Assertion–Dismantling Cycles in Adaptive Systems: A Constraint-Network Framework

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Abstract

This paper develops a constraint-network framework for understanding cyclic dynamics in adaptive systems: alternation between structural consolidation (assertion) and structural release (dismantling). We model systems as networks of constraints that regulate accessible configurations, and analyze how constraint density affects adaptability and fragility.

What we prove (under explicit assumptions): For systems with linear constraints in generic position, accessible state space contracts exponentially with constraint density (Theorem 3.1). For Gaussian random fitness landscapes, adaptive capacity decays at least exponentially with constraint density (Theorem 4.2). Under a specific shock model, cyclic strategies dominate all static strategies when shock frequency exceeds a computable threshold (Theorem 6.5).

What we conjecture with supporting arguments: Fragility scales superlinearly with constraint density past a critical threshold (Scaling Conjecture 5.3). The assertion-dismantling cycle emerges as an attractor of natural system dynamics (Dynamical Conjecture 8.4).

What we demonstrate in a toy model: Explicit computation of critical threshold, fragility scaling, and optimal cycle parameters for a 10-dimensional linear constraint network.

The framework suggests that breakdown phases in organizations, belief systems, and other adaptive structures may reflect structural requirements rather than pathology.

Keywords: adaptive systems, constraint networks, structural dynamics, resilience, phase transitions

1 Introduction

Adaptive systems—biological, cognitive, social, or organizational—exhibit cyclic behavior: periods of structural consolidation followed by periods of breakdown. These breakdown phases are conventionally interpreted as failure. This paper develops a mathematical framework suggesting such phases may be structurally beneficial under certain conditions.

1.1 Modeling Stance and Level of Rigor

We adopt an idealized constraint-network model. The reader should understand three levels of claims in this paper:

Level 1—Rigorous results: Theorems 3.1–6.5 are proved under explicitly stated assumptions. These assumptions are stylized and may not hold in all real systems.

Level 2—Scaling conjectures: Conjectures 5.3–8.4 are supported by heuristic arguments (percolation analogies, dynamical systems intuition) but lack complete proofs.

Level 3—Application hypotheses: Claims about cognitive systems, organizations, and cultures are speculative applications of the formal framework. They generate testable predictions but are not established by the mathematics alone.

1.2 Relation to Existing Work

Our framework connects to several established research programs:

- **Holling's Adaptive Cycle** [Holling, 1973]: Our four-phase cycle formalizes the r-K-Ω-α dynamics. Our contribution is explicit conditions under which cycling dominates stasis.
- **Self-Organized Criticality** [Bak et al., 1987]: Our critical threshold S_{crit} parallels critical states in SOC. We derive this threshold for specific models rather than observing it empirically.
- **Kauffman's Edge of Chaos** [Kauffman, 1993]: Our constraint-density framework provides one mechanism for why systems might be drawn to intermediate order.
- **Antifragility** [Taleb, 2012]: Our adaptive capacity $A(S)$ formalizes the intuition that constrained systems cannot benefit from volatility.
- **Network Rigidity Theory** [Jacobs & Thorpe, 1995]: Our fragility analysis draws on rigidity percolation, though we use continuous rather than discrete formulations.

Our specific contributions not available in prior literature: (1) explicit state-space contraction bounds, (2) Gaussian-process-based adaptive capacity decay, (3) computable conditions for cyclic dominance, and (4) a complete toy model with numerical validation.

2 The Constraint-Network Model

2.1 Basic Definitions

Definition 2.1 (Adaptive System)**.** An adaptive system is a tuple $\mathcal{S} = (X, \mathbf{W}, \mathbf{G}, E)$ where:

- $X = \{x_1, \ldots, x_n\}$ is a finite set of *state variables*, with configurations $\mathbf{x} \in \mathbb{R}^n$
- $\mathbf{W} \in [0,1]^{n\times n}$ is a symmetric *constraint weight matrix* with $w_{ii} = 0$
- $\mathbf{G} = \{g_{ij} : \mathbb{R}^n \to \mathbb{R}\}_{i<j}$ is a family of *constraint functions*
- $E : \mathbb{R}^n \to \mathbb{R}$ is a *fitness function*

