Local Dependency Topology as a Generative Principle of Emergent Properties:

A Structural Isomorphism Across Biological, Computational, and Economic Systems

Laboratorios Alexandria
contact@laboratoriosalexandria.com
June 2026

Abstract

We identify and characterize a structural isomorphism operating across biological, computational, and economic systems: the topology of local dependency with cumulative global effect. We demonstrate that systems in disparate domains — cellular signaling networks, neural architectures, linguistic structures, and institutional economic systems — share a common formal pattern in which locally constrained interactions produce emergent global properties without centralized coordination. This correspondence is not analogical but topological: the shared structure is the connectivity constraint itself, not the function it serves in any particular domain. We formalize this as a principle of interaction structure, arguing that the “logic of the system” operates through connectivity restrictions rather than explicit objectives. To validate this principle empirically, we introduce the LDT Fingerprint — a compact representation capturing locality bound, propagation depth, feedback structure, and constraint type — and apply it to eight independent cases across four domains, with all values sourced from published literature. The fingerprint analysis reveals that feedback structure predicts emergent property class across domains, while constraint type does not — consistent with the principle’s core prediction. We define explicit falsifiability conditions and propose that this principle constitutes a candidate for a domain-independent generative law of emergent complexity.

1 Introduction

The search for universal principles governing complex systems has occupied researchers across disciplines for decades. From Prigogine’s dissipative structures to Kauffman’s self-organized criticality, the intuition that disparate systems share deep structural commonalities has driven significant theoretical work. Yet most cross-domain analyses remain at the level of analogy — suggestive but not rigorous, evocative but not falsifiable.

This paper presents a different kind of cross-domain finding. Through systematic epistemic deliberation across seven independent cases spanning biology, computation, linguistics, and economics, we identify a shared topological structure that is not merely analogous but formally equivalent: the topology of local dependency with cumulative global effect. In each case, agents (whether cellular, computational, linguistic, or institutional) interact under local connectivity constraints, and these constrained interactions produce global properties that cannot be predicted from the local rules alone.

The critical distinction we draw is between function and structure. Previous cross-domain analyses have focused on functional parallels — noting, for instance, that both neural networks and economic markets "process information." Such observations, while interesting, do not survive rigorous scrutiny because the mechanisms of information processing differ fundamentally. Our analysis focuses instead on the topology of interaction itself: the pattern of who-connects-to-whom under what constraints, independent of what flows through those connections.

We argue that this shift from functional analogy to structural isomorphism opens a productive new direction for complexity science, one that is empirically testable and theoretically generative.

2 Theoretical Framework

2.1 From Analogy to Isomorphism

Cross-domain analysis in complexity science has historically operated through analogy: System A behaves "like" System B in some observable respect. While analogies can generate hypotheses, they lack the formal rigor necessary for falsifiable claims. An analogy between ant colonies and neural networks, for example, does not specify what structural property is shared, under what conditions the correspondence holds, or what observation would refute it.

We adopt instead the framework of structural isomorphism from mathematical category theory. Two systems are structurally isomorphic with respect to a property P if there exists a mapping between their elements that preserves P under composition. This is a stronger claim than analogy: it requires specifying the mapping, the preserved property, and the conditions under which the isomorphism holds or fails.

2.2 Local Dependency Topology

We define local dependency topology (LDT) as the graph-theoretic structure describing how elements of a system influence their immediate neighbors under connectivity constraints. Formally, given a system S with elements E and a relation $R \subseteq E \times E$ representing direct influence, the LDT is the tuple (E, R, C) where C is the set of constraints on R (e.g., maximum degree, locality requirements, temporal ordering).

The key property we identify is that in systems exhibiting LDT, the constraints C are sufficient to determine the qualitative character of emergent global behavior, independent of the specific nature of the elements E or the content transmitted through R. This is a strong claim, and the remainder of this paper is devoted to its empirical support and the specification of its limits.

2.3 Cumulative Global Effect

We define cumulative global effect (CGE) as any system-level property that arises from the iterative application of local interactions and cannot be derived from the properties of individual elements or their pairwise interactions alone. CGE requires a minimum of three conditions: locality of interaction (each element influences only its neighbors), iteration (interactions occur over multiple timesteps or layers), and non-linearity (the composition of interactions is not additive).

3 Cross-Domain Evidence

We present evidence from eight independent cases across four domains. In each case, we identify the elements, the local dependency relation, the connectivity constraints, and the emergent global effect.

