Self-Organization to the Edge of Ergodicity Breaking in a Complex Adaptive System

Keywords: Self-organized criticality, Ergodicity breaking, Complex adaptive systems, Spin-glass models, Evolutionary dynamics

Extended Abstract

Motivation. Self-organized criticality (SOC) has long been proposed as an attracting state for driven, dissipative complex systems. However, most studies have focused on simplistic models with homogeneous interactions and without explicit optimization goals. In contrast, living and adaptive systems, from biological to social and economic systems, typically feature heterogeneous interactions and pursue explicit objectives such as survival, energy efficiency, or profit maximization, making true optimization under such constraints highly nontrivial. Key open questions therefore remain: Do genuinely complex adaptive systems self-organize toward criticality without external tuning? And if so, what is the fundamental nature of that criticality, and does such organization confer functional advantages in complex, rugged landscapes?

This work addresses these questions by demonstrating that a minimal complex adaptive system that incorporates the essential ingredients of adaptation and evolution spontaneously self-organizes into an optimal critical state, outperforming any externally fine-tuned parameter regime. Crucially, we identify the precise nature of this self-organized critical state: it resides exactly at the transition point between ergodic and non-ergodic (ergodicity-breaking) phases.

Approach and Methodology. We construct a minimal model embodying the core features of complex adaptive systems: (a) Many-body nonlinear heterogeneous interactions modeled via a spin-glass framework; (b) Adaptive agents (spins) who optimize their energy through reinforcement learning; (c) Darwinian evolution through extinction and replacement of the least-fit agents. Our model is a modification of the Bak-Sneppen rules by explicitly accounting for learning, exploration, and memory. Agents adapt through memory-dependent learning while endogenously evolving their exploratory behaviors (temperatures) through extremal replacement. The coupled learning-evolutionary dynamics are analyzed numerically. To probe the phase structure, we introduce a response-based ergodicity measure using temperature rescaling and total variation distance on reward trajectories. Avalanche statistics are used to characterize criticality, with scaling exponents estimated via local slope analysis on log-log plots of size distributions.

Results. Numerical investigations of this model reveal several striking phenomena: (1) the system evolves autonomously to a steady state whose performance surpasses that achieved by any manual parameter tuning; (2) consistent with classic SOC, avalanche-size distributions exhibit clear power-law scaling, with an exponent close to -1.5, matching mean-field sandpile models and empirical observations in biological neural systems; (3) most importantly, this self-organized optimal state is unambiguously critical, located at the ergodic-to-nonergodic transition point, where ergodicity breaking emerges. Intermediate memory

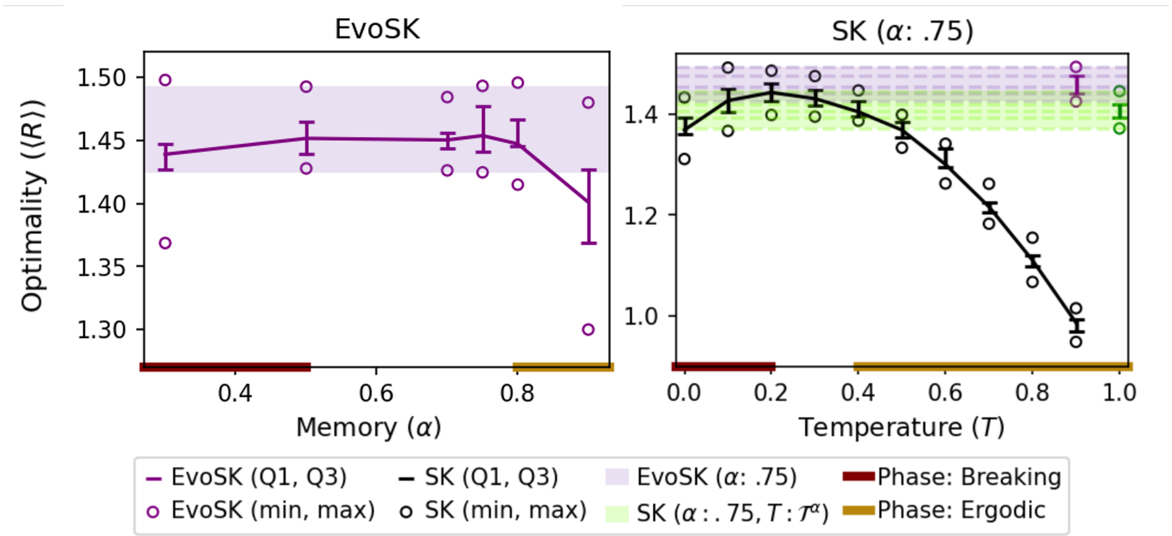

Figure 1: **Optimality.** (a) Stationary rewards $\langle R \rangle$ of EvoSK across memory parameter α (purple lines), showing a wide span of maxima at $\alpha \approx .5 - .8$. This α range coincides with those attaining edge of ergodicity breaking. Line plot and error bars indicate the median and quartile range of $\langle R \rangle$ across 25 independent runs. (b) $\langle R \rangle$ of SK across noise parameter T (black lines) at $\alpha = .75$, showing a range of maxima around $T = 0.2 - 0.3$, which coincides with the edge of $\epsilon(T)$. EvoSK (purple shade) outperforms SK at all constant temperatures. SK with agent's temperatures fixed to $\mathcal{T}^{\alpha} : \{T_i\}, t = t_{stat}$, the stationary temperatures attained following EvoSK runs with $\alpha = .75$, (green shade) underperforms SK. This corroborates that EvoSK's performance gain is the main attribute of the evolutionary search dynamics.

regimes drive the system toward this ergodicity edge, yielding near-optimal collective rewards that outperform fixed-temperature and non-evolutionary baselines.

Conclusions and Outlook. In summary, evolutionary learning can organize adaptive systems toward criticality while simultaneously enhancing performance in rugged landscapes, providing a concrete link between microscopic learning-adaptation rules, macroscopic phase structure, and functional optimality. Future studies will explore extensions to finite-size effects, alternative evolutionary rules, and applications to real-world datasets in neuroscience and economics.

References

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