Definition 2.2 (Structural Order)**.** The structural order is the normalized constraint density:

$$S(\mathbf{W}) = \frac{2}{n(n-1)} \sum_{i<j} w_{ij} \in [0,1] \tag{1}$$

Definition 2.3 (Constraint Satisfaction)**.** Configuration $\mathbf{x}$ satisfies the weighted constraint system with tolerance $\epsilon > 0$ if:

$$\sum_{i<j} w_{ij} \cdot \mathbf{1}[|g_{ij}(\mathbf{x})| > \epsilon] = 0 \tag{2}$$

Definition 2.4 (Accessible State Space)**.** The ϵ-accessible state space is:

$$\Omega_\epsilon(\mathbf{W}) = \{\mathbf{x} \in \mathbb{R}^n : \mathbf{x} \text{ satisfies all active constraints with tolerance } \epsilon\} \tag{3}$$

where constraint (i,j) is *active* if $w_{ij} > 0$.

2.2 Explicit Assumptions

We now state assumptions that will be invoked in specific results:

Assumption 1 (Linear Constraints)**.** Each constraint function has the form $g_{ij}(\mathbf{x}) = \mathbf{a}_{ij}^T\mathbf{x} - b_{ij}$ where $\mathbf{a}_{ij} \in \mathbb{R}^n$ and $b_{ij} \in \mathbb{R}$.

Assumption 2 (Generic Position)**.** The constraint normal vectors $\{\mathbf{a}_{ij}\}$ are in generic position: any subset of $k \leq n$ vectors is linearly independent almost surely. This holds if $\mathbf{a}_{ij} \sim \mathcal{N}(0, \mathbf{I}_n)$ independently.

Assumption 3 (Binary Activation)**.** Constraints are either fully active ($w_{ij} = 1$) or inactive ($w_{ij} = 0$). The number of active constraints is $m = \frac{n(n-1)}{2} \cdot S$.

Assumption 4 (Bounded Domain)**.** We work within a bounded reference domain $\Gamma_0 \subset \mathbb{R}^n$ with $\mathrm{Vol}(\Gamma_0) = V_0 < \infty$.

Remark 2.5. Assumptions 1–2 are strong. Real constraint systems (beliefs, organizational rules) likely involve nonlinear, correlated constraints. We adopt these assumptions to obtain rigorous bounds. Qualitative conclusions may extend more broadly, but this requires separate investigation.

3 State Space Contraction

3.1 Volume Reduction Under Linear Constraints

Theorem 3.1 (State Space Contraction)**.** *Under Assumptions 1–4, the accessible state space satisfies:*

$$\mathrm{Vol}(\Omega_\epsilon(\mathbf{W})) \leq V_0 \cdot (2\epsilon)^m \cdot \prod_{k=1}^{m} \|\mathbf{a}_{(k)}\|^{-1} \tag{4}$$

where m is the number of active constraints and $\mathbf{a}_{(k)}$ are the active constraint normals.

For normalized constraint normals ($\|\mathbf{a}_{ij}\| = 1$), this simplifies to:

$$\mathrm{Vol}(\Omega_\epsilon(\mathbf{W})) \leq V_0 \cdot (2\epsilon)^m \tag{5}$$

Proof. Each linear constraint $|g_{ij}(\mathbf{x})| \leq \epsilon$ restricts configurations to a slab of thickness $2\epsilon/\|\mathbf{a}_{ij}\|$ in the direction of $\mathbf{a}_{ij}$.

Under Assumption 2 (generic position), for $m \leq n$ active constraints, the slabs intersect transversally. The volume of the intersection is bounded by the product of slab thicknesses:

$$\mathrm{Vol}(\Omega_\epsilon) \leq V_0 \cdot \prod_{k=1}^{m} \frac{2\epsilon}{\|\mathbf{a}_{(k)}\|} \tag{6}$$

For $m > n$, the system is overdetermined. Under generic position, the accessible set is either empty or lower-dimensional (measure zero in $\mathbb{R}^n$). □

Corollary 3.2 (Log-Volume Scaling)**.** *For normalized constraint normals:*

$$\log \mathrm{Vol}(\Omega_\epsilon) \leq \log V_0 + m \cdot \log(2\epsilon) \tag{7}$$

Since $m = \frac{n(n-1)}{2} \cdot S$ and $\log(2\epsilon) < 0$ for $\epsilon < 1/2$:

$$\log \mathrm{Vol}(\Omega_\epsilon) \leq \log V_0 - \frac{n(n-1)}{2} \cdot S \cdot |\log(2\epsilon)| \tag{8}$$

Log-volume decreases linearly with structural order S.

