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

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Abstract

This paper proposes that memory is not a system of episodic storage but a process of generative influence, where past states exert continuous, weighted effects on future configurations without requiring discrete retrieval. By synthesizing cognitive science (?), cosmology (?), and spectroscopy (?), we demonstrate that non-Markovian autoregression unifies 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 are driven by history-dependent dynamics. Contributions include an entropic damping model for little red dots (LRDs), discriminative predictions against ΛCDM (?), and applications to cognitive pathology and enhancement. Predictions include 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 is a foundational concept across disciplines, shaping how we understand human cognition, cosmic evolution, and physical systems. In cognitive science, memory has historically been modeled as a storage system, with information organized into discrete compartments for later retrieval, as in the Atkinson-Shiffrin model (?). This archival metaphor resonates in cosmology, where the initial conditions of the universe, such as density perturbations, are thought to "encode" the formation of galaxies and large-scale structures (??). Similarly, in spectroscopy, the spectral lines of stars and galaxies are interpreted as reflections of thermodynamic histories, as pioneered by Cecilia Payne-Gaposchkin (?). Despite their differences, these fields grapple with a shared challenge: reconciling the apparent discreteness of events—episodic memories, halo spins, or spectral lines—with the underlying continuity of processes like attention, entropy flows, and ionization equilibria. This tension suggests a need for a unified framework that transcends domain-specific metaphors.

1.2 Description

We propose that memory is not a static repository but a process of generative influence, where past states shape future ones through weighted, non-Markovian dynamics. This perspective reinterprets cognitive buffers as autoregressive loops (?), galactic spins as dynamically quenched trajectories (?), and spectral features as entropy-driven signatures (?). By framing memory as a continuous, history-dependent process, we bridge cognitive science, cosmology, and spectroscopy under a single paradigm of generative influence, challenging traditional storage-based models.

1.3 Explanation

The stakes of this reframing are profound. In cognition, mischaracterizing memory as storage leads to flawed interventions for pathologies like amnesia or dementia, where patients retain non-episodic influences despite retrieval deficits (?). In cosmology, static spin models fail to capture the dynamical quenching that produces compact galaxies like LRDs, as seen in recent JWST observations (??). In spectroscopy, assuming static compositions overlooks the thermodynamic histories that shape spectral features, as Payne-Gaposchkin demonstrated (?). A generative framework explains emergent phenomena—working-memory span, LRD compactness, Balmer breaks—as outcomes of continuous influence, offering novel predictions and interventions.

1.4 Mathematical Formalisms

A non-Markovian process captures historical dependencies:

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

where f encodes weighted influences, θ represents parameters, and ϵ_t is stochastic noise (**?**). Unlike Markovian models, which depend only on the immediate prior state ($x_t = f(x_{t-1}; \theta) + \epsilon_t$), this allows long-range dependencies, foundational to our thesis across domains.

2 Modal Memory and Its Discontents

2.1 Background

The modal model of memory, introduced by Atkinson and Shiffrin (1968), emerged from the information-processing revolution, drawing inspiration from early computer architectures (**?**). It posits a tripartite system: sensory registers, short-term memory (STM) with a limited capacity, and long-term memory (LTM) as a vast repository. This framework dominated cognitive psychology, explaining phenomena like serial position effects (primacy and recency) and guiding studies of amnesia, such as the famous case of patient H.M. Its influence extended to educational strategies and memory research, shaping how we conceptualize cognitive storage.

2.2 Description

In the modal model, information flows linearly: sensory inputs are briefly held in registers, selected into STM (capacity $\sim 7 \pm 2$ items), and consolidated into LTM via rehearsal (**?**). Retrieval involves querying these stores, with STM acting as a temporary buffer and LTM as an archival database. Episodic memory is likened to discrete files, with sharp boundaries between sensory, short-term, and long-term stores, each governed by distinct processes.

2.3 Explanation

While the modal model accounts for phenomena like serial position effects, it struggles with continuous decay, interference, and generative recall. Amnesic patients like H.M. and Clive Wearing retain procedural and semantic abilities despite LTM deficits, suggesting memory is not purely episodic (**?**). Serial position curves indicate interference rather than buffer overflow, and the model's sharp capacity limits fail to explain flexible recall in complex tasks like conversation. These discontents highlight the need for a model that captures memory as a dynamic, history-dependent process, as proposed by Barenholtz (2025) (**?**).

