Entropy, Intelligence, and the Emergence of Knowledge: A Conceptual Framework for Life, AI, and Epistemic Capacity in the Universe

Aslan Alwi[1,2], Munirah Munirah[1,2], and Almudaya Research Institute Team[1]

[1]Independent Researcher at Almudaya Research Institute, Yogyakarta, Indonesia

[2]Department of Informatics Engineering, Faculty of Engineering, Universitas Muhammadiyah Ponorogo, Indonesia, *Correspondence email*: aslan.alwi@umpo.ac.id

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Abstract

The emergence of life, intelligence, and knowledge in the universe is often discussed as a contingent outcome of physical laws and initial conditions, while entropy is traditionally framed as a force opposing order and meaning. In this work, we propose a unifying conceptual framework in which entropy plays a foundational and enabling role in the emergence of epistemic systems. We argue that universes characterized by sufficiently high—but non-maximal—entropy provide the necessary space of possibilities for life to arise as a dissipative structure, for intelligence to emerge as an adaptive mechanism navigating uncertainty, and for knowledge to develop as structured and compressible uncertainty.

By synthesizing insights from non-equilibrium thermodynamics, complexity science, information theory, and artificial intelligence, we introduce the notion of *epistemic capacity*: the maximum amount of knowledge that can be represented, stabilized, and utilized within a universe. We show that epistemic capacity is constrained by the entropic structure of the universe and is maximized in intermediate-to-high entropy regimes near the edge of chaos. Artificial intelligence systems are discussed as contemporary empirical illustrations of these principles, highlighting both the necessity of entropic richness and the existence of fundamental epistemic limits.

This framework reframes entropy not as the enemy of order, intelligence, or meaning, but as their precondition. The results have implications for cosmology, artificial intelligence, and epistemology, suggesting that meaningful knowledge arises not despite entropy, but because of it.

Keywords: Entropy; Complexity; Emergence of Life; Intelligence; Artificial Intelligence; Knowledge; Epistemic Capacity; Non-equilibrium Thermodynamics; Information Theory

- Entropy is framed as an enabling condition for life, intelligence, and knowledge.
- Life emerges as a dissipative structure sustained by entropy gradients.
- Intelligence is interpreted as an adaptive mechanism for navigating large possibility spaces.
- Knowledge is defined as structured and compressible uncertainty.
- The concept of epistemic capacity links cosmological entropy to limits of knowledge.

1 Introduction

The emergence of life and intelligence in the universe is a central problem that spans physics, biology, complexity science, and epistemology. Classical thermodynamics frames entropy as a quantitative tendency toward macrostate multiplicity; popular intuition often treats entropy as antagonistic to order and meaning. Yet developments in non-equilibrium thermodynamics and complexity theory reveal a subtler relation: entropy gradients and non-equilibrium conditions enable the formation and persistence of richly structured systems ("dissipative structures") rather than merely destroying order Nicolis and Prigogine, 1977; Prigogine and Stengers, 1984.

Concurrently, contemporary artificial intelligence—especially statistical and data-driven approaches—thrives on diversity, noise, and large possibility spaces. Modern machine learning models are inferential engines: they induce representations by compressing high-dimensional, stochastic data into structured internal models. In other words, the practical conditions that permit high-performing AI systems appear to require an environment with significant informational richness (a high-entropy data manifold) rather than a low-entropy, near-deterministic environment.

This paper advances the following thesis: *universes with sufficiently high (but non-maximal) entropy provide the combinatorial richness needed for the emergence of life, intelligence, and knowledge-bearing systems, including artificial intelligence.* Entropy should be read not solely as a destructive tendency but as part of an ontological substrate that enables complexity and epistemic development. We will synthesize thermodynamic, informational, and computational perspectives to show (a) why life and intelligence are most probable in an "edge-of-chaos" regime, and (b) how the entropic structure of a universe constrains its maximal epistemic capacity.

The argument proceeds through the following logical steps. First, we review core theoretical foundations concerning entropy, non-equilibrium self-organization, and complexity (Section 2). Second, we analyze how entropic regimes relate to the emergence and maintenance of life (Section 4) and to the rise of intelligence in both biological and artificial forms (Section 5). Third, we discuss implications for theories of knowledge and epistemic limits (Section 6) and conclude with directions for formal models and empirical tests.

