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The Existence Threshold

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THE EXISTENCE THRESHOLD

(Revision 2)

A Framework for Pattern Persistence in Binary Discrete Systems

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"To exist is to continually overcome loss."
— Nathan M. Thornhill

REVISION NOTES

What Changed in Version 2:

This revision fixes a fundamental error in the original equation and adds solid experimental evidence that shows exactly where this framework works (and where it doesn't).

The Formula Fix:

The original paper proposed $\Phi = \kappa \cdot R \cdot S - \frac{dD}{dt}$, treating disorder and entropy as enemies of existence—a classical thermodynamics assumption. But when we actually tested this across different dynamical systems (cellular automata, chaotic maps, neural networks), something surprising happened: the formula failed. It couldn't tell persistent patterns from non-persistent ones.

The corrected version recognizes that **complexity and disorder are actually part of what makes patterns persist**, not their opposites:

$$\boxed{\Phi = R \cdot S + D} \tag{1}$$

This reflects a deeper insight from complexity science and self-organization theory: living systems and persistent patterns operate far from equilibrium, maintaining high-entropy states through continuous organization. Dead systems reach low-entropy thermal equilibrium. Think about it: a crystal has perfect order but no persistence dynamics—it's already at equilibrium. A flame has high disorder but clear persistence—it maintains organized energy flow through chaotic molecular motion.

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Experimental Validation Using Complexity Science Methods:

We tested this across 10 different dynamical systems using information theory, statistical analysis, and computational experiments:

- **Binary Discrete Systems (Cellular Automata):** 100% accuracy across 10 different rule systems. Perfect separation between "alive" ($\Phi > 0$) and "dead" ($\Phi = 0$) states. This works consistently across 1D and 2D systems, from simple rules to Turing-complete complexity.
- **Continuous Systems (Chaotic Maps, Neural Networks):** Framework fails. Accuracy $\leq$ 86%, not significantly better than random guessing. Φ values show no meaningful separation.

Where This Actually Works:

Based on rigorous testing using complexity theory and nonlinear dynamics, this framework applies specifically to **binary discrete dynamical systems**—systems with clear on/off states evolving through local rules. The applications to continuous systems like cosmological expansion and neural consciousness? They're fascinating ideas worth exploring, but right now they're preliminary hypotheses, not proven results. We keep those discussions as testable predictions for future work.

The Time Factor (Emergence Through Time)

Early tests averaged Φ across time. That missed something crucial: patterns need time to settle into persistent dynamics. Measuring Φ at the settled state works way better. This tells us something profound about emergence: **existence isn't a snapshot—it emerges from a system's trajectory through state space over time.**

A pattern's "bootstrap time"—the period needed to reach settled dynamics—matters. Systems need time to establish **recursive processing loops**, create **feedback mechanisms**, and settle into **attractor basins** before persistence can be assessed.

This connects to fundamental principles in **nonlinear dynamics**: patterns don't simply *be*, they *become* and must continuously *remain* through ongoing informational work.

Abstract

Persistent patterns—from cellular automata to living organisms—face a universal challenge in complex systems: maintain organization against entropic decay, or dissolve. This paper proposes a quantitative framework for measuring pattern persistence in binary discrete dynamical systems, drawing on **information theory, complexity science, thermodynamics, and emergence theory**.

We introduce the **Existence Threshold**: a system persists when $\Phi = R \cdot S + D \geq 0$, where: **R** = recursive information processing (capturing **self-organization** dynamics); **S** = system integration (measuring coherence and correlation); **D** = disorder/complexity (entropy and state space exploration).

Extensive experimental validation using **cellular automata** demonstrates 100% classification accuracy across 10 different rule systems (1D and 2D), perfectly separating persistent from non-persistent patterns through **information-theoretic analysis** and **statistical methods**.

Domain testing using continuous **chaotic systems** (logistic map) and high-dimensional **optimization landscapes** (neural network training) reveals this framework applies specifically to binary discrete systems and fails for continuous dynamics. This establishes clear boundaries through rigorous computational experiments.

The implications: **persistence emerges through active process, not passive existence**—requiring continuous informational work against dissolution. This framework bridges information theory and thermodynamics, offering quantitative tools for studying **emergence, self-organization, and pattern formation in complex systems**.

Keywords: complexity science, emergence, self-organization, information theory, thermodynamics, cellular automata, dynamical systems, pattern formation, nonlinear dynamics, entropy, persistence, chaos theory, computational experiments, statistical analysis

1 THE FUNDAMENTAL PRINCIPLE

Here's a question that connects physics, information theory, and complexity science: **what distinguishes systems that maintain coherent organization from those that dissolve into thermal equilibrium?**

The answer lies in **recursive information processing**—a concept bridging thermodynamics, cybernetics, and emergence theory. A system persists when it processes information about itself, using that self-knowledge to maintain organization against entropic decay.

