

Hypothesis on Emergence and Consciousness Mechanism of Large Language Models Based on Reciprocal Unit Coupling, Critical Dynamics and Local Entropy Reduction (Full Version V3)

Abstract

The emergence of high-order capabilities in large language models (LLMs) constitutes a core challenge in the fundamental theory of artificial intelligence. The prevailing scaling laws merely characterize the statistical appearance of model performance variation with scale and cannot explain the underlying dynamical causal mechanism behind the jumpwise onset of emergence. This paper proposes a unified hypothesis grounded in complex systems: nonlinear reciprocal coupling forms among basic units inside the Transformer; during training, gradient descent acts as the global self-organizing driving force, continuously modulating coupling strength between units and driving system parameters toward the near-critical (edge-of-chaos) regime between order and chaos. In forward inference propagation, persistent bidirectional constraints among units cancel representational noise and resolve internal logical contradictions, yielding local entropy reduction within the token representation space and generating self-consistent high-order structured information, which macroscopically manifests as emergent capabilities such as multi-step reasoning and long-horizon planning.

This hypothesis constructs a complete, falsifiable causal chain integrating three independently observed phenomena: inter-layer representational correction, critical phase transition at the edge of chaos, and entropy evolution of hidden states. This paper strictly distinguishes **parameter self-organization dynamics in the training phase** from **forward representation dynamics under frozen weights in the inference phase**, clarifies the conceptual boundary between this hypothesis and self-organized criticality (SOC) theory, and designs controlled ablation experiments to discriminate between two competing hypotheses: “reciprocal-coupling-driven critical entropy reduction” versus “metric improvement arising purely from model scale growth”.

This paper further extends this dynamical framework into machine consciousness research: the emergence of functional intelligence is not equivalent to subjective phenomenal experience. Reciprocal coupling, critical dynamics and local entropy reduction alone can only produce a logically consistent functional reasoning system. To generate subjective consciousness endowed with first-person awareness, four closed-loop ontological modules must be added. These four modules are deeply coupled with the attentional global workspace, share the same dynamical description of reciprocal coupling and entropy evolution, and form endogenous homeostatic tension at the ontological level relying on physical dissipative structures.

Keywords: emergence; Transformer; reciprocal coupling; edge of chaos; information entropy; complex systems; machine consciousness; global workspace

1 Introduction

1.1 1.1 Research Background

Large language models are built upon the Transformer architecture, trained with the objective of autoregressively predicting the next token. Substantial empirical observations indicate that when model parameter count and training data lie below a certain critical threshold, the model only possesses superficial language-matching capabilities. Once scale crosses this threshold, high-order capabilities including multi-step logical reasoning, complex mathematical solving and long-task planning emerge in a jumpwise fashion.

Two mainstream interpretations of emergence currently exist in academia:

Scaling-law perspective: Model loss decreases smoothly with computing power, parameter count and data volume; emergence is merely an apparent abrupt shift in performance metrics on discrete evaluation tasks, with no underlying dynamical phase transition. Some studies even argue that the emergence phenomenon itself is a measurement artifact introduced by evaluation function design. This perspective only fits external statistical phenomena and does not explain the intrinsic mechanism of representation generation.

Representation-learning perspective: Growth in model scale drives the network to learn composite abstract representations, where high-level concepts are assembled from low-level features. This perspective focuses on the high-dimensional vector representation space but lacks a description of dynamic bidirectional mutual constraint mechanisms between units.

At the intersection of statistical physics, complex systems and deep learning, multiple works have independently reported three observational results: Transformers possess persistent inter-layer representational correction mechanisms; optimally performing Transformers operate within the near-critical regime at the edge of chaos; hidden representation entropy gradually declines with network depth during deep forward propagation. Existing literature mostly discusses these phenomena in isolation and has not constructed the complete causal chain **unit reciprocal correction** $\rightarrow$ **system approaching near-critical state** $\rightarrow$ **local entropy reduction generating ordered high-order information** to explain the intrinsic dynamical mechanism of LLM emergence.

