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

Flyxion

September 2025

Abstract

This paper advances the thesis that memory is not a system of episodic storage but 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 (?), and Cecilia Payne-Gaposchkin's thermodynamic spectroscopy (?), we argue that cognition, galaxy formation, and spectral features exemplify history-dependent dynamics. Contributions include a novel entropic damping model for little red dots (LRDs), discriminative predictions against 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

Memory underpins human cognition, cosmic evolution, and spectroscopic analysis. In cognitive science, memory is traditionally modeled as storage and retrieval (?), a metaphor mirrored in cosmology where initial conditions "store" structure outcomes (?). Spectroscopy, following Payne-Gaposchkin (?), treats spectral lines as reflections of thermodynamic histories. These fields share a challenge: reconciling discrete events (episodes, halos, lines) with continuous influences (attention, entropy flows, equilibria).

1.2 Description

We propose memory as generative influence, where past states shape future ones via weighted, non-Markovian dynamics. This unifies cognitive autoregression (?), RSVP cosmology (?), and thermodynamic spectroscopy (?), replacing modal storage with recursive generation.

1.3 Explanation

Mischaracterizing memory as storage leads to flawed models: cognitive buffers fail to explain amnesia (?); primordial spins miss dynamical quenching (?); static compositions obscure entropy-driven spectra (?). Non-Markovian autoregression resolves these, explaining phenomena like working-memory span, LRD compactness, and Balmer breaks.

1.4 Mathematical Formalisms

A non-Markovian process is:

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

where f encodes historical influences, θ parameters, and ϵ_t noise, contrasting Markovian models (?).

2 Modal Memory and Its Discontents

2.1 Background

The Atkinson-Shiffrin (1968) model posits sensory, short-term (STM), and long-term memory (LTM) stores (?). It shaped research on serial position effects and amnesia, drawing from computational metaphors.

2.2 Description

Information flows from sensory input to STM (7 ± 2 items) to LTM via rehearsal, with retrieval querying discrete buffers. Memory is archival, with sharp boundaries.

2.3 Explanation

The model struggles with continuous decay and generative recall. Amnesic cases (e.g., H.M.) show procedural retention despite LTM loss, suggesting non-episodic influences. Serial position curves indicate interference, not buffer limits (**?**).

2.4 Mathematical Formalisms

Modal storage:

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

with k as capacity and α decay rate. Sharp drop-offs at $k+1$ conflict with gradual forgetting (**?**).

3 Autoregressive Cognition and Memory as Generative Influence

3.1 From Modal Buffers to Autoregressive Loops

The modal model (**?**) treats memory as archival retrieval through discrete stores: sensory input $\to$ STM $\to$ LTM, with retrieval loops. Barenholtz (2025) proposes autoregressive cognition, where memory is generative influence (**?**). Outputs recursively condition inputs, with weights as potentialities, not capsules. This non-Markovian process mirrors RSVP cosmology, where galaxies evolve via path-dependent damping (**?**).

3.2 Formalizing Autoregressive Memory

The autoregressive process is:

$$x_{t+1} = f(x_t, \theta) + \epsilon_t, \tag{3}$$

where θ encodes potentialities, ϵ_t is noise, and f is the generative map. The influence kernel $K(\Delta t)$ measures past state impact:

$$K(\Delta t) \equiv \frac{\partial x_t}{\partial x_{t-\Delta t}} \sim \exp(-\Delta t/\tau_{\text{mem}}), \tag{4}$$

with τ_{mem} as memory depth, paralleling RSVP's $t_\gamma \equiv 1/\gamma$.

3.3 Cognitive Predictions

Autoregression reinterprets:

1. **Serial position effect**: Recency from ongoing influence; primacy from rehearsal extending τ_{mem} (**?**).
2. **Working memory span**: Capacity reflects $K(\Delta t)$ depth, correlating with intelligence (**?**).
3. **Amnesia (H.M., Clive Wearing)**: Episodic deficits as disrupted continuity, not buffer loss.
4. **Conversation continuity**: Coherence beyond STM via recursive generation.