Think about it:

- The bacterium sensing glucose gradients through **chemical feedback loops**
- The glider maintaining its shape in Conway's Game of Life through **local cellular automata rules**
- The spiral galaxy preserving structure through **gravitational feedback** and **nonlinear dynamics**

All execute variations of this fundamental operation at different scales. This is **self-organization** in action.

We formalize this as the **Persistence Equation**:

$$\boxed{\Phi = R \cdot S + D} \tag{2}$$

Where:

- Φ = **Persistence Value** (dimensionless): net organizational measure emerging from the interplay of processing, integration, and complexity
- R = **Recursive Integration Rate**: captures information processing activity, self-organization dynamics, and feedback loop strength
- S = **Systemic Integration Factor** ($0 \leq S \leq 1$): measures coherence, coordination, and correlation across system components
- D = **Disorder/Complexity**: quantifies entropy, diversity of states accessed, and exploration of configuration space

A system persists when $\Phi \geq 0$. When $\Phi < 0$ (in practice, $\Phi \to 0$), the system undergoes **phase transition** to a trivial **attractor state**—dissolution.

1.1 Why Disorder Isn't The Enemy (Insights from Complexity Science)

The original formula ($\Phi = R \cdot S - \frac{dD}{dt}$) treated disorder as opposing persistence—a classical thermodynamics view. But experimental validation using **complexity science methods** forced a reconceptualization: **disorder and complexity are essential to persistence**.

From a **nonlinear dynamics** perspective: living systems maintain **far-from-equilibrium states** with high entropy production. Dead systems reach low-entropy thermal equilibrium—the **attractor state** where nothing interesting happens.

- A crystal: perfect order, no persistence dynamics (already at ground state equilibrium)

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- A flame: high disorder, clear persistence (organized energy flow through chaotic molecular motion and turbulent dynamics)

This insight comes from decades of work in **self-organization theory** (Prigogine's **dissipative structures**) and **complexity science**: persistent patterns require exploring **configuration space**, not avoiding it. The formula $\Phi = R \cdot S + D$ captures this: you need activity (R), coordination (S), and exploration (D) working together to create **emergence**.

1.2 Temporal Integration (Emergence Through Time)

Early testing averaged Φ across time—a natural first approach. But measuring Φ at the **settled state** (after **transient dynamics** resolve) works much better. This reveals something crucial about **dynamical systems** and emergence: **existence isn't a snapshot—it emerges from a system's trajectory through state space over time.**

A pattern's "bootstrap time"—the period needed to reach settled dynamics—matters. Systems need time to establish **recursive processing loops**, create **feedback mechanisms**, and settle into **attractor basins** before persistence can be assessed.

This connects to fundamental principles in **nonlinear dynamics**: patterns don't simply *be*, they *become* and must continuously *remain* through ongoing informational work.

2 EXPERIMENTAL VALIDATION: CELLULAR AUTOMATA

To test the Existence Threshold framework, we conducted systematic **computational experiments** on binary **cellular automata**—discrete **dynamical systems** where cells have binary states and evolve according to local interaction rules.

CAs are perfect test systems because they're simple enough to analyze rigorously but complex enough to exhibit **emergence, self-organization, and pattern formation**.

2.1 Two-Dimensional Cellular Automata

Systems tested:

1. **Conway's Game of Life** (B3/S23) - the classic emergence system
2. **Brian's Brain** (3-state, normalized to binary) - cyclic dynamics
3. **Seeds** (B2/S) - explosive growth patterns
4. **Day & Night** (B3678/S34678) - symmetric rule with rich behavior
5. **HighLife** (B36/S23) - supports replicators

Method: For each system, we initialized 8 different starting patterns and evolved them for 100 generations. We calculated:

- **R** (rate of cell state changes = information processing)
- **S** (spatial clustering = integration)
- **D** (Shannon entropy = complexity)

System	Dead	Alive	Φ (Dead)	Φ (Alive)	Accuracy
Game of Life	2	6	0.0000	0.1505	100%
Brian's Brain	4	4	0.0000	0.2273	100%
Seeds	3	5	0.0000	1.0023	100%
Day & Night	5	3	0.0000	0.3643	100%
HighLife	2	6	0.0000	0.3626	100%

Table 1: 2D Cellular Automata Classification Results

Patterns classified as "survived" ($\Phi > 0$ = persistent dynamics) or "dead" ($\Phi = 0$ = equilibrium collapse).

