Memory as Generative Influence: Unifying Cognition, Cosmology, and Spectroscopy Through Autoregressive Dynamics

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Abstract

This paper advances the thesis that memory is not a system of episodic storage but rather a process of generative influence, where past states exert weighted, continuous effects on future configurations without requiring discrete retrieval. Drawing on cognitive science, cosmology, and spectroscopy, we demonstrate that non-Markovian autoregression provides a unifying framework for understanding these domains. Anchored in the Rapid Serial Visual Presentation (RSVP) paradigm reinterpreted cosmologically, Barenholtz's autoregressive cognition (2025), and Cecilia Payne-Gaposchkin's thermodynamic spectroscopy (1925), we argue that cognition, galaxy formation, and spectral features all exemplify history-dependent dynamics. Contributions include a novel entropic damping model for little red dots (LRDs), discriminative predictions against standard ΛCDM models, and extensions to cognitive pathology and enhancement. Predictions encompass halo-spin decoupling, filament entropy alignment, and spectral-entropy correlations, testable with JWST and neuroimaging.

1 Introduction: Memory as a Universal Problem

1.1 Background

The concept of memory has permeated intellectual inquiry since antiquity, serving as a cornerstone for understanding human cognition, historical narratives, and even physical systems. In cognitive psychology, memory has traditionally been viewed through the lens of storage and retrieval, akin to a library where information is cataloged and accessed as needed. This metaphor extends to cosmology, where the "memory" of initial conditions—such as primordial density perturbations—shapes the evolution of structures like galaxies. Similarly, in spectroscopy, the "memory" of thermodynamic states influences observable line strengths and continuum shapes. However, these disparate fields share a common challenge: reconciling apparent discreteness (episodic events, halo spins, spectral lines) with underlying continuity (temporal dependencies, entropy flows, ionization equilibria).

1.2 Description

This introduction frames memory as a universal problem transcending domains, positing that traditional modal models fail to capture the generative nature of influence. We describe how cognitive buffers, cosmological spin parameters, and spectroscopic equilibria can be reinterpreted as autoregressive processes, where the past informs the future through weighted potentials rather than static records.

1.3 Explanation

The stakes are high: in cognition, misconceptualizing memory leads to ineffective interventions for pathologies like amnesia; in cosmology, it obscures dynamical pathways to compact galaxies; in spectroscopy, it overlooks entropy-driven signatures. By unifying these through non-Markovian dynamics, we explain emergent phenomena like working-memory span, LRD compactness, and Balmer breaks as outcomes of generative continuity.

1.4 Mathematical Formalisms

Consider a general non-Markovian process where the state x_t depends on the history:

$$x_t = f(x_{t-1}, x_{t-2}, \ldots; \theta) + \epsilon_t, \tag{1}$$

where f is a function encoding weighted influences, θ parameters, and ϵ_t noise. In contrast to Markovian models ($x_t = f(x_{t-1}; \theta) + \epsilon_t$), this allows long-range dependencies (LRDs), foundational to our thesis.

Overview of contributions: We critique modal memory, introduce autoregressive cognition, extend RSVP to cosmology, integrate Payne-Gaposchkin's thermodynamics, synthesize frameworks, explore pathologies and discriminants, discuss implications, and conclude with future directions.

2 Modal Memory and Its Discontents

2.1 Background

The modal model of memory, pioneered by Atkinson and Shiffrin (1968), emerged from mid-20th-century information-processing theories inspired by computing architectures **?**. It posits a multi-store system: sensory registers, short-term memory (STM) as a limited buffer, and long-term memory (LTM) as a vast repository. This framework influenced decades of research, from serial position effects to amnesia studies.

2.2 Description

In the modal model, information flows from sensory input to STM (capacity $\sim 7 \pm 2$ items), then to LTM via rehearsal. Retrieval involves querying buffers or reconstructing from episodic traces. Episodic memory is likened to discrete files, with sharp boundaries between stores.

2.3 Explanation

While accounting for phenomena like primacy/recency effects, the model struggles with continuous decay, interference, and generative recall. For instance, amnesic patients like H.M. retain procedural skills despite LTM deficits, suggesting memory is not purely episodic. Classical experiments reveal discontents: serial position curves imply interference, not buffer overflow; amnesia reanalysis shows preserved influences despite absent retrieval.

2.4 Mathematical Formalisms

Modal storage can be modeled as discrete buffers:

$$M_{\text{STM}}(t) = \sum_{i=1}^{k} w_i I_i e^{-\alpha(t-t_i)}, \tag{2}$$

where I_i are inputs, w_i weights, α decay rate, and k capacity. Problems arise in sharp drop-offs at $k+1$, inconsistent with gradual forgetting. We contrast this with autoregressive alternatives in subsequent sections.

3 Autoregressive Cognition (Barenholtz 2025)

3.1 Background

Building on neural network architectures, Barenholtz (2025) proposes autoregressive cognition as a paradigm shift from storage to generation **?**. Rooted in transformer models and predictive coding, it views cognition as a loop where outputs feed back as inputs, eliminating discrete buffers.

3.2 Description

Weights represent potentialities, not encapsulated memories. Autoregression generates sequences: each state predicts the next based on history. Continuous decay replaces buffers, with past influences decaying smoothly via attention mechanisms.

3.3 Explanation

This resolves modal discontents: pathology (e.g., H.M., Clive Wearing) as disrupted autoregression, not buffer loss; working-memory span as emergent from attention weights; IQ correlations as efficiency in generative prediction. For example, amnesia impairs loop closure, but residual influences persist.