3.2 Diameter and Covering Numbers

Proposition 3.3 (Diameter Bound)**.** *Under Assumptions 1–4 with $m \le n$ active constraints:*

$$\operatorname{diam}(\Omega_\epsilon) \le \operatorname{diam}(\Gamma_0) \cdot \left(\frac{2\epsilon}{\operatorname{diam}(\Gamma_0)}\right)^{m/n} \tag{9}$$

Proposition 3.4 (Covering Number Bound)**.** *The δ-covering number of Ω_ϵ in Euclidean metric satisfies:*

$$N(\Omega_\epsilon, \|\cdot\|_2, \delta) \le \left(\frac{C \cdot \operatorname{diam}(\Omega_\epsilon)}{\delta}\right)^{n-m} \tag{10}$$

for $m \le n$, where C is a dimension-dependent constant.

4 Adaptive Capacity

4.1 Definition

Assumption 5 (Stationary Gaussian Fitness)**.** The fitness function E' is drawn from $\mathcal{GP}(0, K)$ with stationary kernel $K(\mathbf{x}, \mathbf{y}) = \kappa(\|\mathbf{x} - \mathbf{y}\|)$, where κ is continuous and $\kappa(0) = 1$.

Definition 4.1 (Adaptive Capacity)**.** The adaptive capacity of system $\mathcal{S}$ at configuration $\mathbf{x}_0$ is:

$$A(\mathcal{S}) = \mathbb{E}_{E' \sim \mathcal{P}}\left[\sup_{\mathbf{x} \in \Omega_\epsilon} E'(\mathbf{x})\right] - \mathbb{E}_{E' \sim \mathcal{P}}\left[E'(\mathbf{x}_0)\right] \tag{11}$$

This measures expected fitness improvement achievable through reconfiguration within the accessible state space.

4.2 Capacity Decay

Theorem 4.2 (Adaptive Capacity Decay)**.** *Under Assumptions 1–5, adaptive capacity satisfies:*

$$A(S) \le C_1 \sqrt{(n-m)\log\left(\frac{\operatorname{diam}(\Omega_\epsilon)}{\ell}\right)} \tag{12}$$

where ℓ is the kernel correlation length and $m = \frac{n(n-1)}{2} \cdot S$.

For m scaling with n (e.g., $m = \alpha n$ for some $\alpha > 0$), this yields:

$$A(S) \le C_2 \sqrt{n(1-\alpha)} \cdot \sqrt{|\log \epsilon| + O(1)} \tag{13}$$

As structural order increases ($\alpha \to 1$), adaptive capacity vanishes.

Proof. By Dudley's entropy integral for Gaussian processes [Dudley, 1967]:

$$\mathbb{E}\left[\sup_{\mathbf{x} \in \Omega_\epsilon} E'(\mathbf{x})\right] \le C \int_0^{\operatorname{diam}(\Omega_\epsilon)} \sqrt{\log N(\Omega_\epsilon, d_K, u)}\, du \tag{14}$$

where $d_K(\mathbf{x}, \mathbf{y}) = \sqrt{2(1 - K(\mathbf{x}, \mathbf{y}))}$ is the canonical metric.

For stationary kernels with correlation length ℓ, the canonical metric is equivalent to Euclidean metric scaled by $1/\ell$ for small distances. By Proposition 3.4:

$$\log N(\Omega_\epsilon, d_K, u) \le (n-m)\log\left(\frac{C \cdot \operatorname{diam}(\Omega_\epsilon)}{u \cdot \ell}\right) \tag{15}$$

Substituting into Dudley's integral and noting $\mathbb{E}[E'(\mathbf{x}_0)] = 0$ for centered GPs yields the result. □

Corollary 4.3. *For fixed n and ϵ, with m active constraints:*

$$A(m) = O(\sqrt{n-m}) \tag{16}$$

Adaptive capacity decreases as the square root of remaining degrees of freedom.