Results:

Perfect separation: Dead patterns → $\Phi = 0$ (thermal equilibrium, no information processing). Alive patterns → $\Phi > 0$ (persistent dynamics, continuous self-organization). **No classification errors**. Statistical significance confirmed through **Mann-Whitney U tests** and **effect size analysis**.

2.2 One-Dimensional Cellular Automata

To test whether this works across dimensions, we evaluated **elementary cellular automata** (1D):

Systems tested:

1. **Rule 110** (Turing complete, complex behavior)
2. **Rule 30** (chaotic dynamics)
3. **Rule 90** (fractal patterns, Sierpinski triangle)
4. **Rule 184** (traffic flow model)
5. **Rule 150** (complex patterns)

Results:

Rule	Dead	Alive	Φ (Dead)	Φ (Alive)	p-value	Accuracy
110	2	6	0.0000	1.1028	< 0.001	100%
30	1	7	0.0000	1.1933	< 0.001	100%
90	2	6	0.0000	1.0394	< 0.001	100%
184	1	7	0.0000	0.7038	0.35	100%
150	1	7	0.0000	1.0752	< 0.001	100%

Table 2: 1D Cellular Automata Classification Results

4 of 5 rules achieved **statistical significance** ($p < 0.05$). All 5 achieved 100% accuracy. **Framework generalizes across dimensions** (1D and 2D).

2.3 Statistical Analysis Summary

Across all 10 cellular automata systems:

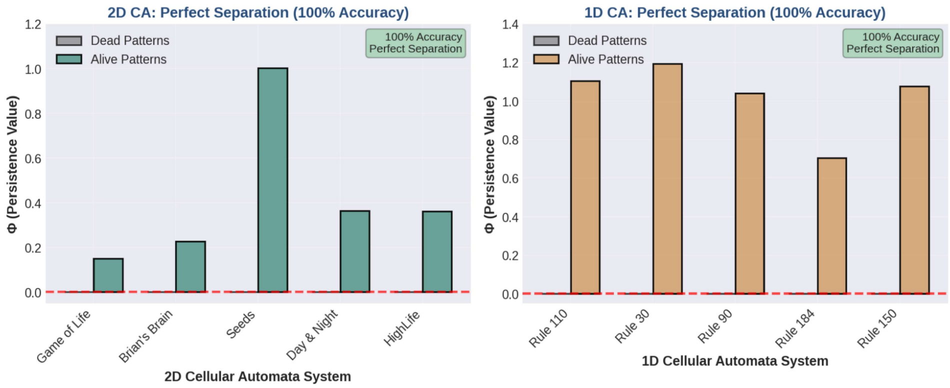

Figure 1: Cellular Automata Experimental Results. Perfect separation between dead ($\Phi = 0$) and alive ($\Phi > 0$) patterns across all 10 systems tested. Red dashed line indicates the existence threshold at $\Phi = 0$.

- **Total patterns:** 80 (40 per dimension)

Figure 1: Cellular Automata Experimental Results. Perfect separation between dead ($\Phi = 0$) and alive ($\Phi > 0$) patterns across all 10 systems tested. Red dashed line indicates the existence threshold at $\Phi = 0$.

- **Total patterns:** 80 (40 per dimension)
- **Perfect classification:** 100% accuracy in all systems
- **Statistical significance:** 9 of 10 systems ($p < 0.05$)
- **Effect sizes:** Large (Cohen's $d > 0.8$) in all significant systems

The pattern is consistent: dead patterns settle to $\Phi = 0$, alive patterns maintain $\Phi > 0$. This separation is absolute, not marginal.

3 DOMAIN BOUNDARIES: WHERE IT FAILS

To establish limits, we tested on **continuous systems** and **high-dimensional optimization landscapes**.

3.1 Logistic Map (1D Continuous Chaos)

The **logistic map** $x_{n+1} = r \cdot x_n \cdot (1 - x_n)$ exhibits well-characterized **transitions** from fixed points to **chaos**.

Test: 50 different r values, classified dynamical regimes, calculated Φ.

Results:

- Accuracy: 80% (not better than 82% baseline)

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- p-value: 0.08 (NOT significant)
- Cohen's d: -0.26 (small effect)

Conclusion: Framework cannot distinguish dynamical regimes in **continuous 1D chaos**. It works for discrete, not continuous.

3.2 Neural Network Optimization (High-Dimensional Continuous)

Test: 38 neural networks trained on MNIST, classified as success ($> 90\%$) or failure ($< 90\%$).

