Non-Markovian Generative Influence: A Unified Framework for Cognition, Cosmology, and Spectroscopy

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September 2025

Abstract

This manuscript proposes a unified framework where memory is modeled as a non-Markovian generative influence process, characterized by autoregressive dynamics with continuous, history-dependent kernels. We integrate the Recognition-Augmented Transformer (RAT) framework (**?**), the Rapid Serial Visual Presentation (RSVP) cosmological model (**?**), and Payne-Gaposchkin's thermodynamic spectroscopy (**?**) to demonstrate that cognitive states, galactic spin evolution, and spectral line formation are governed by analogous autoregressive mechanisms. By formalizing influence kernels $K(\Delta t)$, we derive cross-domain mappings that connect cognitive cue activations, cosmic entropy damping, and thermodynamic response functions. Contributions include a novel entropic damping closure for little red dots (LRDs), discriminative predictions against ΛCDM (**?**), and applications to cognitive pathology. Predictions encompass halo-spin decoupling, filament entropy alignment, spectral-entropy correlations, and cognitive influence metrics, testable via JWST (**?**) and neuroimaging (**?**).

1 Introduction

1.1 Background

Memory underpins diverse disciplines, from cognitive science to cosmology and spectroscopy. Traditional models treat memory as static storage: cognitive science employs discrete buffers (**?**), cosmology assumes primordial conditions encode structure formation (**?**), and spectroscopy interprets spectral lines as fixed compositions (**?**). These paradigms struggle with continuous, history-dependent phenomena, such as amnesia's procedural retention (**?**), the dynamical quenching of galactic spins (**?**), and entropy-driven spectral features (**?**). A unified framework, rooted in non-Markovian autoregressive dynamics, is proposed to reconcile these domains, integrating the Recognition-Augmented Transformer (RAT) (**?**), RSVP cosmology (**?**), and thermodynamic spectroscopy (**?**).

1.2 Description

We model memory as a generative influence process, where past states exert weighted, non-Markovian effects on future states via autoregressive kernels. This framework unifies cognitive RAT, where cue activations drive state transitions (**?**), RSVP cosmology, where entropy gradients dampen spins (**?**), and spectroscopy, where thermodynamic equilibria generate line strengths (**?**). By formalizing cross-domain mappings, we provide a rigorous mathematical structure for memory as continuous influence.

1.3 Mathematical Formalism

A non-Markovian autoregressive process is defined as:

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

with influence kernel:

$$K(\Delta t) = \frac{\partial x_t}{\partial x_{t-\Delta t}}. \tag{2}$$

The memory depth is:

$$D_{\text{mem}} = \sum_{\Delta t=1}^{\infty} K(\Delta t). \tag{3}$$

This formalism applies across domains, with x_t representing cognitive states, spin parameters, or ionization numbers (**???**).

2 Modal Memory Models

2.1 Background

Modal memory models, rooted in the cognitive revolution, describe memory as discrete storage systems. Ebbinghaus's forgetting curves (1885) quantified exponential decay (**?**), Bartlett's reconstructive memory (1932) emphasized schemas (**?**), Craik and Lockhart's levels of processing (1972) prioritized encoding depth (**?**), and Baddeley's working memory model (1974) introduced phonological and visuospatial components (**?**). The Atkinson-Shiffrin model (1968) formalized sensory, short-term (STM), and long-term memory (LTM) stores (**?**), influencing research on amnesia and serial position effects.

2.2 Description

Modal models posit a linear flow: sensory inputs enter STM (capacity $\sim 7 \pm 2$ items), consolidate to LTM via rehearsal, and are retrieved via queries (**?**). This archival structure assumes discrete boundaries, akin to computational memory.

Table 1: Comparison of Memory Models

Model	**Form**	**Limitation**
Ebbinghaus	$R(t) = e^{-\alpha t}$	Ignores interference
Bartlett	Schemas	Qualitative
Craik-Lockhart	$M \propto \int d(t)dt$	Static encoding
Baddeley	Buffers	Discrete limits
Atkinson-Shiffrin	$M_{\text{STM}} = \sum w_i I_i e^{-\alpha t}$	Buffer drop-offs
Autoregressive	$x_{t+1} = f(x_t, \theta) + \epsilon_t$	Validation needed

2.3 Mathematical Formalism

STM is modeled as:

$$M_{\text{STM}}(t) = \sum_{i=1}^{k} w_i I_i e^{-\alpha(t-t_i)}, \tag{4}$$

with interference:

$$M_{\text{int}}(t) = M_{\text{STM}}(t) - \beta \sum_{j \neq i} I_j, \tag{5}$$

and processing depth:

$$M_{\text{LTM}} \propto \int d(t)dt. \tag{6}$$

These models fail to capture continuous influence (**?**).