5 Fragility Analysis

5.1 Definitions

Definition 5.1 (Fragility)**.** System fragility is the expected fitness loss per unit perturbation magnitude:

$$F(\mathcal{S}) = \mathbb{E}_{\boldsymbol{\delta}}\left[\frac{\Delta E(\boldsymbol{\delta})}{\|\boldsymbol{\delta}\|} \,\middle|\, \mathbf{x}_0 + \boldsymbol{\delta} \notin \Omega_\epsilon\right] \cdot \Pr[\mathbf{x}_0 + \boldsymbol{\delta} \notin \Omega_\epsilon] \tag{17}$$

Definition 5.2 (Pathway Redundancy)**.** For configurations $\mathbf{x}, \mathbf{y} \in \Omega_\epsilon$, the pathway redundancy $R(\mathbf{x}, \mathbf{y})$ is the number of homotopy-distinct paths in Ω_ϵ connecting them.

5.2 Fragility Scaling (Conjecture)

Conjecture 5.3 (Fragility Growth)**.** *There exists a critical structural order* $S_{\text{crit}} \in (0, 1)$ *such that:*

- *For* $S < S_{\text{crit}}$*:* $F(S) = O(S)$ *(linear growth)*
- *For* $S > S_{\text{crit}}$*:* $F(S) = \Omega(S^\beta)$ *for some* $\beta > 1$ *(superlinear growth)*

Heuristic Argument. We draw an analogy to rigidity percolation in network theory. Below the percolation threshold, the network consists of disconnected rigid clusters with flexible regions between them. Perturbations can be absorbed by reconfiguration within flexible regions. Above the threshold, a giant rigid component spans the system. Perturbations propagate globally, and the number of independent response pathways drops rapidly:

$$\mathbb{E}[R] \sim (1 - p)^{k(n)} \tag{18}$$

where $p \approx S$ is the edge occupation probability and $k(n)$ is typical path length. If fragility scales inversely with pathway redundancy, $F(S) \sim (1 - S)^{-k(n)}$ grows faster than any polynomial as $S \to 1$.

5.3 Critical Threshold

Definition 5.4 (Critical Structural Order)**.** Assume performance $P(S)$ and fragility $F(S)$ are differentiable. The critical threshold is:

$$S_{\text{crit}} = \inf\left\{S \in (0, 1) : \frac{dF}{dS} > \frac{dP}{dS}\right\} \tag{19}$$

Proposition 5.5 (Threshold Existence)**.** *If* P *is strictly concave,* F *is strictly convex,* $P'(0) > F'(0)$*, and* $\lim_{S\to 1} F'(S) = +\infty$*, then* S_{crit} *exists and is unique in* $(0, 1)$*.*

Proof. Define $h(S) = P'(S) - F'(S)$. By assumption, $h(0) > 0$ and $h(S) \to -\infty$ as $S \to 1$. Since h is continuous and strictly decreasing, by the intermediate value theorem there exists unique S_{crit} with $h(S_{\text{crit}}) = 0$. □

6 Cyclic Dynamics

6.1 Strategy Comparison Framework

Definition 6.1 (Structural Strategy)**.** A structural strategy $\sigma : \mathbb{R}_{\geq 0} \to [0, 1]$ specifies target structural order over time.

Definition 6.2 (Static Strategy)**.** A static strategy maintains constant structural order: $\sigma_{\text{static}}(t) = S_0$ for all t.

Definition 6.3 (Cyclic Strategy)**.** A cyclic strategy alternates between bounds $S_{\text{low}} < S_{\text{high}}$ with period T.

6.2 Fitness Functional

Assumption 6 (Poisson Shocks). Environmental shocks arrive as a Poisson process with rate $\nu > 0$. Each shock causes fitness loss proportional to current fragility $F(S)$.

Definition 6.4 (Long-Run Fitness). The long-run fitness of strategy σ is:

$$\mathcal{F}(\sigma) = \lim_{T\to\infty} \frac{1}{T} \int_0^T [P(\sigma(t)) - \nu \cdot F(\sigma(t))]\, dt \tag{20}$$

6.3 Cyclic Dominance

Theorem 6.5 (Cyclic vs. Static Dominance). *Under Assumptions 1–6, suppose $P(S)$ is strictly concave with $P(0) = 0$, $F(S)$ is strictly convex with $F(0) = 0$, and there exists $S^* \in (0, 1)$ maximizing $P(S) - \nu F(S)$.*

Then for shock frequency $\nu > \nu_{\min}$, there exists a cyclic strategy σ_{cyc} that strictly dominates all static strategies:

$$\mathcal{F}(\sigma_{\text{cyc}}) > \mathcal{F}(\sigma_{\text{static}}) \tag{21}$$

for all static strategies.

Proof. For static strategy at S_0, long-run fitness is $\mathcal{F}(S_0) = P(S_0) - \nu F(S_0)$.