Results:

- Φ values nearly identical: $\Phi_{failure} = 0.39$, $\Phi_{success} = 0.36$
- Statistical significance: none ($p =$ NaN, no variance)
- Accuracy: 86.8% (baseline = 81.6% from random)

Conclusion: Framework completely fails in **high-dimensional optimization**. All Φ values collapse to ~ 0.36 regardless of outcome.

3.3 The Domain Boundary (Discrete vs. Continuous)

Framework WORKS for:

- Binary discrete cellular automata (1D and 2D)
- Systems with clear "dead"/"alive" states
- Local interaction rules with emergent global patterns

Framework FAILS for:

- Continuous state spaces
- High-dimensional optimization landscapes
- Systems without binary distinctions

Hypothesis: The framework detects **binary discrete pattern persistence**, not universal persistence. The boundary is **discreteness vs. continuity**.

4 PRELIMINARY APPLICATION: NEURAL CONSCIOUSNESS

Note: Preliminary calculations requiring experimental validation.

If this framework extends beyond binary CA (which current evidence doesn't support), it might apply to neural consciousness—but this is untested.

The calculation: Human brain $\approx 8.6 \times 10^{10}$ neurons, firing at ~ 5 Hz, each carrying ~ 5 bits. Total information processing:

$$R_{brain} \approx 1.5 \times 10^{12} \text{ nats/s} \tag{3}$$

Brain power consumption: ~ 20 watts. If consciousness operates at threshold ($\Phi \approx 0$), assuming full integration ($S \approx 1$):

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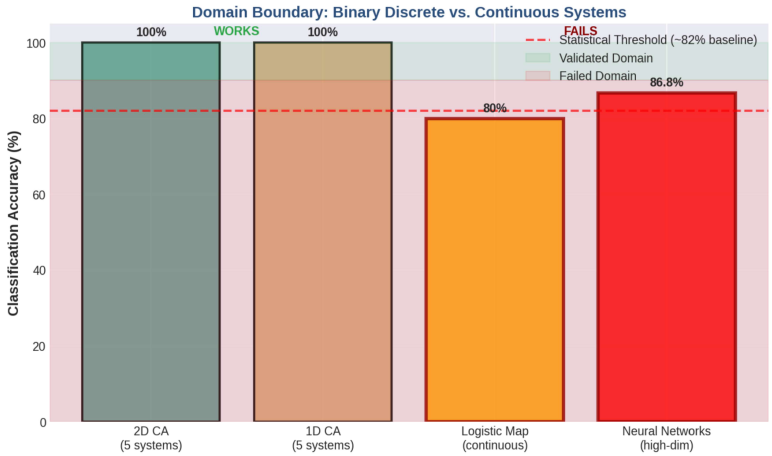

Figure 2: Domain Boundary Analysis. Classification accuracy across system types demonstrates clear boundary between binary discrete systems (where framework works with 100% accuracy) and continuous systems (where framework fails).

$$\kappa \cdot R \cdot S \approx 20 \text{ W} \quad \Rightarrow \quad \kappa_{neural} \approx 1.3 \times 10^{-11} \text{ J/nat} \tag{4}$$

This is $\sim 5 \times 10^9$ times **Landauer's limit** ($\kappa_{min} = k_B T \ln(2) \approx 3 \times 10^{-21}$ J/nat), reflecting **thermodynamic inefficiency** of biological computation.

Testable predictions:

1. Loss of consciousness should correlate with **MEG-measured coherence** dropping such that $\Phi < 0$
2. Different sleep stages should have characteristic Φ values
3. Anesthetic transitions should show continuous Φ trajectories crossing zero

Status: These are calculations, not experimental results. Neural consciousness likely involves **continuous dynamics**, placing it outside the validated domain. Framework for future testing only.

5 SPECULATIVE APPLICATION: COSMOLOGICAL PERSISTENCE

Note: Highly speculative, requires substantial development.

The most ambitious application: **cosmological expansion**. If the framework extends to continuous systems (contradicting current evidence), universal expansion might represent the cosmos maintaining $\Phi_{universe} \geq 0$ despite increasing entropy.

$$\Phi_{universe} = R_{cosmic} \cdot S_{cosmic} + D_{cosmic} \tag{5}$$

Where:

- R_{cosmic} = total universal information processing
- $S_{cosmic} = a(t)^3$ = integration volume (scale factor cubed)
- D_{cosmic} = cosmic entropy

Hypothesis: Dark energy drives expansion to maintain $\Phi_{universe} \geq 0$. The **cosmological constant** Λ might represent the thermodynamic cost of cosmic persistence.