2.4 Mathematical Formalisms

Modal storage is modeled as:

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

where I_i are inputs, w_i weights, α decay rate, and k capacity (~ 7). The sharp drop-off at $k+1$ conflicts with gradual forgetting observed in experiments (**?**), necessitating an autoregressive alternative.

3 Autoregressive Cognition and Memory as Generative Influence

3.1 From Modal Buffers to Autoregressive Loops

The modal model of memory (**?**) envisions cognition as a pipeline of discrete stores: sensory input feeds into a short-term memory buffer, which transfers to long-term memory via rehearsal, with retrieval loops accessing stored episodes. This archival metaphor assumes memory is a static repository, with information packaged into discrete units for later recall. Barenholtz (2025) challenges this with an autoregressive framework inspired by transformer-based language models, where memory is a generative process (**?**). Each cognitive state recursively conditions the next, with outputs feeding back as inputs. Weights encode potentialities—dynamic influences of past states—rather than static capsules. This non-Markovian process mirrors the RSVP cosmology model, where galactic compactness arises from path-dependent entropy damping rather than fixed spins (**?**). The shift from retrieval to generation reinterprets memory as a continuous, history-dependent loop, unifying cognitive and cosmic dynamics.

3.2 Formalizing Autoregressive Memory

Autoregressive cognition is modeled as:

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

where θ encodes weights, ϵ_t is stochastic noise, and f is a generative map (**?**). The influence kernel $K(\Delta t)$ quantifies how past states affect the present:

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

where τ_{mem} is the memory depth, analogous to RSVP's damping timescale $t_\gamma \equiv 1/\gamma$ (**?**). Unlike modal buffers with abrupt cut-offs, $K(\Delta t)$ decays smoothly, capturing long-range dependencies observed in cognitive tasks.

3.3 Cognitive Predictions

Autoregression reinterprets classic phenomena:

1. **Serial position effect**: Recency arises from ongoing influence via $K(\Delta t)$, not a dedicated STM store; primacy stems from rehearsal extending τ_{mem} (**?**).
2. **Working memory span**: Capacity reflects the effective depth of $K(\Delta t)$, correlating with fluid intelligence measures (**?**).
3. **Amnesia (H.M., Clive Wearing)**: Episodic deficits result from disrupted autoregressive continuity, not buffer failure, with semantic influences persisting (**?**).
4. **Conversation continuity**: Coherent discourse beyond STM limits is enabled by recursive generation, leveraging long-range dependencies (**?**).

3.4 Metrics and Applications

Barenholtz (2025) advocates influence metrics over recall accuracy (**?**). Cross-correlations or perturbation-response functions measure $K(\Delta t)$. Applications include:

- **Pathology screening**: Dementia as a collapse of $K(\Delta t)$ depth, detectable via EEG or fMRI (**?**).
- **Enhancement**: Structured rehearsal to maximize influence, not rote storage.
- **AI analogues**: LLMs as heuristic models for cognition (**?**).

3.5 Summary

Autoregressive cognition reframes memory as non-Markovian generative influence, paralleling RSVP's entropic quenching of galactic spins (**?**). This shift from storage to generation resolves modal discontents and offers new diagnostic and enhancement strategies.

4 RSVP Cosmology as Non-Markovian Memory

4.1 Background

Originally a cognitive paradigm for studying attention, the Rapid Serial Visual Presentation (RSVP) framework is reinterpreted here as a cosmological model for non-Markovian galaxy formation (**?**). Building on scalar-vector-tensor theories, RSVP describes cosmic evolution through coupled fields: scalar density Φ, vector velocity **v**, and entropy S. This approach challenges the ΛCDM paradigm, where galaxy properties are "stored" in primordial conditions like halo spin (**??**). The discovery of little red dots (LRDs) by JWST (**??**) provides a testbed for RSVP's dynamical perspective.

4.2 Description

RSVP posits galaxies as autoregressive entities: their current states are generated by past accretion histories through entropic damping, termed lamphrodyne quenching (**?**). For LRDs, compactness arises not from low primordial spins but from dynamic suppression of angular momentum in specific environments, driven by coherent entropy flows. This mirrors the cognitive shift from modal buffers to autoregressive loops (**?**).

4.3 Explanation

In ΛCDM, LRDs are explained by the low-spin tail of halo distributions ($\lambda \lesssim 0.015$) (**?**). RSVP attributes their rarity, compactness, and redshift evolution ($z \sim 4 - 8$) to environments where entropy alignment suppresses torques, producing compact cores (**?**). This non-Markovian process parallels cognitive autoregression, where memory emerges from continuous influence, not static storage (**?**).