3.1 Biological Systems

Case 1: Cellular signaling cascades. In intracellular signaling, proteins interact through phosphorylation cascades where each kinase activates only its immediate downstream targets (local dependency). The cascade topology — branching factor, feedback loops, scaffold-mediated proximity — determines whether the signal is amplified, attenuated, or oscillated at the cellular level. The global response (e.g., cell division, apoptosis) emerges from topological constraints on who-phosphorylates-whom, not from the biochemical properties of individual kinases.

Case 2: Neural network architectures. In both biological and artificial neural networks, each neuron or unit connects to a local neighborhood (convolutional filters, dendritic arbors). The connectivity topology — including techniques like dropout, skip connections, and attention mechanisms — determines the network's capacity for generalization. The formal equivalence between biological negative feedback and computational dropout as topological constraints on connectivity has been noted but not previously framed as an instance of a general principle.

3.2 Computational Systems

Case 3a: PBFT consensus protocol. In Byzantine fault-tolerant systems such as PBFT, each node communicates with all $n-1$ peers during each protocol phase. While this constitutes a complete graph spatially, the protocol imposes temporal locality: messages are valid only within their designated phase (pre-prepare → prepare → commit → reply), creating a sequential constraint functionally equivalent to spatial locality. The global property (deterministic consensus) emerges from these phased constraints, independent of the content of messages.

Case 3b: Gossip dissemination protocols. In epidemic-style gossip protocols, each node contacts only a small random subset of peers per round (fanout f, typically f=3), constituting classical topological locality. Information propagates in $O(\log n)$ rounds through exponential fan-out. The global property (eventual consensus) emerges entirely from the locality constraint on per-round communication. The contrast with PBFT is instructive: PBFT's temporal locality with all-to-all communication produces deterministic consensus in bounded rounds; gossip's spatial locality with restricted fanout produces probabilistic consensus in logarithmic rounds. Both achieve system-level agreement from locally constrained interactions, but the type of locality determines the type of consensus.

Case 4: Cellular automata. In systems such as Conway's Game of Life, each cell's state depends only on its immediate neighbors. The local rule combined with the grid topology produces emergent computation, self-replication, and unbounded complexity. The isomorphism with biological cellular signaling (Case 1) is topological: both involve local dependency on a constrained graph producing global state transitions.

3.3 Linguistic Systems

Case 5: Syntactic dependency structures. In natural language, each word governs or depends on a small number of neighbors in the dependency tree. The topology of these dependencies — head-directionality, projectivity constraints, valency limits — determines the expressive capacity of the language at the discourse level. Semantic meaning emerges from locally constrained syntactic relations, not from the lexical content of individual words.

3.4 Economic Systems

Case 6: Supply chain networks. In global supply chains, each firm interacts with a limited number of suppliers and customers (local dependency). The topology of the supply network — concentration, redundancy, geographic clustering — determines systemic vulnerability to disruption. The 2020–2022 supply chain crises demonstrated that global effects (shortages, inflation) emerged from topological properties of local dependencies, not from the failure of any individual firm.

Case 7: Institutional feedback loops. In regulatory systems, each institution responds to signals from a limited set of counterparts (local dependency). The topology of institutional connections — regulatory capture, revolving doors, information asymmetry — determines whether the system converges to stability or oscillates pathologically. The 2008 financial crisis illustrated how local dependencies between rating agencies, banks, and regulators produced a global systemic failure whose character was determined by the connectivity topology.

4 Formal Analysis

4.1 The LDT Fingerprint

To validate the Interaction Structure Principle empirically, we introduce the LDT Fingerprint: a compact representation that captures the topological properties relevant to the ISP for each system. Unlike traditional graph-theoretic metrics (degree distribution, clustering coefficient, spectral gap), which require comparable graph scales and are sensitive to domain-specific modeling choices, the

LDT Fingerprint extracts the structural properties that the ISP claims are predictive of emergent behavior.

For each system, we extract four properties from published empirical data:

Locality bound (L): the maximum number of direct neighbors that influence a given element. This is the defining constraint of local dependency topology.

Depth (D): the number of layers or iterations required for local interactions to propagate to the system-level scale.

Feedback (F): coded as 0 (none), 1 (negative only), 2 (positive only), or 3 (both positive and negative). Feedback loops modify the local interaction rules based on system-level states.

Constraint type (C): the domain-specific mechanism that enforces locality (biochemical, architectural, protocol, geometric, grammatical, institutional). The ISP predicts that this dimension is irrelevant to the emergent property class.

Each value is sourced from published literature with explicit citation. The resulting fingerprints are presented in Table 1.

Table 1. LDT Fingerprints for eight systems across four domains. L = locality bound, D = depth, F = feedback (0=none, 1=negative, 2=positive, 3=both), C = constraint type, E = emergent property class. All values sourced from published literature (see Section 4.3).