3.4 Metrics and Applications

Metrics shift to influence: cross-correlations or perturbation-response functions (**?**). Applications:

- **Pathology screening**: Dementia as $K(\Delta t)$ collapse.
- **Enhancement**: Rehearsal to maximize influence.
- **AI analogues**: LLMs as cognitive models (**?**).

3.5 Summary

Autoregressive cognition treats memory as non-Markovian generative influence, paralleling RSVP's entropic quenching (**?**).

4 RSVP Cosmology as Non-Markovian Memory

4.1 Background

The RSVP paradigm, originally cognitive, is reinterpreted cosmologically to model non-Markovian galaxy formation (**?**). It uses scalar density Φ, velocity $\mathbf{v}$, and entropy S fields, drawing from scalar-vector-tensor theories.

4.2 Description

Galaxies are autoregressive: accretion histories generate configurations via entropic damping. LRDs arise from lamphrodyne quenching, not low-spin halos (?).

4.3 Explanation

ΛCDM assumes primordial spin storage (?); RSVP posits generative damping, explaining LRD abundance, compactness, and redshift evolution ($z \sim 4-8$) (?).

4.4 Mathematical Formalisms

Spin evolution:

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

with compaction:

$$\int \left[\gamma - \frac{\tau_{\text{ext}}}{\lambda_{\text{eff}}}\right] dt \gtrsim \ln\left(\frac{\lambda_0}{\lambda_{\text{LRD}}}\right), \quad \lambda_{\text{LRD}} \simeq 0.015. \tag{6}$$

See Appendix A.

5 Thermodynamic Spectroscopy (Payne-Gaposchkin 1925)

5.1 Background

Payne-Gaposchkin (1925) showed stellar spectra reflect thermodynamic equilibria, not static compositions (?).

5.2 Description

Line strengths arise from ionization states driven by entropy and temperature, not elemental "memory."

5.3 Explanation

LRD Balmer breaks and V-shaped SEDs reflect entropy-driven reprocessing, akin to stellar spectra (?), not just dust (?).

5.4 Mathematical Formalisms

Saha equation:

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

6 Integrative Framework: Generative Memory Across Domains

6.1 Background

We synthesize cognition (?), cosmology (?), and spectroscopy (?) under generative memory.

6.2 Description

Past states as weighted influences: autoregression in cognition, RSVP quenching in cosmology, thermodynamic equilibria in spectroscopy.

6.3 Explanation

Tools: TARTAN for prioritization, Simulated Agency for sparse projection, entropy smoothing, Cyclex for adaptation

6.4 Mathematical Formalisms

Unified kernel:

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

7 Pathology, Enhancement, and Observational Discriminants

7.1 Background

Pathologies and enhancements test the framework; discriminants validate predictions.

7.2 Description

Cognitive: dementia as autoregressive failure (?). Astrophysical: RSVP vs. ΛCDM (?).

7.3 Explanation

Amnesia as disrupted continuity; LRDs as entropy-scaled spectra (?).

7.4 Mathematical Formalisms

Influence function:

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

8 Philosophical and Theoretical Implications

8.1 Background

Generative memory redefines agency and structure.

8.2 Description

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

8.3 Explanation

Unifies cognition and cosmology

8.4 Mathematical Formalisms

Agency optimization:

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

9 Conclusion

Memory as generative influence unifies cognition, cosmology, and spectroscopy. Metrics like χ and $K(\Delta t)$ enable tests via JWST (**?**) and neuroimaging (**?**).

A RSVP Entropic Damping Closure

A.1 A.1 Effective Spin Dynamics

In RSVP, the effective halo spin evolves as (**?**):

$$\frac{d\lambda_{\text{eff}}}{dt} = -\gamma(\Phi, S, \nabla S, \omega)\, \lambda_{\text{eff}} + \tau_{\text{ext}}(t), \tag{11}$$

where Φ is density, S entropy, $\omega = \|\nabla \times \mathbf{v}\|$ vorticity, and τ_{ext} tidal torques.