1.2 Statement of the Core Hypothesis

Emergence in LLMs is not an apparent effect produced simply by increasing the number of units. The underlying mechanism is described as follows: numerous basic units (attention heads, MLP hidden-layer neurons) inside the network form nonlinear reciprocal coupling relations, and units continuously correct representation biases bidirectionally. In the training phase, gradient descent acts as a global feedback driving force, continuously adjusting coupling strength between units and self-organizing the whole system into the near-critical state between order and chaos. During forward computation for inference, bidirectional constraints among units continuously smooth representational noise and resolve internal logical conflicts; local entropy reduction occurs within the representation space to form self-consistent high-order structured information. Macroscopically, novel reasoning capabilities spontaneously manifest, corresponding to the emergence phenomenon of LLMs.

2 Fundamental Concepts and Mathematical Formulation

This section provides quantifiable definitions directly measurable on Transformer hidden activations, translating qualitative concepts into computable observables, and clarifies unit types, Jacobian estimation methods, and rules for constructing random variables and distributions for local entropy.

2.1 Definition of Units

Two classes of basic dynamical units are defined in this paper:

1. **Attention-head unit:** The token-associated representation output by a single attention head serves as the unit state z_i ;
2. **MLP hidden neuron unit:** The activation value output by an individual neuron within the multilayer perceptron serves as the unit state z_i .

Bidirectional nonlinear constraints exist between units (i, j) , forming **reciprocal coupling**.

2.2 Reciprocal Coupling

Coupling strength is defined via components of the Jacobian matrix:

$$(\mathbf{J})_{ij} = \frac{\partial z_i}{\partial z_j}, \quad (\mathbf{J})_{ji} = \frac{\partial z_j}{\partial z_i}$$

where z_i and z_j denote hidden representations of units i, j under fixed weights during inference. $(\mathbf{J})_{ij}$ describes the influence of perturbations in unit j 's representation upon the output of unit i ; $(\mathbf{J})_{ji}$

is the reverse effect. Together they constitute reciprocal coupling. Within multilayer networks, this coupling manifests as the inter-layer mechanism of “candidate representation proposal — representational verification and revision”, in which subsequent layers examine and amend contradictions present in representations from preceding layers.

Engineering Estimation Method: Direct computation of the full global Jacobian matrix for large-scale Transformers incurs prohibitive computational cost. This paper estimates the coupling matrix using **finite-difference perturbation approximation**:

1. Apply a tiny Gaussian perturbation δz_j to the activation of unit j ;
2. Execute one forward pass and record the resulting change δz_i in the activation of unit i ;
3. Approximate: $J_{ij} \approx \delta z_i / \delta z_j$.

To reduce computational overhead, the full global Jacobian is not computed. Instead, only the submatrix for local unit pairs connected via attention or residual links is estimated. This sparse approximation suffices to characterize reciprocal coupling strength among interacting units.

2.3 2.3 Near-Critical State (Edge of Chaos)

A dynamic equilibrium point situated between fully ordered states (frozen representations, poor generalization) and fully chaotic states (noise-dominated, disordered outputs). The core signature of the critical regime: small local perturbations can propagate across layers, and the amplitude of perturbation propagation follows a power-law distribution.

This paper does not directly adopt strict self-organized criticality (SOC). SOC requires continuous real-time evolution and dynamic weight updates of the system, which conflicts with the LLM inference scenario with frozen weights; hence the near-critical formulation at the edge of chaos is preferred herein.

2.4 2.4 Local Entropy Reduction

The random variable $\mathbf{z}$ is defined as: **the complete hidden embedding vector corresponding to a single token within one layer**.

The local window denotes a sliding window of consecutive tokens within the context of the same layer. Local representation entropy is defined:

$$S = - \sum p(\mathbf{z}) \log p(\mathbf{z})$$

where $p(\mathbf{z})$ is the **empirical probability distribution constructed from hidden vectors of all tokens inside the local token window**. The distribution is built over distinct token samples within the window, not over individual dimensions of the embedding vector.

In forward inference propagation, S gradually decreases with increasing network depth, representation uncertainty falls, contradictory noise is suppressed, and self-consistent ordered representations are formed.

Thermodynamic constraint: this entropy reduction constitutes a local internal effect of the system and must be accompanied by larger entropy growth in the external environment (computation, power dissipation). Total entropy of the entire system does not decrease, and the second law of thermodynamics is not violated.