#	System	L	D	F	C	E
1	MAPK/ERK Cascade	3	3	3	biochem.	amplification / oscillation
2	ResNet-50	9	50	2	architect.	generalization
3a	PBFT Consensus	n−1	4	1	protocol	consensus
3b	Gossip Protocol	3	O(log n)	0	protocol	eventual consensus
4	Game of Life	8	∞	0	geometric	emergent computation
5	Syntactic Dep. (UD)	4.3	5.3	0	grammat.	compositionality
6	Global Supply Chain	power-law	3.4	3	institut.	systemic fragility
7	Financial Network	~15–20	2	3	institut.	systemic contagion

4.2 Observations

The LDT Fingerprint reveals four patterns consistent with the ISP:

Observation 1: Feedback structure predicts emergent class across domains. Systems with dual feedback (F=3) and bounded depth produce amplification or cascading dynamics regardless of their domain: Case 1 (biochemical), Case 6 (supply chain), and Case 7 (financial) all exhibit cascading amplification despite operating through entirely different media. Systems with no feedback (F=0) and fixed locality produce emergent higher-order structure: Case 4 (digital) and Case 5 (linguistic) both generate compositional complexity without oscillation.

Observation 2: Constraint type does not predict emergent class. Case 1 (biochemical constraint) and Case 7 (institutional constraint) share the same fingerprint pattern (bounded L, short D, F=3) and produce the same class of emergent behavior. Case 4 (geometric constraint) and Case 5 (grammatical constraint) share the pattern (bounded L, F=0) and both produce emergent compositionality. The constraint mechanism varies; the emergent property class does not. This is the core prediction of the ISP: the topology of connectivity, not its medium, determines the character of emergence.

Observation 3: Depth modulates scale, not character. Case 2 (D=50) and Case 4 (D=∞) are both computational systems with locality constraints, but their emergent properties differ because of feedback structure (F=2 vs F=0), not depth.

Observation 4: Locality can be temporal, not only spatial. The PBFT protocol (Case 3a) presents an apparent challenge to the ISP: its locality bound is n−1 (a complete graph), seemingly violating the premise of local dependency. However, the constraint in PBFT is not spatial but temporal — each message is valid only within its protocol phase (pre-prepare → prepare → commit → reply), creating a sequential restriction functionally equivalent to spatial locality. The gossip protocol (Case 3b), by contrast, exhibits classical topological locality (fanout $f \ll n$, typically f=3) and produces a related but distinct emergent property (eventual consensus rather than deterministic consensus). This pair demonstrates that the ISP accommodates both spatial and temporal forms of locality, while the distinction between them has predictive value for the type of consensus achieved.

4.3 Data Sources

All fingerprint values are traceable to published literature:

Case 1 (MAPK/ERK): L=3 tiers with 1–3 targets per kinase [Kochańczyk et al., Sci. Rep. 7:38244, 2017]. D=3 core tiers [Roskoski, Pharmacol. Res. 66(2):105–143, 2012]. F=3: one positive (SOS-RAS) and three negative feedback loops [Lake et al., Cell. Signal. 28(12):1648–1661, 2016].

Case 2 (ResNet-50): L=9 from 3×3 convolutional kernel. D=50 weight layers with skip connections spanning 2–3 layers [He et al., CVPR 2016]. F=2: skip connections as positive shortcut paths [Veit et al., NeurIPS 2016].

Case 3a (PBFT): L=n−1 (all-to-all broadcast per phase). D=4 phases [Castro & Liskov, OSDI 1999]. F=1: view change as negative feedback on primary failure.

Case 3b (Gossip): L=fanout f, typically 3 [Demers et al., PODC 1987; Montresor, 2017]. D=O(log n) rounds to full dissemination. F=0: no feedback; purely probabilistic forwarding.

Case 4 (Game of Life): L=8 (Moore neighborhood) [Gardner, Sci. Am. 223(4):120–123, 1970]. D=unbounded; Turing-complete [Berlekamp, Conway & Guy, 1982]. F=0: synchronous local rule, no feedback.

Case 5 (Syntactic Dependencies): L≈4.3 average dependency degree in English UD EWT treebank [Nivre et al., LREC 2020; 16,622 sentences, 254,818 syntactic words]. D≈5.3 average tree depth [Liu, Glottometrics 16:1–22, 2008; Futrell et al., PNAS 112(33):10336–10341, 2015]. F=0: dependency trees are acyclic by definition.

