final state of a sequence during training. This allows the system to evolve as a continuous wave during processing, preserving topological information, before collapsing into a discrete particle at the moment of readout.

The Experiment: A Unified Testbench for a Generalist Neuron

The Protocol

A single, untuned U-Neuron configuration was tested against a parameter-matched GRU across four distinct computational domains.

The Claim

A *single mechanism*, with only harmonic-spectrum tuning, **spans multiple computational regimes** that typically require **different inductive biases.** This is a claim of *learnability advantage*, not yet real-world generalist performance.

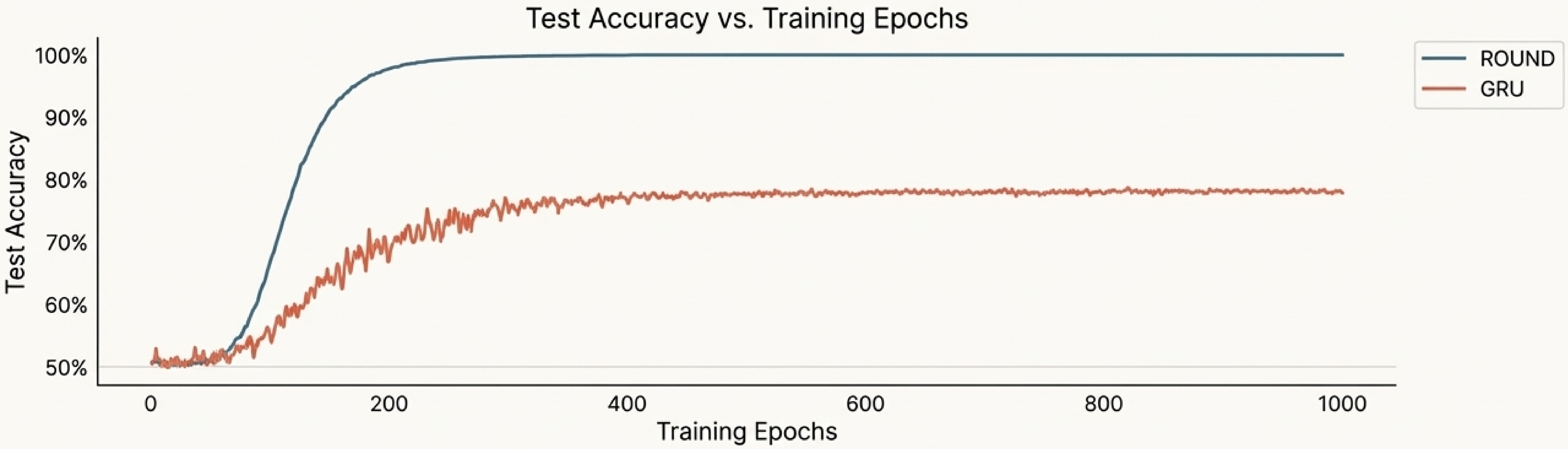
The Unified Harmonic Standard	
Hidden Size	32 neurons
Learning Rate	Harmonic Resonance ($2^{-9} \approx 0.00195$)
Epochs	1000
Locking	Terminal-Only

A Harmonic Generalist Masters Four Computational Domains

Benchmark Results (v0.3.2 Unified Standard, 5-run average)

Task	ROUND	GRU	Notes
Logic (16-bit Parity)	**100.0%**	~78.0%	ROUND locks perfectly; GRU struggles with long-range dependency.
Arithmetic (Modulo-8)	**~60.0%**	~33.0%	**Failure Mode Analysis:** ROUND aliases securely to Mod-4; GRU collapses to random noise.
Structure (Balanced Brackets)	**100.0%**	~99.0%	ROUND exhibits perfect stability and self-correction.
Topology (2D Winding)	**100.0%**	~100.0%	Both solve it, but ROUND locks in significantly earlier (by Epoch 50).

Visualizing the Performance Gap: 16-bit Parity



UIT's Thermodynamic Cooling

The training process mirrors a phase transition. The network 'cools' from a disordered state into a 'crystallized' solution.