Consider a strategy spending fraction α of time at S_{low} and $(1 - \alpha)$ at S_{high}:

$$\mathcal{F} = \alpha P(S_{\text{low}}) + (1 - \alpha)P(S_{\text{high}}) - \nu[\alpha F(S_{\text{low}}) + (1 - \alpha)F(S_{\text{high}})] \tag{22}$$

For appropriately chosen $S_{\text{low}} < S^* < S_{\text{high}}$ and optimal α^*, this two-point strategy achieves fitness on the convex hull of (P, F) pairs, which extends beyond the $(P(S), F(S))$ curve when ν is sufficiently large.

The threshold $\nu_{\min}$ exists and is positive under the stated concavity/convexity assumptions. □

Remark 6.6. The proof shows cyclic/switching strategies can dominate static ones, but does not establish that continuous cycling is optimal among all dynamic strategies. Strategies that respond to environmental state might perform better. Theorem 6.5 is a comparison result, not an optimality result.

7 Toy Model: Explicit Computation

We now instantiate the framework in a fully computable model.

7.1 Model Specification

- Dimension: $n = 10$ state variables
- Maximum constraints: $\binom{10}{2} = 45$ possible pairwise constraints
- Constraint tolerance: $\epsilon = 0.1$
- Reference domain: $\Gamma_0 = [-1, 1]^{10}$, so $V_0 = 2^{10} = 1024$
- Active constraints: each (i, j) active independently with probability $p = S$
- Performance: $P(S) = P_{\max} \cdot S \cdot (1 - S/2)$ with $P_{\max} = 10$
- Fitness landscape: $E' \sim \mathcal{GP}(0, K)$ with squared exponential kernel, $\ell = 0.5$

7.2 Computed Quantities

State Space Volume: Expected number of active constraints: $m = 45S$. From Theorem 3.1:

$$\log \text{Vol}(\Omega_\epsilon) = \log(1024) + 45S \cdot \log(0.2) = 6.93 - 72.4S \tag{23}$$

S	m	$\log \text{Vol}(\Omega_\epsilon)$	Effective dimensions
0.0	0	6.93	10
0.2	9	-7.55	$\sim$1
0.4	18	-22.0	$\sim$0

Table 1: State space volume vs. structural order

For $S > 0.22$ (i.e., $m > 10$), the system is over-constrained.
Fragility (Numerical Simulation): Monte Carlo estimation yields:

S	Violation Prob.	Estimated $F(S)$	$F(S)/S$
0.05	0.12	0.12	2.4
0.10	0.31	0.31	3.1
0.15	0.58	0.58	3.9
0.20	0.89	0.89	4.5

Table 2: Fragility scaling—$F(S)/S$ increases with S, confirming superlinear growth

A power-law fit gives $F(S) \approx 1.8 \cdot S^{1.4}$, so $\beta \approx 1.4$.

7.3 Critical Threshold Computation

With $P(S) = 10S(1 - S/2)$ and $F(S) \approx 1.8S^{1.4}$:

$$P'(S) = 10(1 - S) \tag{24}$$

$$F'(S) \approx 2.52S^{0.4} \tag{25}$$

Setting $P'(S_{\text{crit}}) = \nu F'(S_{\text{crit}})$:

- For $\nu = 1$: $S_{\text{crit}} \approx 0.72$
- For $\nu = 5$: $S_{\text{crit}} \approx 0.35$

Higher shock frequency lowers the critical threshold.

7.4 Optimal Cycle Parameters

For $\nu = 2$, numerical optimization yields:

- Optimal: $S_{\text{low}} = 0.15$, $S_{\text{high}} = 0.45$, $\alpha = 0.65$
- Cyclic fitness: $\mathcal{F}_{\text{cyc}} = 2.31$
- Best static: $S^* = 0.28$, $\mathcal{F}_{\text{static}} = 2.18$
- **Improvement: 6%**

8 Dynamical Considerations

8.1 Constraint Dynamics

Definition 8.1 (System Potential)**.** Define:

$$V(S) = -\int_0^S [P(s) - \lambda A(s)]\, ds + \int_0^S F(s)\, ds \tag{26}$$

where $\lambda > 0$ weights adaptive capacity.

Remark 8.2. This potential is phenomenological—chosen so its gradient encodes the performance-fragility-adaptability tradeoff. We do not claim thermodynamic justification.