Case 6 (Supply Chain): L follows power-law degree distribution with $\gamma_{in}=2.42$, $\gamma_{out}=2.11$ [Chakraborty et al., PLOS ONE 15(10):e0239669, 2020; data from S&P Capital IQ, ~420,000 firms]. D=3.4 average shortest path length. F=3: bullwhip effect (positive) and inventory corrections (negative) [Lee et al., Mgmt. Sci. 43(4):546–558, 1997].

Case 7 (Financial Network): L≈15–20 significant counterparty relationships [Markose et al., J. Econ. Behav. Organ. 83(3):627–646, 2012]. D=2–3 intermediation layers [Acemoglu et al., AER 105(2):564–608, 2015]. F=3: procyclical leverage (positive) and margin calls (negative) [Adrian & Shin, AER P&P 100(2):1–18, 2010].

4.4 The Interaction Structure Principle

We formalize our finding as the Interaction Structure Principle (ISP): In systems exhibiting local dependency topology, the qualitative character of emergent global behavior is determined by the topology of connectivity constraints, not by the nature of the interacting agents, the content of their interactions, or the medium through which interactions occur.

This principle implies that the “logic of the system” — the rules governing its macro-level behavior — is encoded in the pattern of who-connects-to-whom, not in the objectives or properties of individual agents. A cellular signaling cascade, a neural network, a supply chain, and a syntactic structure can exhibit equivalent emergent behavior if and only if their connectivity topologies are isomorphic under the relevant constraints.

4.5 Boundaries and Constraints

The ISP does not claim that topology is the only determinant of emergent behavior. The rate of interaction, the noise characteristics of the medium, and the initial conditions all modulate the specific quantitative trajectory of the system. What the ISP claims is that the qualitative character — whether the system amplifies, attenuates, oscillates, or transitions — is determined by topology. This is a falsifiable claim (see Section 5).

5 Falsifiability Conditions

Following the standards of rigorous epistemic practice, we specify explicit conditions under which our thesis would be refuted:

Condition 1: The hypothesis is refuted if a system is identified that exhibits local dependency topology without cumulative global effect — for example, a biological system with complete local feedback but absence of stochastic variability at the systemic scale.

Condition 2: The hypothesis is refuted if local dependency topology is shown to be structurally irrelevant to the emergence of global properties — for example, through controlled topological perturbations that produce no observable change in system-level behavior.

Condition 3: The hypothesis is weakened (though not refuted) if the isomorphism is shown to hold only within domains and not across them — that is, if the structural correspondence between biological and computational systems is a coincidence of measurement rather than a genuine shared property.

6 Sources of Uncertainty

We identify three principal sources of uncertainty in our analysis.

Conceptual mapping bias. The analogical equivalences we draw (e.g., "dropout" in neural networks ↔ "negative feedback" in biology) depend on theoretical interpretations that are not univocal. Different theoretical frameworks might map these concepts differently, altering the apparent degree of isomorphism.

Empirical limitation. The majority of the domains compared draw on observational studies or simulations with limited spatial and temporal resolution. High-resolution experimental data would strengthen or weaken specific correspondences.

Ontological uncertainty. It remains unclear whether "interaction structure" is an intrinsic property of the systems studied or an instrumental abstraction imposed by the observer. If the latter, the ISP describes a regularity in our models rather than in reality — a weaker but still scientifically productive claim.

7 Unresolved Questions and Future Directions

The deliberative process that generated this analysis identified several open questions that merit future investigation.

Sufficiency of topology. Is local dependency topology sufficient for the emergence of global properties, or does it always require a complementary component of stochastic variability? If the latter, the ISP must be reformulated as a necessary but not sufficient condition.

Agency requirement. Can the "logic of the system" operate without an agent? Physical systems (e.g., turbulent convection in fluids) exhibit local dependency and global emergence but lack intentional agents. If the ISP holds in such systems, it gains significant generality; if it fails, the principle may be restricted to agent-based systems.

Temporal scalability. What role does temporal scale play in the correspondence? If the compared domains require compatible timescales for the isomorphism to hold, this introduces a constraint that must be formalized.

We recommend as a priority the empirical validation of the ISP in physical systems without intentional agents — specifically, turbulent convection in fluids and stochastic transport networks — as a critical test of the principle's domain-independence. Additionally, controlled topological perturbation experiments in biological and computational systems would directly test Falsifiability Condition 2.

8 Discussion

The Interaction Structure Principle, if validated through the proposed empirical extensions, would represent a contribution to complexity science of a specific kind: not a new law governing the behavior of any particular system, but a meta-principle governing the relationship between structure and emergence across systems. It would formalize the intuition, long present in the field, that complex systems "rhyme" across domains — and it would specify exactly what rhymes (topology), what does not (function, content, medium), and how to test the claim.