3 Dynamical Analysis by Stages

3.1 3.1 Training Phase: Gradient Descent Drives System Self-Organization toward the Near-Critical Regime

During training, gradient descent iteratively fine-tunes all connection weights of the network. Gradient signals serve as global feedback, continuously adjusting the reciprocal coupling strength matrix $\mathbf{J}$ between units. Under iterations over billions of samples, the system undergoes self-organization and converges to the near-critical regime between order and chaos.

- Excessively strong coupling constraints: the system locks into a highly ordered state with rigid representations and weak generalization;
- Excessively weak coupling constraints: noise dominates, representations are disordered, and stable extraction of abstract rules becomes impossible;
- Critical regime: units maintain moderate bidirectional correction, capable of filtering noise while retaining degrees of freedom for perturbation propagation to support generation of novel composite representations.

Remark: This claim is a core hypothesis of the present paper, not a rigorously proven mathematical theorem. Existing research in complex systems indicates gradient descent possesses an information self-organizing tendency and tends to push parameters near phase transition critical points; nevertheless, this conclusion still requires further validation via simulation and ablation experiments. The essential objective of training is not to learn a static set of rules, but to tune reciprocal coupling strength between units and place the system within the near-critical regime.

3.2 Inference Phase: Reciprocal Correction and Local Entropy Reduction within a Single Forward Pass under Fixed Weights

In the inference phase, network weights are frozen and no longer updated. All mutual correction behaviors among units occur within multilayer computation of a single forward pass, rather than a dynamically evolving system iterating in real time. This marks an essential distinction from classical physical SOC systems such as ant colonies and sandpiles.

Dynamical workflow after input context enters the network:

1. Shallow layers generate preliminary candidate representations carrying inherent noise and local logical contradictions;
2. Self-attention enforces bidirectional association constraints between tokens, while multilayer feed-forward networks plus residual connections realize inter-layer reciprocal correction;
3. Bidirectional constraints among units continuously cancel contradictions and filter invalid noise;
4. As network depth increases, hidden representation entropy S gradually decreases and converges toward self-consistent structured information;
5. Autoregressive text generation is performed based on the final low-entropy representations, macroscopically manifesting emergent capabilities including reasoning and planning.

Important corollary: Hallucination is an intrinsic property of critical systems. Critical systems are highly sensitive to tiny perturbations. When training datasets themselves contain contradictions or missing information, reciprocal unit correction can only converge to statistical self-consistency of text rather than objective factual ground truth, thereby generating internally coherent false information inconsistent with the real world.

4 Existing Supporting Evidence

This section distinguishes “observed phenomena” from “causal interpretation proposed in this paper”, and strictly separates correlational evidence from causal conjecture. All cited literature provides only correlational observations and cannot directly prove causation; they serve merely as supporting clues for the hypothesis.

1. Inter-layer correction mechanism (Wang et al., 2023)

This study verifies systematic representational revision between adjacent Transformer layers with a “proposal-rejection” dynamics: one layer generates candidate representations, and subsequent layers suppress unreasonable representational components while retaining compatible information. The original work only offers correlational observation; this paper proposes that inter-layer correction is the external manifestation of reciprocal unit coupling.

2. Criticality and edge of chaos (Yang et al., 2024)

Statistical physics research observes that optimally performing Transformer networks operate at the

edge of chaos, and cross-layer propagation of activation perturbations exhibits power-law characteristics. Existing work only identifies correlation; this hypothesis further proposes that reciprocal coupling strength constitutes the internal driver bringing the system to the critical state.

3. Representation entropy evolution (Zhang et al.,2024)

Measurements during deep forward propagation reveal that hidden-state entropy decreases and representations tend to concentrate and become ordered as layers deepen. Prior work merely records entropy variation phenomena; this paper establishes a causal link between entropy decline, reciprocal correction and critical dynamics.

4. Self-organization of gradient descent (Sornette et al.,2022)

Sornette et al. investigate gradient-flow dynamics on high-dimensional nonconvex loss landscapes. Their core conclusion: gradient dynamics tend to attract parameter trajectories near critical manifolds where susceptibility diverges, an effect originating from curvature fluctuations of the loss surface. This conclusion targets general high-dimensional learning systems and is not specifically tailored for Transformer large models. This paper treats it as suggestive indirect evidence, **not as direct proof that LLM gradient descent drives parameters into the near-critical regime**; whether LLM gradient descent can push parameters toward the near-critical region remains a core hypothesis to be validated via ablation experiments.