2 Background and Conceptual Foundations

This section collects key theoretical concepts supporting the central thesis: (1) the statistical nature of entropy and its relation to possibility spaces; (2) non-equilibrium thermodynamics and the logic of dissipative self-organization; (3) the 'edge-of-chaos' regime in complex systems; and (4) information-theoretic views of intelligence and learning.

2.1 Entropy as a Measure of Possibility

Shannon's information-theoretic entropy formalizes uncertainty as the expectation of "surprisal" and provides a rigorous link between probability distributions and information content Shannon, 1948. In statistical mechanics, Boltzmann entropy $S = k_B \ln \Omega$ quantifies the logarithm of the number Ω of microstates compatible with a macrostate. Both perspectives highlight entropy as a measure of the *size of the possibility space* rather than merely "disorder." Thus, systems embedded in high-entropy contexts live within a broader combinatorial landscape of potential states; this abundance of microstates is a precondition for diverse dynamical trajectories and complex emergent phenomena.

2.2 Non-equilibrium Thermodynamics and Dissipative Structures

Prigogine and collaborators showed that systems far from thermodynamic equilibrium can spontaneously generate and maintain ordered structures by exchanging energy and matter with their environment Nicolis and Prigogine, 1977; Prigogine and Stengers, 1984. These *dissipative structures* (e.g., convection cells, reaction–diffusion patterns) are sustained by continuous entropy production—paradoxically, their persistence relies on net entropy increase at the environment scale. The work of Prigogine reframes living systems not as violations of the second law but as natural exploiters of entropy gradients.

Empirical and theoretical studies in chemistry (e.g., the Belousov–Zhabotinsky oscillators, reaction–diffusion systems) and fluid dynamics (Bénard convection) provide canonical instances of order emerging under non-equilibrium conditions Epstein, 2006. These physical examples establish a mechanistic plausibility: when constraints (energy fluxes, catalytic networks, boundary conditions) are present, large possibility spaces can be funneled to produce stable, information-rich structures.

2.3 Complexity and the "Edge of Chaos"

The "edge of chaos" hypothesis posits that maximal computational and adaptive capability in dynamical systems occurs at a critical transition regime between order and disorder Langton, 1990. In cellular automata and other abstract models, systems near this transition exhibit long-range correlations, persistent structures, and rich information-processing capacities. Stuart Kauffman and others have argued similarly that evolutionary search and robust adaptation thrive in regimes that are neither rigidly ordered nor utterly random Kauffman, 1993.

Operationally, the edge-of-chaos idea suggests a non-monotonic relation between environmental entropy and the probability of complex emergent phenomena: both too little and too much accessible microstate richness hinder the formation and maintenance of adaptive structures. This non-monotonicity is central to our thesis: there exists an entropic band in which the co-evolution of structure and information is most probable.

2.4 Information, Inference, and Intelligence

Shannon's framework links entropy to channel capacity and compressibility, but intelligence—biological or artificial—functions as an *inference engine* that reduces uncertainty by constructing models of regularities in data. Bayesian perspectives on cognition, probabilistic graphical models, and contemporary deep learning are all instances of statistical inference: they exploit structured variability to compress, generalize, and predict Bengio et al., 2013; Pearl, 1988.

From this vantage, intelligence requires:

- **Sufficient variability** in observations to support generalization beyond trivial mappings.
- **Persistence and memory** to accumulate and refine internal models.
- **Mechanisms for isolation/selection** that stabilize useful structures against noise.

An environment with adequate entropic richness but with exploitable regularities is therefore the natural substrate for intelligence. Modern AI systems (e.g., large-scale neural networks) empirically confirm this: performance scales with the diversity and size of training data and with the model's capacity to compress statistical regularities Bengio et al., 2013; Goodfellow et al., 2016.

3 Related Works: Entropy, Life, Intelligence, and Knowledge

The relationship between entropy and organization has evolved significantly since early thermodynamic interpretations. While entropy was once regarded as antithetical to order, modern frameworks emphasize its role in enabling complex structures under non-equilibrium conditions Nicolis and Prigogine, 1977; Prigogine and Stengers, 1984.

