Hyper-Aether: Evolving State Spaces, Criticality, and the Emergence of Meaning in Graph-Based Intelligent Systems

Abstract

We propose Hyper-Aether, a computational framework in which intelligence emerges as a dynamical process over evolving graph-structured state spaces. Unlike conventional architectures that assume fixed representations, Hyper-Aether models both computation and meaning as trajectories over a growing state space Ω_t. A value function $V(G)$ induces an energy landscape whose attractors correspond to meaning, whose phase transitions correspond to concept formation, and whose structural expansion enables creativity. We formalize this framework, analyze critical regimes, and address the problem of incorrect attractors. This work unifies reinforcement learning, statistical physics, and open-ended evolution into a single theoretical model of intelligence.

1 Introduction

Artificial intelligence systems are traditionally defined over fixed representations and static computational structures. However, intelligent behavior in natural systems suggests a more dynamic picture in which both representations and the space of possibilities evolve.

We introduce **Hyper-Aether**, a framework in which:

- computation is graph transformation,
- meaning is defined through a value function,
- and the space of possible structures expands over time.

This perspective enables a unified interpretation of meaning, concept formation, and creativity.

2 Hyper-Aether Framework

Hyper-Aether consists of three interacting layers:

(1) Graph Substrate A computational state is represented as a graph:

$$G \in \Omega_t. \tag{1}$$

(2) Dynamic State Space The state space evolves:

$$\Omega_{t+1} = \Omega_t \cup \Delta\Omega_t, \tag{2}$$

where $\Delta\Omega_t$ represents newly generated structures.

(3) Value Field A value function evaluates structures:

$$V : \Omega_t \to \mathbb{R}. \tag{3}$$

This induces an energy landscape:

$$U(G) = -V(G). \tag{4}$$

(4) Dynamics The system evolves as:

$$G_{t+1} \sim \Phi(G_t, \eta_t), \tag{5}$$

where η_t controls stochasticity.

3 Probabilistic Interpretation

The system induces a distribution:

$$P_t(G) \propto \exp(\beta V(G)), \quad G \in \Omega_t, \tag{6}$$

where $\beta = 1/\eta_t$.

4 Meaning as Attractors

begindefinition
A semantic attractor is a local maximum of $V(G)$.
enddefinition

$$\mathcal{M}_t = \{G^* \in \Omega_t \mid G^* \text{ is a local maximum}\}. \tag{7}$$

Meaning is identified with these attractors.

5 Concept Formation as Phase Transition

We define concepts as high-probability regions:

$$C = \{G \mid P_t(G) \geq \epsilon\}. \tag{8}$$

Concept formation occurs when:

$$\text{Topology}(C) \text{ changes due to } \Omega_t \text{ or } V. \tag{9}$$

This corresponds to phase transitions.

6 Creativity as State Space Expansion

In Hyper-Aether, creativity is defined as:

$$\exists G \in \Delta\Omega_t \text{ such that } V(G) > \max_{G' \in \Omega_t} V(G'). \tag{10}$$

Thus, creativity arises from the expansion of Ω_t.

7 Criticality

The system operates in different regimes:

- Low η: convergence to attractors
- High η: random exploration
- Intermediate η: critical regime

We hypothesize:

$$\eta = \eta_c \Rightarrow \text{maximal creativity}. \tag{11}$$

8 Incorrect Attractors

Not all attractors correspond to valid meaning:

$$\exists G_{\text{bad}} \in \mathcal{M}_t. \tag{12}$$

We propose correction mechanisms:

- stochastic escape
- structural perturbation
- external grounding
- multi-objective value functions

9 Control-Theoretic View

The system can be formulated as:

$$\max_{\pi} \mathbb{E}\left[\sum_t V(G_t)\right]. \tag{13}$$

Control variables:

- policy π
- exploration parameter η_t

10 Discussion

Hyper-Aether suggests:

- Meaning = attractor structure
- Concepts = phases
- Creativity = expansion of Ω_t
- Intelligence = controlled exploration over evolving spaces

11 Conclusion

We introduced Hyper-Aether as a unified framework for modeling intelligent systems as dynamical processes over evolving state spaces. This approach integrates learning, structure formation, and creativity within a single mathematical model.

Future work includes:

- modeling $\Delta\Omega_t$
- empirical validation
- scalable implementations

References

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