3.4 Mathematical Formalisms

Autoregressive model:

$$p(x_t | x_{<t}) = \prod_{i=1}^{t} p(x_i | x_{<i}), \tag{3}$$

with attention weights:

$$a_{ij} = \frac{\exp(q_i k_j^T / \sqrt{d})}{\sum \exp(q_i k_l^T / \sqrt{d})}, \tag{4}$$

where q, k are queries/keys, d dimension. Decay is embedded in softmax, enabling LRDs without explicit buffers.

4 RSVP Cosmology as Non-Markovian Memory

4.1 Background

The Rapid Serial Visual Presentation (RSVP) paradigm, originally a cognitive tool for attention studies, is here reinterpreted cosmologically as a framework for non-Markovian galaxy formation **?**. Drawing from scalar-vector-tensor theories, RSVP models cosmic fields with density Φ, velocity $\mathbf{v}$, and entropy S.

4.2 Description

RSVP posits galaxies as autoregressive entities: past states (accretion histories) generate future configurations via entropic damping. For LRDs, compactness arises from lamphrodyne quenching, not primordial spin.

4.3 Explanation

In standard ΛCDM, halo spin is "stored" primordially; RSVP views it as generative influence, damped by entropy flows. This explains LRD abundance (rare coherent environments), compactness (suppressed λ_{eff}), and redshift evolution (peak coherence at $z \sim 4 - 8$).

4.4 Mathematical Formalisms

Effective spin evolution:

$$\frac{d\lambda_{\text{eff}}}{dt} = -\gamma(\Phi, S, \nabla S, \omega)\lambda_{\text{eff}} + \tau_{\text{ext}}, \tag{5}$$

with compaction criterion:

$$\int \left[\gamma - \frac{\tau_{\text{ext}}}{\lambda_{\text{eff}}}\right] dt \gtrsim \ln\left(\frac{\lambda_0}{\lambda_{\text{LRD}}}\right). \tag{6}$$

Damping γ parametrization detailed in Appendix A.

5 Thermodynamic Spectroscopy (Payne-Gaposchkin 1925)

5.1 Background

Cecilia Payne-Gaposchkin's seminal thesis (1925) revolutionized stellar spectroscopy by emphasizing thermodynamic equilibria over compositional assumptions **?**. It shifted focus from "stored" abundances to generative ionization states.

5.2 Description

Stars are thermodynamic systems where line strengths reflect temperature and entropy-driven equilibria. No explicit "memory" of elements is needed; spectra emerge from current states influenced by history.

5.3 Explanation

Extending to galaxies: LRD Balmer breaks and V-shaped SEDs as entropy signatures, akin to stellar lines. Red slopes from entropic reprocessing, not just dust.

5.4 Mathematical Formalisms

Ionization equilibrium (Saha equation):

$$\frac{n_{i+1}}{n_i} = \frac{2U_{i+1}}{U_i n_e}\left(\frac{2\pi m_e kT}{h^2}\right)^{3/2} e^{-\chi_i/kT}, \tag{7}$$

where n densities, U partitions, χ ionization potential. Entropy S links to temperature T, generating spectral features.

6 Integrative Framework: Generative Memory Across Domains

6.1 Background

Synthesizing prior sections, we integrate cognitive, cosmological, and spectroscopic analogues under generative memory.

6.2 Description

Common principle: past as weighted influences. Cognitive: Barenholtz autoregression; Cosmological: RSVP quenching; Spectroscopic: Payne-Gaposchkin equilibria.

6.3 Explanation

Conceptual tools: TARTAN (temporal-attention recursive tiling) for prioritization; Simulated Agency as sparse projections; entropy smoothing for overload mitigation; Cyclex for iterative adaptation.

6.4 Mathematical Formalisms

Unified non-Markovian kernel:

$$x_t = \int K(t,s) x_s ds + \epsilon_t, \tag{8}$$

with kernel K encoding influences (attention in cognition, γ in cosmology, Saha in spectroscopy).

7 Pathology, Enhancement, and Observational Discriminants

7.1 Background

Pathologies highlight framework utility; enhancements suggest applications; discriminants test predictions.

7.2 Description

Cognitive: dementia as autoregressive failure; enhancement via input structuring. Astrophysics: RSVP vs. ΛCDM (halo decoupling, alignment, vorticity suppression).

7.3 Explanation

Amnesia: lost generative continuity; LRDs: entropy scaling in spectra.

7.4 Mathematical Formalisms

Resilience χ (Appendix A); influence functions for pathology:

$$I(\theta) = \nabla_\theta \log p(x|\theta). \tag{9}$$

8 Philosophical and Theoretical Implications

8.1 Background

Beyond empirics, generative memory redefines agency and structure.

8.2 Description

Memory as constraint, not content; non-Markovian basis for emergence.

8.3 Explanation

Bridges cognition and cosmos: generativity as universal principle.

8.4 Mathematical Formalisms

Agency as optimization over influences:

$$\max_\pi \mathbb{E}\left[\sum r_t\right], \quad r_t = g(x_t, a_t). \tag{10}$$

9 Conclusion

Reiterate thesis: generative influence unifies domains. Call for metrics like χ, influence functions. Future: neuroscience tests, JWST validations.

Figure 1: (a) Modal storage vs. (b) autoregressive dynamics.

A Entropic Damping Closure

$\gamma = \gamma_0(\Phi/\Phi_0)^\alpha(\hat{n} \cdot \nabla S/|\nabla S|_0)^\beta \exp[-(\omega/\omega_{\text{crit}})^\eta] + \gamma_{\text{amb}}$. Resilience $\chi = \gamma_{\text{core}}/\gamma_{\text{disrupt}}$.

B Semi-Analytic λ_{eff} Model

Stochastic differential equation: $d\lambda = (-\gamma\lambda + \tau)dt + \sigma dW$, with feedback modulation.

C Influence-Function Metrics

$I = \nabla \log p$; screening via threshold on variance.