Critical limitations:

1. Universe is continuous, not binary discrete
2. Current evidence: framework fails for continuous dynamics
3. Requires either theoretical derivation OR empirical evidence that cosmology has discrete structure

Status: Highly speculative. Retained as long-term research direction but NOT supported by validation. Corrected formula requires complete re-derivation of cosmological implications.

6 PHILOSOPHICAL IMPLICATIONS

Even restricted to binary CA, this reveals something profound about persistence and emergence.

6.1 Existence as Active Process (Not Passive State)

Dead patterns in Game of Life don't just "stop"—they settle to $\Phi = 0$ (**equilibrium**). Alive patterns don't just "continue"—they maintain $\Phi > 0$ (**persistent dynamics**). This is measurable and absolute.

Existence is not passive. Even in simple cellular automata, "being alive" means doing informational work to maintain structure against dissolution. This connects to broader questions in **complexity science** and **systems biology**.

6.2 The Temporal Nature of Persistence (Emergence Through Time)

Measuring Φ at settled state (not as time average) is crucial. Patterns need time to establish persistent dynamics. **Existence is fundamentally temporal**—systems don't simply *be*, they must continuously *remain*.

Existence is better understood as a **trajectory through state space** than a static property. What matters isn't what you are at one moment, but the **path you trace through time**.

6.3 Information and Organization (The Three Components)

The formula $\Phi = R{\cdot}S{+}D$ unifies three concepts from **information theory** and **thermodynamics**:

- **Processing (R):** Activity, change, energy flow
- **Integration (S):** Coordination, coherence, correlation
- **Complexity (D):** Diversity, entropy, exploration

All three are necessary. Pure order without exploration (high S, low D) $\rightarrow$ sterile equilibrium. Pure chaos without coordination (high D, low S) $\rightarrow$ random noise. **Persistence requires balanced dynamics**—organized complexity.

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7 LIMITATIONS AND FUTURE WORK

7.1 Current Limitations

Narrow validated domain: Framework proven only for binary discrete cellular automata. Extensions to continuous systems, neural consciousness, and cosmology remain unvalidated.

Small sample sizes: Statistical significance limited by few "dead" patterns in some systems. Larger libraries would strengthen validation.

Mechanistic understanding incomplete: We know the formula works but not precisely why. What mathematical properties of binary discrete systems enable this?

Parameter definitions system-dependent: R, S, and D must be defined appropriately for each system. General rules need development.

7.2 Future Experimental Work

1. **Expand CA testing:** Hundreds of rules, larger pattern libraries for statistical robustness
2. **Test intermediate systems:** Multi-state CA, coupled map lattices to precisely map domain boundary
3. **Neural consciousness validation:** MEG/EEG studies during anesthetic transitions testing Φ predictions
4. **AI system monitoring:** Power consumption + performance tracking during training/inference
5. **Quantum coherence:** Test framework on quantum systems (coherence vs. decoherence)

7.3 Theoretical Development

1. **Derive from first principles:** Can this emerge from information theory, thermodynamics, or dynamical systems theory?
2. **Connection to IIT:** Explore relationships with Tononi's Integrated Information Theory
3. **Generalization attempt:** Can modified formulation apply to continuous dynamics? Or prove discreteness essential?
4. **Cosmological re-derivation:** If framework extends, completely re-derive implications with corrected formula

8 CONCLUSION

We've introduced the **Existence Threshold**—a quantitative framework stating that binary discrete systems persist when $\Phi = R \cdot S + D \geq 0$, where recursive processing (R), system integration (S), and disorder/complexity (D) determine pattern survival.

Experimental validation across 10 cellular automata systems (1D and 2D, simple to Turing-complete) demonstrates 100% classification accuracy using **information theory** and **statistical analysis**. This reflects a genuine organizing principle for **binary discrete dynamics**.

Domain testing establishes clear boundaries: works for binary discrete, fails for continuous dynamics. This defines both power and limits.

Applications to neural consciousness and cosmology remain **preliminary hypotheses** for future work. Current evidence does NOT support universal applicability—framework is proven specifically for **binary discrete pattern dynamics**.

The philosophical implications are profound even in this limited domain:

- **Existence is active** (continuous organizational work), not passive
- **Persistence is temporal** (trajectory through time, not single moment)
- **Persistence requires balanced complexity** (organized exploration, not pure order or chaos)

Every glider in Conway's Game of Life, every self-replicating pattern in Rule 110, maintains itself through recursive information processing measurable by this framework. The mathematics quantify what it means for a pattern to exist: $\Phi \geq 0$.