Mathematical Formalisms The effective spin evolves as:

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

with compaction when:

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

The damping rate γ is detailed in Appendix A (**?**).

5 Thermodynamic Spectroscopy (Payne-Gaposchkin 1925)

5.1 Background

Cecilia Payne-Gaposchkin's 1925 thesis revolutionized spectroscopy by showing that stellar line strengths reflect thermodynamic equilibria, not static elemental compositions (**?**). This insight shifted astronomy from cataloging abundances to understanding dynamic processes, influencing modern interpretations of galactic spectra (**?**).

Description Stars are thermodynamic systems where spectral features emerge from ionization states driven by temperature and entropy, not "stored" compositions (**?**). This principle extends to galaxies, where LRDs exhibit Balmer breaks and V-shaped SEDs as signatures of entropy-driven gas dynamics (**?**).

Explanation LRD spectral features, such as red slopes and Balmer V-shapes, reflect entropic reprocessing in compact cores, not just dust or AGN activity

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 entropy S links to temperature T, driving spectral features (**?**).

6 Integrative Framework: Generative Memory Across Domains

Background This section synthesizes cognitive autoregression (**?**), RSVP cosmology (**?**), and thermodynamic spectroscopy (**?**) under the generative memory paradigm. Each domain rejects static storage for dynamic influence, unifying disparate fields.

Description The common principle is that past states act as weighted influences, not discrete records. Cognitive memory is autoregressive (**?**), galactic compactness is entropy-driven (**?**), and spectral features are thermodynamically generated (**?**). Tools like TARTAN, Simulated Agency, entropy smoothing, and Cyclex facilitate integration (**?**).

Explanation TARTAN prioritizes salient features, Simulated Agency projects sparse decisions, entropy smoothing mitigates overload, and Cyclex enables iterative adaptation

Mathematical Formalisms Unified kernel:

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

where K encodes influences across domains

7 Pathology, Enhancement, and Observational Discriminants

Background Pathologies and enhancements test the generative framework, while discriminants validate predictions across domains

Description Cognitive pathology (dementia, amnesia) reflects autoregressive failure (**?**). Astrophysical discriminants contrast RSVP with ΛCDM

Explanation Amnesia disrupts generative continuity, not buffers (**?**). LRDs show entropy-scaled spectra, testable via JWST

Mathematical Formalisms Influence function:

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

See Appendix C.

8 Philosophical and Theoretical Implications

Background Generative memory redefines agency and structure across disciplines

Description Memory is a constraint, not content, with non-Markovian dynamics as the basis for emergence.

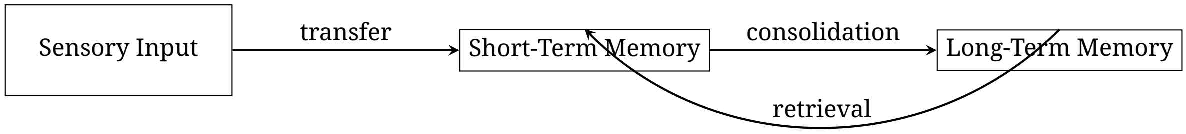
Explanation This bridges cognition and cosmology, viewing agency as influence optimization

Mathematical Formalisms Agency optimization:

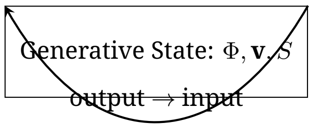
$$\max_\pi \mathbb{E}\left[\sum r_t\right], \quad r_t = g(x_t, a_t). \tag{10}$$

9 Conclusion

Memory as generative influence unifies cognition (**?**), cosmology (**?**), and spectroscopy



(a) Modal Storage Model



(b) Autoregressive RSVP Dynamics

Figure 1: Contrasting models of memory and dynamics. (a) The modal model (**?**) depicts memory as discrete storage buffers (sensory, short-term, long-term) with explicit transfer and retrieval processes. (b) Autoregressive RSVP dynamics (**?**) illustrate non-Markovian recursion: outputs feed back as inputs, governed by entropy history ($\Phi, \mathbf{v}, S$), producing compact states like little red dots (LRDs).

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 $\gamma_0 \sim 5\,\text{Gyr}^{-1}$, $\alpha = 0.75$, $\beta = 1$, $\eta = 2$, $\omega_{\text{crit}} \sim 1/t_{\text{dyn}}$, and γ_{amb} a 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

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

D.1 D.1 RSVP Spin Evolution

```
# 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

```
# 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))
```