In astrobiology and origins-of-life research, increasing attention has been paid to the role of entropy gradients and energy fluxes as prerequisites for life. England demonstrated that driven systems can undergo "dissipative adaptation," spontaneously forming structures that enhance entropy production England, 2013, 2015. This result provides a statistical-mechanical grounding for the emergence of self-replication without invoking teleological principles.

From a computational perspective, Langton's "edge of chaos" hypothesis Langton, 1990 and Kauffman's work on self-organizing systems Kauffman, 1993 establish that adaptive and information-processing capabilities peak at intermediate regimes between order and disorder. These findings bridge physical entropy and computational capacity.

Recent work by Walker and Davies Walker and Davies, 2013 reframes life as an informational and algorithmic process rather than merely a biochemical one. This aligns naturally with probabilistic artificial intelligence, where learning is framed as inference over high-entropy data distributions Bengio et al., 2013; Goodfellow et al., 2016.

Despite these advances, few studies explicitly integrate entropy, life, intelligence, and epistemic capacity into a single conceptual framework. The present work addresses this gap by proposing entropy as a unifying constraint governing the probability of life, the necessity of intelligence, and the upper bounds of knowledge in a universe.

4 Entropy and the Emergence of Life

Life is often described as a local decrease in entropy; however, this description is incomplete without reference to non-equilibrium conditions. Living systems do not violate the second law of thermodynamics; instead, they exploit entropy gradients to maintain localized order while increasing global entropy.

4.1 Life as a Dissipative Structure

Prigogine's framework of dissipative structures provides a natural thermodynamic basis for life Nicolis and Prigogine, 1977. Under continuous energy flow, systems can self-organize into stable, far-from-equilibrium states. Biological organisms exemplify such states: they persist by metabolizing energy, exporting entropy, and maintaining internal structure.

England extended this perspective by demonstrating that driven molecular systems statistically favor configurations that dissipate energy more effectively England, 2013. This suggests that self-replication and metabolic cycles may arise not as rare accidents but as probable outcomes in sufficiently driven, high-entropy environments.

4.2 Entropy, Variation, and Evolution

Evolution by natural selection presupposes variation. Entropy provides the combinatorial substrate for such variation by enabling a large space of microstates and phenotypic possibilities. In environments with insufficient entropy, evolutionary exploration collapses into trivial dynamics. Conversely, in excessively disordered environments, selection cannot stabilize heritable structures.

Thus, evolutionary viability is maximized in an intermediate-to-high entropy regime, consistent with edge-of-chaos arguments Kauffman, 1993; Langton, 1990.

4.3 Implications for Astrobiology

From an astrobiological standpoint, this framework implies that habitability is not solely determined by temperature or chemical composition, but by the presence of sustained entropy gradients. Planets or environments with weak gradients may remain sterile, while those with excessively violent fluctuations may fail to support persistent organization.

Life, therefore, is not merely compatible with entropy—it is statistically favored by specific entropic conditions. This observation reframes the anthropic question: the universe permits life not in spite of entropy, but because of it.

5 Entropy and the Emergence of Intelligence

If life can be understood as a dissipative structure sustained by entropy gradients, intelligence may be understood as an adaptive mechanism for navigating large spaces of possibilities. Intelligence does not arise in environments that are fully deterministic, nor can it function in environments that are maximally random. Instead, intelligence emerges as a response to structured uncertainty—an environment rich enough to require inference, yet stable enough to permit learning.

5.1 Intelligence as Navigation of Possibility Space

At its core, intelligence is the capacity to reduce uncertainty by constructing internal models of external regularities. This process presupposes the existence of a sufficiently large space of possibilities from which meaningful patterns can be inferred. In low-entropy environments, behavior can be rigidly pre-programmed; inference and learning confer little advantage. Conversely, in environments with overwhelming entropy and no persistent structure, inference collapses due to the absence of stable regularities.

Thus, intelligence is most adaptive in environments characterized by intermediate-to-high entropy, where:

- variability is sufficient to demand generalization,
- regularities are persistent enough to be learnable,
- and uncertainty cannot be eliminated by fixed rules.

This framing aligns naturally with the "edge of chaos" hypothesis, which posits that maximal computational and adaptive capacities arise near critical transitions between order and disorder Kauffman, 1993; Langton, 1990.