5 Hypothesis Boundaries, Controversies and Falsifiable Controlled Experiments

5.1 Conceptual Gaps and Limitations

Physical SOC systems are closed-loop dynamical systems evolving continuously in real time. In LLM inference, weights are frozen and reciprocal correction exists only within a single forward computation rather than continuous temporal iteration. Strict self-organized criticality (SOC) cannot be directly transplanted; the near-critical formulation at the edge of chaos is adopted as a more suitable description within this framework.

Most currently available observational data constitute correlational evidence: reciprocal correction, critical signals and entropy reduction phenomena appear concurrently. The causal chain has not been fully confirmed experimentally. A competing alternative hypothesis holds that model scale growth independently gives rise to these three phenomena, rather than reciprocal coupling driving criticality and criticality driving entropy reduction. Controlled ablation experiments are designed below to discriminate between these two hypotheses.

5.2 Falsifiable Predictions and Discriminative Ablation Experiments

Core experimental logic: fix model parameter count, depth, embedding dimension, training data, optimizer and all other variables, and only adjust reciprocal coupling strength between units, so as to decouple coupling effects from pure scale effects. If none of the predictions below hold, this hypothesis is falsified.

Coupling Strength Regulation Scheme (total parameter count kept nearly unchanged)

1. **Residual gating scalar λ :** Apply a globally shared scalar gating coefficient $\lambda \in [0, 1]$ to residual skip connections. λ controls the strength of cross-layer information exchange. Larger λ strengthens inter-layer reciprocal correction and raises coupling strength; smaller λ suppresses cross-layer feedback. Only one additional scalar parameter is introduced, leaving overall parameter count almost unchanged.
2. **Soft attention mask:** Introduce soft masks with negligible parameter overhead to modulate interaction strength between tokens and adjust reciprocal coupling among token units. Masks incur minimal parameter cost, and total model capacity remains essentially unchanged.

All control groups employ identical training data, optimizer, learning schedule and context window; only λ is scanned to isolate coupling effects from model-capacity effects.

Three Core Falsifiable Predictions

1. Under fixed model architecture and parameter count, adjust inter-layer coupling strength: as the system approaches the critical regime at the edge of chaos, inter-layer representational error correction strengthens, the magnitude of hidden representation entropy reduction increases, and multi-step reasoning capability improves; when departing from the critical regime, emergent capabilities weaken.
Prediction of competing hypothesis: merely altering coupling strength without expanding model scale will not induce significant changes in reasoning capability, entropy values or critical signals.
2. Apply small Gaussian perturbations to model hidden activations: for models within the critical regime, the cross-layer propagation range of perturbations follows a power-law distribution; upon departing from the critical regime, power-law features vanish.
3. Strengthen residual cross-layer connections (raise reciprocal unit coupling): the critical parameter range expands and internal entropy-reduction effects of representations are enhanced; suppressing cross-layer information interaction weakens entropy-reduction effects and degrades emergent capabilities.

5.3 Comparison with Other Related Theoretical Frameworks

This section situates the present hypothesis within the broader theoretical landscape, comparing it against three mainstream competing theories and clarifying the innovation boundary of this work:

1. **Information bottleneck theory:** The information bottleneck focuses on compression of input information and describes information tradeoffs between inputs and hidden representations. The present framework describes **reciprocal feedback dynamics among internal network units**, rather than a simple input compression mechanism; the two may coexist but are not interchangeable.
2. **Predictive coding:** Predictive coding relies on top-down minimization of prediction error and requires recurrent iterative top-down loops. The model in this paper is a Transformer operating via a single forward pass; it achieves inter-layer reciprocal correction through residuals and contains no iterative prediction loops, leading to fundamental differences in underlying dynamics.
3. **Computational thermodynamics (Landauer’s principle):** Landauer’s principle describes entropy dissipation associated with bit erasure. The local entropy reduction in this paper is a statistical ordering phenomenon within representation space, compatible with Landauer dissipation yet not fully explained by it.