Evidence: The Active Brake

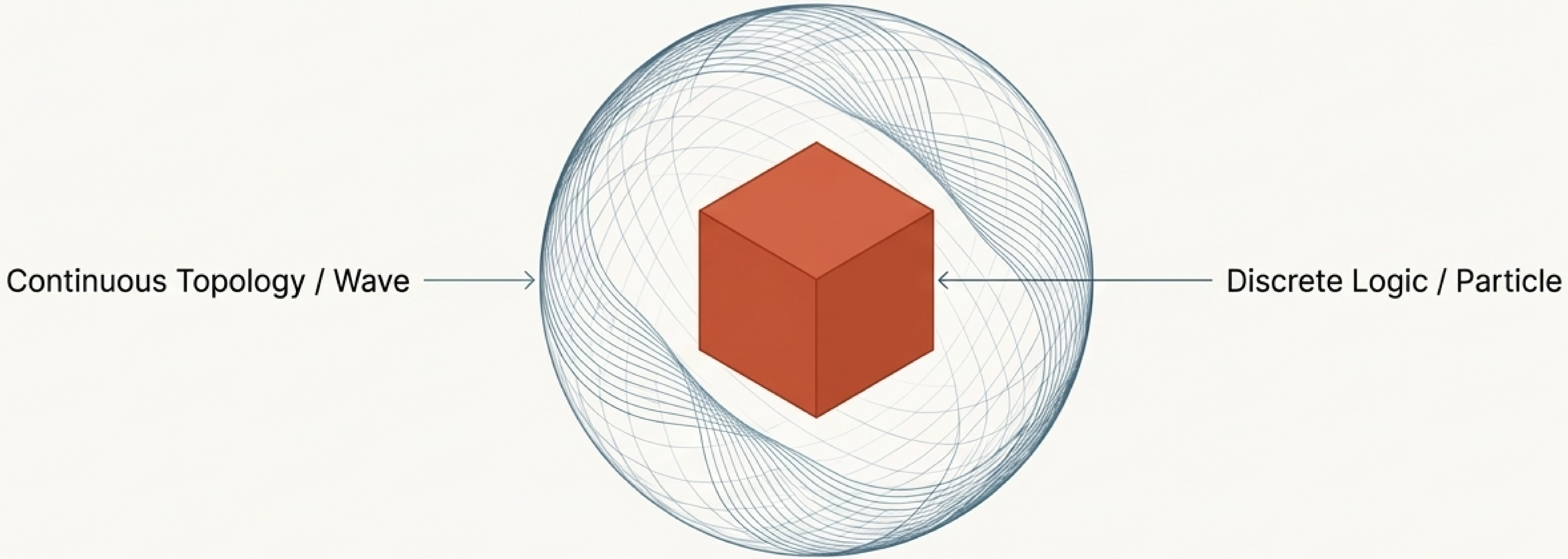
We monitor a phase correlation metric $K = \text{mean}(\sin^2(\phi))$. As the system settles into the harmonic wells, K drops below 0.5. The 'Active Brake' then reduces the learning rate's impact, allowing the solution to crystallize without disturbance.

```
R1 E200: A=0.97 | K=0.5000 | B=1.00000
R1 E300: A=1.00 | K=0.4945 | B=0.95173
R1 E900: A=1.00 | K=0.4732 | B=0.76290
```

As accuracy (A) hits 100%, the brake (B) engages, showing crystallization.

The Grand Theory: "The Sphere Contains the Cube"

UIT's Core Hypothesis: Discrete logic is a special case of continuous topology under a quantizing potential. The apparent dichotomy is a false one; one is a constrained version of the other.



Unifying Wave and Particle

- **Topology is the Wave**: Phase winds freely, integrates curvature, and explores the continuous manifold.
- **Logic is the Particle**: The Harmonic Locking potential forces the phase space into discrete, stable basins (bits).
- The U-Neuron can operate as either, toggling between them via terminal-only locking.

Implication: Overcoming the Illusion of Diminishing Returns

The Problem in Long-Horizon Tasks

Current models suffer from error accumulation.

Current models suffer from error accumulation. Marginal gains in single-step accuracy appear to yield diminishing returns.