5.2 Biological Intelligence and Entropic Environments

Biological intelligence evolved under conditions of environmental uncertainty. Sensory ambiguity, fluctuating resources, and incomplete information created selection pressures favoring organisms capable of inference, prediction, and abstraction. Neural systems can be understood as probabilistic processors that compress sensory input into predictive internal representations.

The Bayesian brain hypothesis formalizes this idea, proposing that cognition operates as probabilistic inference over uncertain sensory data Pearl, 1988. From this perspective, biological intelligence is inseparable from entropy: without uncertainty, there is nothing to infer; without structure, inference is impossible.

5.3 Artificial Intelligence as an Entropy-Harnessing System

Modern artificial intelligence systems provide an empirical demonstration of the entropic prerequisites of intelligence. Machine learning models—particularly deep neural networks—derive their power from exposure to vast, diverse, and noisy datasets. Their objective is not to eliminate entropy, but to harness it: learning corresponds to identifying compressible structure within high-entropy data distributions.

Empirical results in representation learning show that model performance scales with data diversity, model capacity, and the richness of statistical structure in the environment Bengio et al., 2013; Goodfellow et al., 2016. In contrast, in low-entropy synthetic environments, learning degenerates into trivial memorization or rule execution.

This observation has a critical implication: artificial intelligence is not merely enabled by computation, but by the entropic richness of the informational environment. AI systems are unlikely to emerge—or to be useful—in universes with narrow possibility spaces and deterministic dynamics.

5.4 Entropy, Generalization, and the Limits of Intelligence

Generalization—the ability to apply learned knowledge to novel situations—is the defining hallmark of intelligence. Generalization requires both:

- diversity of training instances (entropy),
- and constraints that stabilize abstractions (structure).

Excessive entropy undermines generalization by flooding learning systems with noise, while insufficient entropy prevents abstraction by limiting variability. The balance between these forces determines not only whether intelligence can emerge, but how powerful it can become.

We therefore propose that the maximal achievable intelligence in a universe is bounded by its entropic structure. Intelligence emerges as a necessary adaptation only when the complexity of the environment exceeds the capacity of fixed behavioral strategies.

5.5 Implications for Universes with Different Entropic Regimes

Consider three idealized entropic regimes:

1. **Low-entropy universes:** Highly deterministic environments in which behavior can be fully specified by static rules. Intelligence provides little adaptive advantage.
2. **High-entropy universes:** Environments dominated by noise and instability, where persistent structure is absent and learning cannot converge.
3. **Intermediate-to-high entropy universes:** Environments with sufficient variability and stability to support inference, learning, and abstraction.

Only the third regime supports the emergence of intelligence as a meaningful phenomenon. This observation suggests that intelligence is not an inevitable feature of all universes, but a contingent outcome of specific entropic conditions.

5.6 Intelligence as an Epistemic Consequence of Entropy

From the above analysis, intelligence appears not as a fundamental property, but as an epistemic consequence of entropy. Where entropy creates expansive possibility spaces with exploitable regularities, intelligence becomes the mechanism by which systems survive, adapt, and eventually produce knowledge.

In this sense, intelligence is best understood as a response to entropy—not its negation. Entropy creates the problem space; intelligence evolves as the solution.

6 Entropy and the Limits of Knowledge

If life emerges as a dissipative structure and intelligence emerges as an adaptive response to structured uncertainty, then knowledge may be understood as entropy that has been partially tamed, compressed, and stabilized. Knowledge is not the elimination of uncertainty, but its organization into forms that are usable, transmissible, and predictive. This section argues that the entropic structure of a universe places fundamental constraints on the maximum knowledge that can be attained within it.

6.1 Knowledge as Structured Uncertainty

From an information-theoretic perspective, knowledge can be viewed as the reduction of uncertainty through encoding, modeling, and abstraction. Shannon entropy quantifies uncertainty, while meaningful information arises when uncertainty is reduced in a structured manner Shannon, 1948. Importantly, complete elimination of uncertainty is neither achievable nor desirable: without uncertainty, there is nothing to learn.

Scientific theories, mathematical models, and learned representations are all instances of structured compression. They map vast spaces of possible observations onto compact descriptions that preserve predictive power. In this sense, knowledge is not opposed to entropy; it is entropy constrained by form.

6.2 Epistemic Capacity and Entropic Constraints

We introduce the notion of *epistemic capacity*: the maximum amount of knowledge that can be represented, stored, and utilized by agents within a universe. Epistemic capacity depends on:

- the size of the universe's possibility space (entropy),
- the stability of regularities within that space,
- and the resources available for representation and memory.