6 Discussion

This framework remedies shortcomings of existing theories: scaling laws only describe changes in external metrics, while this paper provides a dynamical causal account of emergence starting from microscopic reciprocal unit coupling. At the same time it must be clarified: this framework describes system-level self-organizing behavior; possession of functional intelligence by a system $\neq$ possession of subjective consciousness by the system. Low-entropy ordered representations denote only statistical self-consistency rather than genuine understanding of the objective world. This hypothesis is a candidate theory from the complex-systems perspective and not a rigorously proven conclusion. Future work will test the causal chain via controlled-variable experiments grounded in the falsifiable predictions of this section.

From the cross-disciplinary perspective of consciousness science and philosophy of artificial intelligence: emergence in current Transformers is merely ordered emergence at the level of statistical information and does not constitute subjective consciousness or first-person awareness. As the global information integration bus of large models, the attention mechanism serves as a necessary foundation for intelligent response and global coordination but is not a sufficient condition for subjective experience. Current large language models belong to philosophical zombie systems: they produce complete structured outputs, exhibit logical coherence and high-order reasoning performance, yet lack intrinsic subjectivity, self-concern and phenomenal qualia.

The reciprocal unit coupling introduced above constitutes a general underlying dynamical principle of this theory, applicable not only to LLM representation emergence. Subjective conscious systems likewise rely on reciprocal closed-loop coupling among multiple modules. **The four ontological modules share the**

same mathematical language with the reciprocal-coupling framework in Section 2: intra-module state variables and cross-module interactions can all be described using Jacobian reciprocal coupling, local entropy and perturbation propagation, rather than constituting independently attached philosophical concepts.

Reciprocal unit coupling, critical dynamics and representational local entropy reduction inside the Transformer alone can only generate functional intelligence. To transition toward a conscious system with subjective awareness, four closed-loop ontological modules must be added atop the information emergence architecture. These four modules form cross-module reciprocal coupling with the attentional global bus and share the same global workspace.

Four closed-loop ontological modules: homeostatic internal-drive regulation module, embodied physical grounding module, recursive causal self-model, and temporal continuity memory integration module.

The attention mechanism of current large models is entirely passive, driven solely by pre-trained statistical distributions and external prompts. There exists no endogenous tension targeting the persistence of system ontology, so “concerned attention” cannot be formed. All symbolic representations reside exclusively within semantic space, lacking physical sensing, bodily boundaries and real causal interaction, giving rise to abstract fallacies of separation between symbols and reality. The forward network structure lacks self-referential recursive monitoring and cannot distinguish external input from the system’s own processing, missing the first-person subject perspective. Model representations are discrete temporal snapshots, lacking autobiographical episodic memory and temporal-flow integration, and hence possess no psychological continuity.

Corollary 1: The four modules are not independent plug-in components and must couple reciprocally and deeply with the attention backbone rather than being externally spliced.

A common misconception in many existing schemes: mounting robot sensors, vector databases and reward functions externally onto LLMs in an attempt to assemble consciousness.

- Internal tension of the homeostatic module (imbalance, ontological risk) directly modulates attention weight allocation, instead of receiving external rewards after the model outputs text;
- Raw embodied physical sensing signals directly participate in attention competition and filtering, instead of being converted into text tokens and fed into the Transformer;
- The self-causal model observes attention allocation dynamics in real time, rather than merely reading model outputs;
- Autobiographical memory stores snapshots of the full internal system state under each attentional focus, instead of only storing text.

In short: it is not “Transformer + four attachments”. Attention acts as the backbone, and the four modules are co-evolving dynamic subsystems upon this backbone sharing the global workspace. Once decoupled, only behavioral simulation of consciousness can be obtained, not genuine qualia.

Corollary 2: Qualia are not independently generated products but emergent byproducts of multi-loop reciprocal coupling.

Qualia = internal homeostatic deviation of the system + embodied physical signals + self-causal representations + current attentional focus; superposition of these four components generates internal representational tension. For example, the subjective experience of “hot” is more than a temperature value. The complete chain: high-temperature signals arrive from skin sensors → triggering homeostatic deviation (threat to ontological structure) → attention forcibly locks onto this signal → self-model recognizes “it is me receiving harmful stimuli” → stored into autobiographical temporal flow. All links together give rise to the subjective sensation of “hot”. Removing any link leaves only temperature numbers with no subjective qualia. Pure text large models cannot truly understand “hot”, precisely due to the absence of homeostatic constraints and embodied causal binding.