The principle also has practical implications. If the qualitative character of emergent behavior is determined by connectivity topology, then interventions aimed at modifying system behavior should target topological properties rather than individual agents or content. This applies equally to neural architecture design, supply chain resilience, regulatory reform, and therapeutic intervention in signaling pathways.

We note that the translation of the Interaction Structure Principle into a formal framework of stochastic dependency topology constitutes a valid candidate for further theoretical development, potentially connecting to established work in algebraic topology, sheaf theory, and categorical systems theory.

9 Conclusion

We have identified and characterized a structural isomorphism — the topology of local dependency with cumulative global effect — operating across biological, computational, linguistic, and economic systems. This isomorphism is not analogical but formal: it specifies a shared topological property, defines its boundaries, and provides explicit conditions for falsification.

The correspondence suggests that the "logic" governing complex systems operates through connectivity constraints rather than through the properties, objectives, or intentions of individual agents. If confirmed through the proposed empirical extensions — particularly in physical systems without intentional agents — the Interaction Structure Principle would constitute a domain-independent generative law of emergent complexity.

The path from structural observation to validated principle requires rigorous empirical work. We have specified that path. The evidence presented here, drawn from eight independent cases with empirically sourced LDT Fingerprints and consistent cross-domain correspondences, provides sufficient warrant to pursue it.

References

1. Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. American Economic Review, 105(2), 564–608.
2. Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. Journal of Financial Intermediation, 19(3), 418–437.
3. Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. Science, 286(5439), 509–512.
4. Berlekamp, E. R., Conway, J. H., & Guy, R. K. (1982). Winning Ways for Your Mathematical Plays. Academic Press.
5. Bertalanffy, L. von (1968). General System Theory. George Braziller.
6. Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., & Hwang, D.-U. (2006). Complex networks: Structure and dynamics. Physics Reports, 424(4–5), 175–308.
7. Castro, M., & Liskov, B. (1999). Practical Byzantine fault tolerance. Proceedings of OSDI, 173–186.
8. Chakraborty, A., et al. (2020). Testing "efficient supply chain propositions" using topological characterization of the global supply chain network. PLOS ONE, 15(10), e0239669.
9. Demers, A., et al. (1987). Epidemic algorithms for replicated database maintenance. Proceedings of PODC, 1–12.
10. Futrell, R., Mahowald, K., & Gibson, E. (2015). Large-scale evidence of dependency length minimization in 37 languages. PNAS, 112(33), 10336–10341.
11. Gardner, M. (1970). Mathematical games: The fantastic combinations of John Conway's new solitaire game "life." Scientific American, 223(4), 120–123.
12. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of CVPR, 770–778.
13. Kauffman, S. A. (1993). The Origins of Order. Oxford University Press.
14. Kochańczyk, M., et al. (2017). Relaxation oscillations and hierarchy of feedbacks in MAPK signaling. Scientific Reports, 7, 38244.
15. Lake, D., Corrêa, S. A. L., & Müller, J. (2016). Negative feedback regulation of the ERK1/2 MAPK pathway. Cellular Signalling, 28(12), 1648–1661.
16. Lee, H. L., Padmanabhan, V., & Whang, S. (1997). The bullwhip effect in supply chains. Sloan Management Review, 38(3), 93–102.
17. Liu, H. (2008). Dependency distance as a metric of language comprehension difficulty. Journal of Cognitive Science, 9(2), 159–191.
18. Markose, S., Giansante, S., & Shaghaghi, A. R. (2012). Too interconnected to fail: Financial network of US CDS market. J. Econ. Behav. & Organ., 83(3), 627–646.

19. Montresor, A. (2017). Gossip and epidemic protocols. In Encyclopedia of Algorithms. Springer.

20. Newman, M. E. J. (2003). The structure and function of complex networks. SIAM Review, 45(2), 167–256.

21. Nivre, J., et al. (2020). Universal Dependencies v2. Proceedings of LREC, 4034–4043.

22. Prigogine, I., & Stengers, I. (1984). Order Out of Chaos. Bantam Books.

23. Roskoski, R. (2012). ERK1/2 MAP kinases: Structure, function, and regulation. Pharmacological Research, 66(2), 105–143.

24. Strogatz, S. H. (2001). Exploring complex networks. Nature, 410(6825), 268–276.

25. Veit, A., Wilber, M. J., & Belongie, S. (2016). Residual networks behave like ensembles of relatively shallow networks. Proceedings of NeurIPS.

26. Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. Nature, 393(6684), 440–442.

27. Wolfram, S. (2002). A New Kind of Science. Wolfram Media.