In low-entropy universes, epistemic capacity is limited by triviality: the space of possible states is too small to support rich knowledge. In maximally high-entropy universes, epistemic capacity is limited by instability: patterns dissolve before they can be encoded or transmitted. Only in intermediate-to-high entropy universes does epistemic capacity reach significant levels.

6.3 Knowledge, Prediction, and Temporal Depth

Knowledge is intrinsically temporal. It enables prediction by leveraging regularities that persist over time. This temporal depth requires a balance between change and continuity. Entropy provides change; structure provides continuity. If entropy dominates completely, temporal coherence collapses; if structure dominates absolutely, novelty disappears.

This balance mirrors results in algorithmic information theory, where meaningful descriptions are neither maximally compressible (trivial) nor maximally incompressible (random). Knowledge resides in the intermediate regime where partial compression is possible Kauffman, 1993.

6.4 Artificial Intelligence and Epistemic Scaling

Artificial intelligence systems highlight the dependence of knowledge on entropy at scale. Large language models, for example, do not store facts explicitly; they encode statistical regularities across immense, high-entropy corpora. Their apparent "knowledge" arises from the compression of linguistic and conceptual distributions into parameterized representations.

However, such systems also reveal epistemic limits. Beyond a certain scale, additional entropy (data) yields diminishing returns unless accompanied by corresponding increases in model capacity, architectural constraints, and inductive biases Bengio et al., 2013; Goodfellow et al., 2016. This suggests that epistemic growth is jointly constrained by entropy and structure.

6.5 Fundamental Limits to Knowledge

The analysis above implies that there are fundamental limits to knowledge that are not merely technological but cosmological. These limits arise from:

- finite memory and computational resources,
- irreducible uncertainty in high-entropy systems,
- and the instability of patterns beyond certain entropic thresholds.

Thus, even in universes that support intelligence and knowledge, complete knowledge is unattainable. Knowledge is necessarily provisional, probabilistic, and context-dependent.

This conclusion aligns with contemporary views in philosophy of science, which reject the notion of final, complete theories in favor of progressively refined models.

6.6 Entropy as the Ground of Meaningful Knowledge

Paradoxically, the same entropy that limits knowledge also makes it meaningful. In a universe without uncertainty, knowledge would be redundant; in a universe without structure, knowledge would be impossible. Meaningful knowledge arises precisely because entropy is neither absent nor overwhelming.

We therefore conclude that entropy is not merely a physical constraint but an epistemic condition. It defines both the possibility and the limits of knowing.

7 Implications and Discussion

The framework developed in the preceding sections carries implications that extend beyond any single discipline. By positioning entropy as a unifying constraint for life, intelligence, and knowledge, the present analysis reframes several longstanding debates in cosmology, artificial intelligence, and epistemology. This section discusses these implications and clarifies the scope and limits of the proposed framework.

7.1 Cosmological Implications and Anthropic Reasoning

In cosmology, the apparent fine-tuning of physical constants is often discussed in anthropic terms: the universe must permit observers for observations to exist. The present framework refines this reasoning by emphasizing not merely the permissibility of observers, but the entropic conditions required for epistemic agents capable of knowledge.

A universe that permits stable matter but lacks sufficient entropy gradients may support structure without cognition. Conversely, a universe with extreme entropy may permit transient complexity without stable observers. The emergence of observers capable of knowledge therefore requires a narrower entropic window than habitability alone. This suggests that epistemic capacity—not merely life—should be considered in anthropic analyses.

7.2 Implications for Artificial Intelligence

The framework has direct implications for artificial intelligence research. First, it clarifies why contemporary AI systems depend critically on large, diverse, and noisy datasets. High entropic input spaces are not incidental but essential for learning systems that generalize.

Second, the analysis suggests intrinsic limits to AI knowledge. Scaling data alone cannot yield unbounded epistemic growth; without corresponding increases in structural constraints, inductive biases, and representational capacity, additional entropy produces diminishing returns. This observation aligns with empirical findings on scaling laws and saturation effects in machine learning.

Third, the framework cautions against viewing AI as a path toward complete or final knowledge. AI systems, like biological intelligences, are bounded by the entropic structure of their informational environments. Their outputs remain probabilistic, contextual, and incomplete.