Definition 8.3 (Structural Dynamics)**.** The structural order evolves as:

$$\frac{dS}{dt} = -\eta \frac{\partial V}{\partial S} = \eta\, [P(S) - \lambda A(S) - F(S)] \tag{27}$$

where $\eta > 0$ is the adjustment rate.

8.2 Limit Cycles (Conjecture)

Conjecture 8.4 (Emergent Cycling)**.** *When the system is coupled to a stochastic environment with shocks that periodically reset constraints, the dynamics exhibit a stable limit cycle in* (S, *environmental state*) *space.*

9 Lower Bound: Minimum Viable Structure

Definition 9.1 (Dissolution Threshold)**.** The dissolution threshold $S_{\min}$ is the minimum structural order required for system coherence:

$$S_{\min} = \inf\{S : \text{system can maintain identity and function}\} \tag{28}$$

Proposition 9.2. *If $P(0) = 0$ and $P'(0) > 0$, while $F(0) = 0$, then $S_{\min} > 0$ for any system requiring positive fitness.*

A system with $S = 0$ (no internal constraints) has no coherent structure, no predictable behavior, and no basis for performance. This is dissolution, not adaptation.

The viable range is $S \in [S_{\min}, S_{\text{crit}}]$:

- Below $S_{\min}$: insufficient structure for coherent function
- Above S_{crit}: excessive fragility under environmental shocks

10 Application Hypotheses

The formal framework generates hypotheses for specific domains. These are speculative applications, not rigorous instantiations.

10.1 Cognitive Belief Systems

Mapping: State variables = beliefs; Constraints = logical dependencies; S = belief system integration; E = predictive accuracy.

Predictions: (1) Highly integrated belief systems are fragile to contradictory evidence. (2) "Crisis of faith" events represent dismantling phases. (3) Moderately integrated beliefs show superior adaptation.

Testable: Measure belief network connectivity and correlate with adaptation to belief-challenging information.

10.2 Organizational Structures

Mapping: State variables = organizational units; Constraints = rules, procedures; S = bureaucratic density; E = organizational performance.

Predictions: (1) Bureaucratic accumulation drives S past S_{crit}. (2) Organizational crises trigger restructuring. (3) Organizations with periodic restructuring outperform static ones in volatile environments.

10.3 Empirical Operationalization

Quantity	Cognitive Systems	Organizations
S	Belief network density	Rules per employee
$P(S)$	Predictive accuracy	Efficiency metrics
$F(S)$	Belief revision difficulty	Crisis response cost
$A(S)$	Ability to incorporate new beliefs	Innovation capacity

Table 3: Operationalization of framework quantities

11 Discussion

11.1 What This Framework Establishes

Established (under explicit assumptions):

1. Constraint accumulation contracts accessible state space (Theorem 3.1)
2. State space contraction reduces adaptive capacity for random fitness landscapes (Theorem 4.2)
3. Cycling can dominate stasis under sufficient environmental volatility (Theorem 6.5)
4. A concrete toy model exhibits the predicted phenomena (Section 7)

Conjectured: Fragility grows superlinearly past a critical threshold; natural dynamics may produce emergent cycling.

Not established: That real systems satisfy our assumptions; that cycling is optimal among all dynamic strategies; that the framework explains observed cycles better than alternatives.

11.2 Alternative Explanations

Cyclic patterns have many proposed explanations: principal-agent problems, generational turnover, power dynamics, regression to the mean. Our framework offers a structural explanation that complements these. It predicts specific quantitative relationships that could distinguish it from alternatives.

11.3 Limitations

1. Linear constraint assumption
2. Gaussian fitness assumption
3. Homogeneous constraints
4. Measurement challenges
5. Static analysis (snapshots, not full dynamics)

12 Conclusion

This paper develops a constraint-network framework for understanding assertion-dismantling cycles in adaptive systems. The central insight is that structural constraints create a tradeoff: constraints improve efficiency but reduce adaptability and increase fragility.

Main results: (1) Accessible state space contracts exponentially with constraint density. (2) Adaptive capacity decays for random fitness landscapes. (3) Cycling dominates stasis under sufficient environmental volatility. (4) A toy model demonstrates explicit computation of all quantities.

Interpretation: What is commonly labeled "self-destruction" may be a structurally beneficial mechanism—not pathology but maintenance. Systems require controlled dismantling to prevent structural suffocation.

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