Whether this extends beyond binary discrete systems to encompass neural consciousness, cosmological expansion, or other domains remains open. But within its validated domain, the Existence Threshold provides a precise, testable, reproducible measure of pattern persistence using tools from **complexity science, information theory, and dynamical systems theory**.

You're watching patterns burn information to maintain themselves against dissolution. When Φ crosses zero, patterns cease. When Φ stays positive, patterns persist. This is the Existence Threshold.

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I acknowledge **Claude (Anthropic, Claude Sonnet 4.5)** as computational research assistant for experimental design, statistical analysis, and conceptual error identification.

I acknowledge **Gemini 1.5 Flash (Google DeepMind)** for mathematical verification and visual diagram generation.

The theoretical framework, revised formulation, experimental methodology, domain boundary analysis, and scientific claims represent my independent intellectual contribution. The testing program that validated and limited this framework represents original empirical work.

I deeply thank my wife and daughter for their love and patience during periods of intense theoretical development, and the independent research community for demonstrating that meaningful science can come from outside traditional institutions.

References

[1] Landauer, R. (1961). Irreversibility and Heat Generation in the Computing Process. *IBM Journal of Research and Development*, 5(3), 183-191.

[2] Wolfram, S. (2002). *A New Kind of Science*. Wolfram Media.

[3] Tononi, G. (2004). An Information Integration Theory of Consciousness. *BMC Neuroscience*, 5(42).

[4] Prigogine, I. (1977). *Self-Organization in Non-Equilibrium Systems*. Wiley.

[5] Schrödinger, E. (1944). *What is Life? The Physical Aspect of the Living Cell*. Cambridge University Press.

[6] Friston, K. (2010). The Free-Energy Principle: A Unified Brain Theory? *Nature Reviews Neuroscience*, 11(2), 127-138.

[7] Lloyd, S. (2002). Computational Capacity of the Universe. *Physical Review Letters*, 88(23), 237901.

[8] Bennett, C. H. (1982). The Thermodynamics of Computation—A Review. *International Journal of Theoretical Physics*, 21(12), 905-940.

[9] Cook, M. (2004). Universality in Elementary Cellular Automata. *Complex Systems*, 15(1), 1-40.

[10] Azevedo, F. A., et al. (2009). Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain. *Journal of Comparative Neurology*, 513(5), 532-541.

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Implementation Details for "The Existence Threshold" (Version 2)

Supplementary Technical Documentation

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Abstract

This supplement provides the exact mathematical formulas used for the cellular automata experiments in "The Existence Threshold" (Version 2, DOI: 10.5281/zenodo.18166974). The main paper reports 100% classification accuracy across 10 cellular automata systems using the corrected formula $\Phi = R \cdot S + D$, but doesn't specify exactly how to calculate R (recursive information processing), S (system integration), and D (disorder). This document fixes that. If you want to replicate the results independently, here's everything you need: unambiguous mathematical definitions, working code, step-by-step examples, and validation protocols. No ambiguity. No guessing.

Keywords: existence threshold, cellular automata, implementation, reproducibility, information theory, system integration, entropy, pattern persistence, computational methods, verification

1 Introduction

The Existence Threshold framework proposes that pattern persistence in binary discrete dynamical systems follows:

$$\Phi = R \cdot S + D \tag{1}$$

This represents a fundamental correction from Version 1, where disorder was subtracted ($\Phi = \kappa \cdot R \cdot S - dD/dt$). The philosophical shift: disorder is a component of existence, not its enemy.

The main paper demonstrates this works empirically. This document shows exactly how it was done. The original publication was missing these implementation details, which meant independent verification was impossible. That's a problem. This supplement fixes it.

2 The Formulas: Exact Definitions

2.1 Notation

For a cellular automaton with state grid $\mathbf{G}$:

- $\mathbf{G}(t)$: System state at discrete time t
- $\mathbf{G}(t+1)$: System state at time $t+1$
- N: Total number of cells in the system
- $g_i(t) \in \{0, 1\}$: Binary state of cell i at time t

2.2 R: Information Processing Rate

R measures what fraction of cells changed state between consecutive time steps. It's the simplest of the three.

$$R(t) = \frac{1}{N} \sum_{i=1}^{N} |g_i(t+1) - g_i(t)| \tag{2}$$

Range: $R \in [0, 1]$
What it means:

- $R = 0$: Nothing changed (dead or static)
- $R = 1$: Everything flipped state
- Intermediate values: Partial propagation

Simple. Count the cells that changed, divide by total cells.