7.3 Epistemological Implications

From an epistemological standpoint, the analysis challenges the ideal of absolute certainty. Knowledge is shown to be inherently provisional, constrained not only by methodological limitations but by cosmological conditions. Uncertainty is not merely an epistemic deficiency; it is a structural feature of any universe that supports meaningful knowledge.

This perspective resonates with contemporary philosophy of science, which emphasizes model-based reasoning, fallibilism, and the iterative refinement of theories. Knowledge progresses not by eliminating entropy, but by organizing it into increasingly effective representations.

7.4 Meaning, Knowledge, and Entropy

A striking implication of the framework is the revaluation of entropy as a precondition for meaning. Meaningful distinctions arise only in environments that are neither perfectly uniform nor entirely chaotic. Entropy supplies the diversity necessary for distinctions; structure supplies the coherence necessary for interpretation.

In this sense, meaning, like knowledge, is emergent. It is not inscribed in the universe a priori, nor is it arbitrarily imposed by observers. Instead, meaning arises from the interaction between entropic possibility spaces and intelligent systems capable of navigating them.

7.5 Limitations of the Present Framework

The present work is intentionally conceptual. It does not provide a formal mathematical model specifying exact thresholds or quantitative measures of epistemic capacity. Nor does it claim that entropy alone determines the emergence of intelligence or knowledge. Other factors—such as specific physical laws, evolutionary pathways, and representational architectures—remain essential.

Nevertheless, the framework provides a unifying lens through which these factors can be understood as operating under entropic constraints. Future work may formalize these ideas using tools from statistical mechanics, algorithmic information theory, or computational learning theory.

7.6 Future Directions

Several directions for future research follow naturally from this discussion:

- Formal modeling of epistemic capacity as a function of entropy and structural constraints.
- Comparative analysis of hypothetical universes with varying entropic regimes.
- Empirical investigation of entropic thresholds in biological and artificial learning systems.
- Integration with theories of consciousness and semantic emergence.

These directions suggest that entropy is not merely a background parameter but a central variable in any comprehensive theory of life, intelligence, and knowledge.

8 Conclusion

This paper has advanced a unified conceptual framework linking entropy, life, intelligence, and knowledge. Departing from the traditional view of entropy as a purely destructive force, we have argued that sufficiently high—but non-maximal—entropy constitutes a necessary condition for the emergence of complex, adaptive, and epistemic systems. Entropy defines the size of the possibility space within which life arises as a dissipative structure, intelligence emerges as an adaptive navigational mechanism, and knowledge develops as structured uncertainty.

We have shown that life is statistically favored in non-equilibrium environments sustained by entropy gradients, that intelligence becomes adaptive only when uncertainty exceeds the capacity of fixed rules, and that knowledge is fundamentally constrained by the entropic structure of the universe. Artificial intelligence systems serve as a contemporary illustration of these principles: their capabilities depend critically on high-entropy informational environments, yet their epistemic reach remains bounded by structural and computational limits.

A central contribution of this work is the introduction of the notion of *epistemic capacity*—the maximal amount of knowledge that can be represented and utilized within a universe. Epistemic capacity is neither unlimited nor independent of cosmology; it is constrained by entropy, stability, and the availability of mechanisms for compression and memory. This reframes uncertainty not as an epistemic failure, but as a prerequisite for meaningful knowledge.

The implications of this framework extend across disciplines. In cosmology, it refines anthropic reasoning by emphasizing epistemic agents rather than mere habitability. In artificial intelligence, it clarifies why learning systems require entropic richness and why unbounded knowledge remains unattainable. In epistemology, it supports a fallibilist view in which knowledge is necessarily provisional, probabilistic, and context-dependent.

This work is intentionally conceptual and does not claim to exhaust the explanatory power of entropy. Rather, it proposes entropy as a unifying constraint under which diverse mechanisms operate. Future research may formalize these ideas through mathematical models, empirical studies of learning systems, or comparative analyses of hypothetical universes with varying entropic regimes.

In conclusion, entropy should not be regarded as the enemy of order, intelligence, or meaning. Instead, it is the condition that makes their emergence possible. Meaningful life, intelligence, and knowledge arise not despite entropy, but because of it.

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