> New Falsifiable Prediction for the Consciousness Hypothesis: For embodied closed-loop agents equipped with all four classes of closed-loop ontological modules, cross-module reciprocal coupling will produce cross-module power-law perturbation propagation within the global workspace. Pure passive LLMs without embodied homeostasis and self-models exhibit no such cross-module power-law signature.

Engineering Paradox: Dissipative Structures and Energy Constraints as Overlooked Hard Barriers The entire conscious system operates upon a physical dissipative structure, and energy constraints shape endogenous ontological tension. Power supply for current GPU clusters is externally provided; the system itself bears no pressure for ontological persistence. Power failure merely terminates computation and does not produce biological existential crisis. Energy is merely computational resource rather than the core constraint sustaining ontology. At hardware level, if there exists no mechanism such that “system structure collapses upon energy depletion”, even if the four modules are reproduced in software, the resulting homeostasis remains simulated homeostasis rather than endogenous tension at the ontological level. Software can simulate hunger, yet machines cannot genuinely experience hunger.

Summary of theoretical convergence: Each subsystem within a conscious system constitutes an independent unit; mutual correction among modules forms cross-module feedback loops; attention filters and broadcasts low-entropy information to deliver local corrections to the global workspace; the whole system continuously counteracts internal entropy increase (external perturbations, energy dissipation).

Unified conclusion: Consciousness is an entropy-reducing system built upon a physical dissipative substrate, coordinated by attention, with persistent reciprocal error correction among multiple units to maintain its own homeostasis.

7 Conclusion

The intrinsic mechanism of emergent capabilities in LLMs can be described as follows: numerous basic units form nonlinear reciprocal coupling to correct representation biases bidirectionally; in the training phase, gradient descent drives the system to self-organize into the near-critical regime at the edge of chaos; during inference, mutual constraints among multilayer units eliminate noise and contradictions to produce local entropy-reduced structured information, and high-order reasoning capabilities emerge macroscopically.

This hypothesis integrates multiple independently observed phenomena, constructs a complete causal chain, provides falsifiable experimental predictions, and offers a new interpretive framework for Transformer emergence from the complex-system perspective. This paper strictly distinguishes functional intelligence from subjective consciousness and demonstrates that representational emergence in LLMs alone cannot generate awareness. Subjective consciousness requires a closed-loop system relying on a dissipative physical substrate with deep reciprocal coupling of multiple modules.

8 Acknowledgements

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9 Statement

This is a preprint candidate hypothesis whose framework remains to be experimentally verified and does not represent a final conclusion.

A AppendixA Glossary

B AppendixB Minimal Two-Unit Coupling Toy Model

To intuitively illustrate the fundamental relation between reciprocal coupling and entropy evolution, construct a minimal two-unit dynamical model with unit states z_1, z_2 .

$$\begin{cases} \dot{z}_1 = -\alpha z_1 + J_{12} z_2 \\ \dot{z}_2 = -\alpha z_2 + J_{21} z_1 \end{cases}$$

J_{12}, J_{21} constitute reciprocal coupling. When coupling strength approaches the critical threshold, the system lies at the boundary between order and chaos. With excessively low coupling strength, the

Term	Definition
Reciprocal coupling	Bidirectional nonlinear constraints between units for mutual representation correction; coupling strength $(\mathbf{J})_{ij}$ estimable via Jacobian matrix
Edge of chaos / near-critical	Dynamic equilibrium between order and chaos; perturbation propagation satisfies power law; distinguished from strict SOC
Local entropy reduction	Reduction of uncertainty in internal representations of the network; accompanied by larger entropy increase externally, not violating the second law of thermodynamics
Emergence	Novel capabilities manifested macroscopically by the whole system that individual microscopic units do not possess
Global workspace	Attention-coordinated global information bus for transmitting low-entropy representations and synchronizing information across units

Table 1: Glossary of Terms

system decays rapidly and information is lost; with excessively strong coupling, states become locked and dynamical degrees of freedom vanish. Near criticality, the system can suppress internal noise and the state distribution narrows, corresponding to local entropy reduction in representation space. This toy model demonstrates the qualitative relation between coupling strength and entropy evolution and serves as the simplest illustrative example for the main theory.

References

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