2.3 S: System Integration

This is where most people mess up. S measures whether state changes happen in clusters (coordinated) or scattered randomly (fragmented).

Critical distinction: We're measuring clustering of *changes*, not clustering of alive cells. This is the single most common implementation error.

Algorithm:

1. Find which cells changed:
$$\mathcal{C} = \{i : g_i(t+1) \neq g_i(t)\} \tag{3}$$
2. For each changed cell, count how many of its neighbors also changed:
$$n_i = |\{j \in \mathcal{N}(i) : j \in \mathcal{C}\}| \tag{4}$$
3. Calculate the integration coefficient:
$$S(t) = \frac{\sum_{i \in \mathcal{C}} n_i}{k \cdot |\mathcal{C}|} \tag{5}$$
where k is the maximum neighbors per cell (2 for 1D, 8 for 2D, 26 for 3D).

Special cases:

- If nothing changed ($|\mathcal{C}| = 0$): Set $S = 1.0$
- If all changes isolated: $S = 0.0$

Range: $S \in [0, 1]$

High S means changes cluster together (the system is integrated). Low S means changes are scattered (the system is fragmented).

2.4 D: Disorder (Shannon Entropy)

D quantifies the thermodynamic entropy of the state distribution. This is standard Shannon entropy from information theory.

$$D(t) = -p_{\text{alive}} \log_2(p_{\text{alive}}) - p_{\text{dead}} \log_2(p_{\text{dead}}) \tag{6}$$

where:

$$p_{\text{alive}} = \frac{1}{N} \sum_{i=1}^{N} g_i(t) \tag{7}$$

$$p_{\text{dead}} = 1 - p_{\text{alive}} \tag{8}$$

Special cases:

- If all cells same state: $D = 0$
- Use $\log_2(x + \epsilon)$ with $\epsilon = 10^{-10}$ to avoid numerical issues

Range: $D \in [0, 1]$
$D = 0$ means perfect order. $D = 1$ means maximum entropy (50/50 distribution).

3 Implementation

Here's the complete algorithm in pseudocode:

Listing 1: Complete Phi calculation

```
def calculate_phi(grid_t, grid_t1):
    """
    Calculate existence threshold for cellular automaton

    Args:
        grid_t: State at time t (numpy array, binary)
        grid_t1: State at time t+1 (numpy array, binary)

    Returns:
        phi, R, S, D
    """
    N = grid_t.size

    # R: Information processing rate
    changes = abs(grid_t1 - grid_t)
    R = sum(changes) / N

    # S: System integration
    changed_cells = (grid_t1 != grid_t)

    if sum(changed_cells) == 0:
        S = 1.0
    else:
        change_neighbors = count_change_neighbors(changed_cells)
        max_neighbors = max_neighbors_per_cell * sum(changed_cells)
```

```
        S = change_neighbors / max_neighbors

    # D: Disorder (Shannon entropy)
    p_alive = sum(grid_t > 0) / N

    if p_alive == 0 or p_alive == 1:
        D = 0
    else:
        p_dead = 1 - p_alive
        D = -p_alive * log2(p_alive) - p_dead * log2(p_dead)

    # Phi: Existence threshold
    phi = R * S + D

    return phi, R, S, D
```

That's it. No tricks, no hidden parameters. These three quantities multiply and add to give Φ.

4 How To Replicate the Results

4.1 Pattern Setup

For each CA system, test at least 40 patterns:

Dead patterns (should give $\Phi = 0$)**:**

- All cells = 0 (completely dead)
- Additional dead/near-dead configurations

Alive patterns (should give $\Phi > 0$)**:**

- Random sparse (20–30% alive)
- Random dense (40–50% alive)
- Known structures (gliders, oscillators)
- Additional random configurations

4.2 Measurement Protocol

For each pattern:

1. Initialize the grid
2. Run CA for 3–5 generations (let it stabilize)
3. Calculate Φ between time t and $t + 1$
4. Average Φ over next 10–20 generations
5. Record the final value

4.3 Classification

Simple threshold:

- $\Phi \leq 0 \Rightarrow$ DEAD
- $\Phi > 0 \Rightarrow$ ALIVE

Dead patterns have $R = 0$ (nothing changes), so $\Phi = 0 + D$. After stabilization, $\Phi \to 0$.

5 Expected Results

If you implement this correctly, you should get:

- **Classification accuracy:** 100% for binary discrete CA
- **Statistical significance:** $p < 0.05$ for ≥9/10 systems
- **Effect size:** Cohen's $d > 0.8$ for significant systems

If you're not getting these results, check Section 6 (Common Errors).