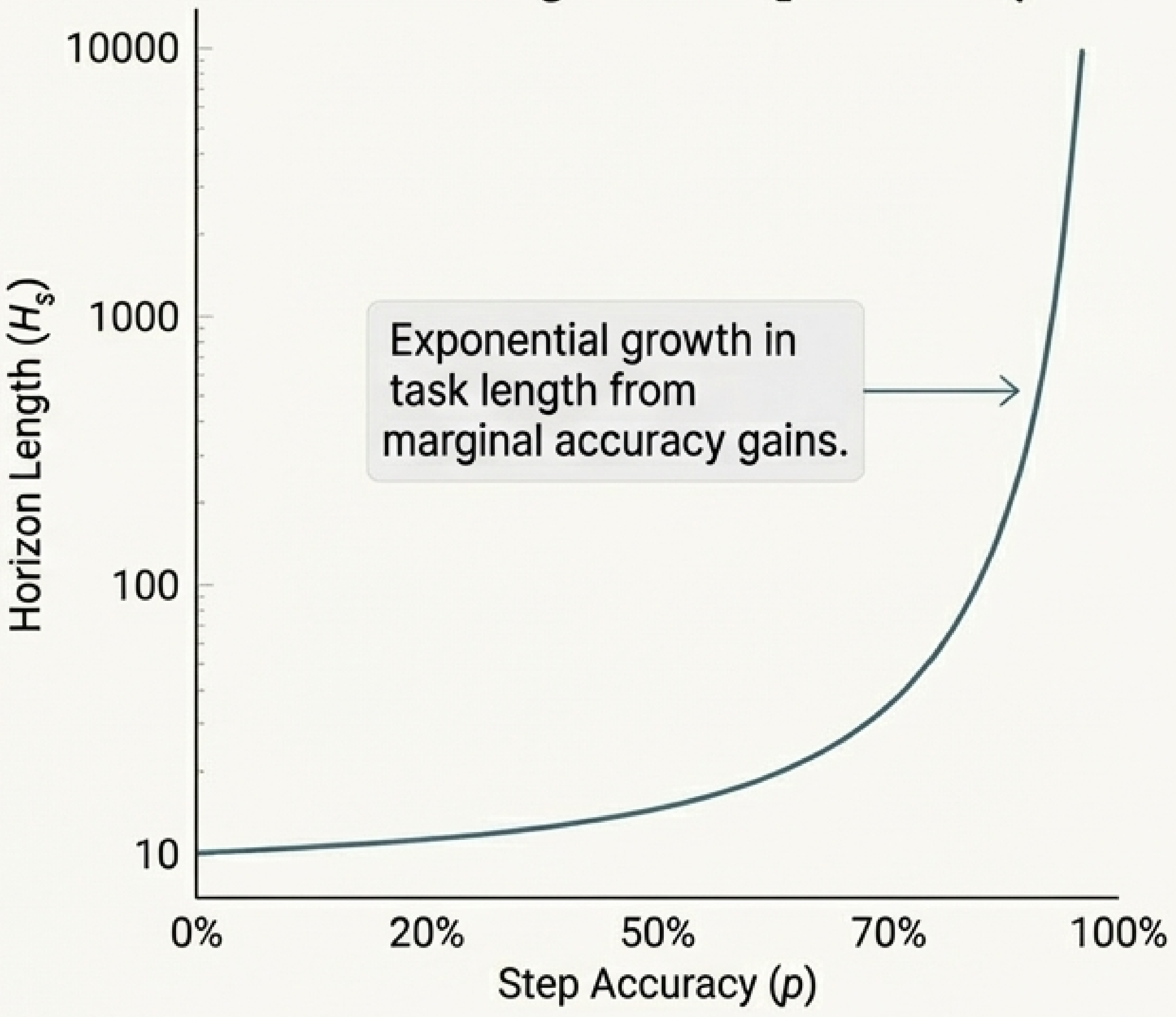
A key reason is **self-conditioning**: models become more likely to make mistakes when their context contains their own prior errors, creating a feedback loop of performance degradation.

(Sinha et al., 2025)

The U-Neuron's Advantage: Intrinsic Stability

- The U-Neuron's non-volatile memory (the 'gyroscope') resists this degradation. Its state does not drift or decay.
- This 'self-conditioning' is positive: the neuron robustly maintains its state, preventing the error propagation that plagues volatile-memory models.
- This transforms marginal single-step accuracy gains into exponential improvements in the length of a task a model can successfully complete.

Horizon Length vs. Step Accuracy



The U-Neuron: A Unified Neural Dynamo

THE WAVE (Topology)

- Continuous Manifold
- Phase Accumulation ($\phi + \Delta\phi$)
- Limit Cycle Dynamics

Tasks: Winding, Structure

U-Neuron Dynamo

THE PARTICLE (Logic)

- Quantized States
- Harmonic Locking Wells
- Stable Fixed Points

Tasks: Parity, Arithmetic

Intrinsic Stability: Non-volatile, gyroscope-like memory.

Computational Efficiency: Updates via addition, not complex gating.

Unified Mechanism: A single architecture for both continuous and discrete tasks.

Explore the Code, Reproduce the Results, and Build What's Next

This repository contains a reference implementation of the ROUND neuron, the harmonic locking loss function, and the full benchmark suite. The work is shared under an MIT License to encourage open collaboration and further research. All results are fully reproducible by running a single script.

github.com/Lexideck-Technologies/ROUND_Harmonic

If you build on this work, please cite the repository. A `CITATION.cff` file is included for direct GitHub integration.
Validated: Dec 13, 2025 — Lexideck Research Team.