A.2 A.2 Phenomenological Closure for γ

The damping closure is:

$$\gamma(\mathbf{x}, t) = \gamma_0 \left(\frac{\Phi}{\Phi_0}\right)^{\alpha} \left(\frac{|\hat{\mathbf{t}}_{\text{fil}} \cdot \nabla S|}{|\nabla S|_0}\right)^{\beta} \exp[-(\omega/\omega_{\text{crit}})^{\eta}] + \gamma_{\text{amb}}, \tag{12}$$

with γ_0 maximal rate, α, β exponents, ω_{crit} vorticity scale, η suppression, and γ_{amb} floor (**?**).

A.3 A.3 Compaction Condition

Compaction occurs when:

$$\int_{t_0}^{t_c} \left[\gamma - \frac{\tau_{\text{ext}}}{\lambda_{\text{eff}}}\right] dt \gtrsim \ln\left(\frac{\lambda_0}{\lambda_{\text{LRD}}}\right), \quad \lambda_{\text{LRD}} \simeq 0.015. \tag{13}$$

B Autoregressive Influence Kernels

B.1 B.1 Generative Memory Dynamics

Autoregressive cognition (**?**):

$$x_{t+1} = f(x_t, \theta) + \epsilon_t, \tag{14}$$

with θ weights, ϵ_t noise.

B.2 B.2 Influence Kernel Formalism

Influence kernel:

$$K(\Delta t) \equiv \frac{\partial x_t}{\partial x_{t-\Delta t}} \sim \exp(-\Delta t/\tau_{\text{mem}}). \tag{15}$$

B.3 B.3 Serial Position Reinterpretation

Recall probability:

$$P_{\text{recall}}(i) \propto K(\Delta t_i). \tag{16}$$

C Influence-Based Metrics and Resilience Parameters

C.1 C.1 RSVP Resilience Parameter

Resilience:

$$\chi \equiv \frac{\gamma_{\text{core}}}{\gamma_{\text{disrupt}}} \approx \frac{\gamma_0 (\Phi/\Phi_0)^{\alpha} (\text{align})^{\beta}}{\langle \omega_{\text{fb}} \rangle / \omega_{\text{crit}}}. \tag{17}$$

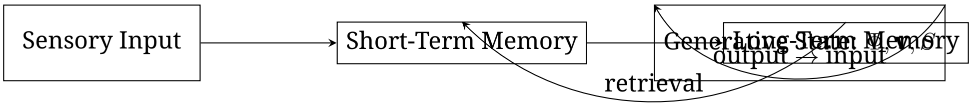
C.2 C.2 Cognitive Influence Depth

Memory depth:

$$D_{\text{mem}} = \sum_{\Delta t=1}^{\infty} K(\Delta t). \tag{18}$$

C.3 C.3 Cross-Domain Analogy

χ and D_{mem} measure influence persistence in cosmology and cognition



(a) Modal storage

(b) Autoregressive RSVP

Figure 1: Contrasting models of memory. (a) The classical modal model depicts memory as distinct storage buffers with explicit transfer and retrieval. (b) Autoregressive RSVP dynamics illustrate non-Markovian recursion: outputs recursively feed into inputs, and entropy history ($\Phi, \mathbf{v}, S$) governs compact states such as little red dots (LRDs).

D Toy Simulation for λ_{eff} and $K(\Delta t)$

D.1 D.1 RSVP Spin Evolution

A minimal simulation for λ_{eff}:

```
# Pseudocode
gamma_0, alpha, beta, eta = 5, 0.75, 1, 2
phi, grad_s, omega = compute_fields()
gamma = gamma_0 * (phi/phi_0)**alpha * (dot(fil, grad_s)/grad_s_0)**beta * exp(-(omega/c
d_lambda = (-gamma * lambda_eff + tau_ext) * dt
lambda_eff += d_lambda
```

D.2 D.2 Cognitive Influence Kernel

For $K(\Delta t)$:

```
# Pseudocode
tau_mem = 10  # Memory depth
K = lambda delta_t: exp(-delta_t / tau_mem)
x_t = f(x_prev, theta) + noise
influence = sum(K(delta_t) * x_(t-delta_t))
```