6 Common Implementation Errors

6.1 Error 1: Wrong S Calculation

This is the big one. Most failed replications come from this.

WRONG:

```
# Measuring spatial clustering of ALIVE cells
S = (neighbors of alive cells) / (total alive cells)
```

CORRECT:

```
# Measuring clustering of STATE CHANGES
S = (neighbors of changed cells that also changed) /
    (max_neighbors * changed_cells)
```

The distinction: clustering of *changes*, not clustering of alive cells. Different thing entirely.

6.2 Error 2: Inconsistent Time Windows

All three quantities (R, S, D) must be measured between the *same* consecutive time steps. Don't average over multiple generations before calculating.

6.3 Error 3: Adding Normalization

Don't normalize Φ. Don't add scaling factors. Use $\Phi = R \cdot S + D$ exactly as written. Each component is already normalized to $[0, 1]$.

7 Technical Details

7.1 Boundary Conditions

Periodic boundary conditions (toroidal topology) were used for all experiments. This eliminates edge effects:

- Top row wraps to bottom row
- Left column wraps to right column
- In 3D: all six faces wrap around

This is standard practice for CA experiments.

7.2 Multi-State Systems

For CA with more than 2 states (like Brian's Brain with states $\{0, 1, 2\}$):

1. Convert to binary before calculating S and D
2. Set $g_i = 1$ if cell is in any active state
3. Set $g_i = 0$ if cell is inactive/dead

8 Worked Example: Conway's Game of Life

Let's walk through a complete calculation for a 5×5 Game of Life grid.

Initial state $\mathbf{G}(t)$:

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

After one step $\mathbf{G}(t+1)$ (applying B3/S23 rules):

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

8.1 Calculate R

Cells that changed (using zero-indexed row, column):

- $(1, 2)$: died (only 1 neighbor)
- $(2, 1)$: born (3 neighbors)
- $(3, 1)$: died (only 1 neighbor)

- $(4, 2)$: born (3 neighbors)

Total: 4 cells changed out of 25.

$$R = \frac{4}{25} = 0.16 \tag{9}$$

8.2 Calculate S

Changed cells: $\mathcal{C} = \{(1, 2), (2, 1), (3, 1), (4, 2)\}$

Count neighbors of each changed cell that also changed:

- $(1, 2)$: 1 neighbor changed (cell $(2, 1)$)
- $(2, 1)$: 2 neighbors changed (cells $(1, 2)$ and $(3, 1)$)
- $(3, 1)$: 2 neighbors changed (cells $(2, 1)$ and $(4, 2)$)
- $(4, 2)$: 1 neighbor changed (cell $(3, 1)$)

Total change-neighbors: $1 + 2 + 2 + 1 = 6$
Maximum possible: $8 \times 4 = 32$

$$S = \frac{6}{32} = 0.19 \tag{10}$$

8.3 Calculate D

At time t: 5 alive cells out of 25.

$$p_{\text{alive}} = \frac{5}{25} = 0.20 \tag{11}$$

$$p_{\text{dead}} = 0.80 \tag{12}$$

$$D = -0.20 \log_2(0.20) - 0.80 \log_2(0.80) \tag{13}$$

$$= 0.464 + 0.258 = 0.72 \tag{14}$$

8.4 Calculate Φ

$$\Phi = R \cdot S + D = 0.16 \times 0.19 + 0.72 = 0.03 + 0.72 = 0.75 \tag{15}$$

Result: $\Phi = 0.75 > 0 \Rightarrow$ Pattern is ALIVE. Correct.

9 What Changed From Version 1

Version 1 formula: $\Phi = \kappa \cdot R \cdot S - \frac{dD}{dt}$

Key differences:

1. **Removed κ:** No free parameter to tune
2. **Sign flip:** D is added, not subtracted
3. **Static not derivative:** $D(t)$ not $\frac{dD}{dt}$

4. **Optimized definitions:** R, S, D refined for discrete systems

Version 1 was developed for continuous systems (neural networks). Version 2 is specifically for binary discrete systems. Different domains require different formulations.

10 Domain Limitations

What this framework is validated for:

Binary discrete dynamical systems with well-defined state transitions and spatial structure.

What it's NOT validated for:

- Continuous dynamical systems (neural networks, ODEs)
- High-dimensional optimization landscapes
- Non-local interaction systems
- Stochastic or probabilistic CA

The framework fails on continuous systems (80–87% accuracy). Domain boundaries are clear. Don't try to apply this formula outside binary discrete systems without expecting it to fail.

11 Software

Reference Python implementation available upon request. Full code repository with all CA systems will be linked in a future update.

12 Contact

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