3 Autoregressive Cognition with RAT

3.1 Background

The Recognition-Augmented Transformer (RAT) extends autoregressive cognition by integrating cue-driven relevance fields (**?**). Unlike modal models (**?**), RAT treats memory as generative, with past states influencing future ones via continuous kernels.

Description RAT models cognitive states as:

$$x_{t+1} = f(x_t, \theta) + \epsilon_t, \tag{7}$$

with relevance fields:

$$R(x) = \sum_i \alpha_i e^{-\|x-\mu_i\|^2/2\sigma^2}, \tag{8}$$

and cue activations:

$$A_c(x) = \phi(\|x - x_c\|) w_c. \tag{9}$$

The gradient flow is:

$$\frac{dx}{dt} = f(\nabla R(x), \theta). \tag{10}$$

The influence kernel $K(\Delta t)$ reflects cue decay, with memory depth D_{mem} (**?**).

3.2 Mathematical Formalism

The kernel is:

$$K(\Delta t) \sim \exp(-\Delta t/\tau_{\text{mem}}), \tag{11}$$

with transformer self-attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V. \tag{12}$$

This unifies cognitive and LLM dynamics (**?**).

4 RSVP Cosmology

4.1 Background

RSVP reinterprets galaxy formation as non-Markovian, contrasting ΛCDM (**?**). Alternatives like tidal torque (**?**), merger-driven compaction (**?**), and dissipative collapse (**?**) assume static spins, but RSVP emphasizes entropic damping (**?**).

Description The spin parameter evolves as:

$$\frac{d\lambda_{\text{eff}}}{dt} = -\gamma(\Phi, S, \nabla S, \omega)\lambda_{\text{eff}} + \tau_{\text{ext}}, \tag{13}$$

with damping:

$$\gamma(\mathbf{x}, t) = \gamma_0 \left(\frac{\Phi}{\Phi_0}\right)^{\alpha} \left(\frac{|\hat{\mathbf{t}}_{\text{fil}} \cdot \nabla S|}{|\nabla S|_0}\right)^{\beta} \exp[-(\omega/\omega_{\text{crit}})^{\eta}] + \gamma_{\text{amb}}. \tag{14}$$

LRDs arise from entropy-driven compaction (**?**).

4.2 Mathematical Formalism

Compaction occurs when:

$$\int \left[\gamma - \frac{\tau_{\text{ext}}}{\lambda_{\text{eff}}}\right] dt \gtrsim \ln\left(\frac{\lambda_0}{\lambda_{\text{LRD}}}\right). \tag{15}$$

At $z = 6$, $t_\gamma \sim 0.2\,$Gyr vs. dynamical time $\sim 1\,$Gyr.

5 Thermodynamic Spectroscopy

5.1 Background

Payne-Gaposchkin's work showed spectra reflect thermodynamic equilibria (**?**), influencing galactic spectroscopy (**?**).

Description Ionization equilibrium is:

$$\frac{n_{i+1}n_e}{n_i} = \frac{2}{\Lambda^3}\frac{g_{i+1}}{g_i}\exp\left(-\frac{\chi_i}{kT}\right), \tag{16}$$

Table 2: Cross-Domain Autoregressive Mapping

Domain	State	Kernel	Cue	Outcome
RAT	Cognitive state	$K(\Delta t)$	Cue activations	Memory, creativity
RSVP	λ_{eff}	γ	Entropy gradients	LRD compactness
Spectroscopy	n_i	$K(\Delta t)$	Entropy field	Balmer lines

with kernel:

$$K(\Delta t) \sim \exp\left(-\frac{\Delta t}{\tau_{\text{ion}}}\right). \tag{17}$$

Balmer lines reflect entropy-driven states (**?**).

5.2 Mathematical Formalism

For Balmer breaks, $n_e \sim 10^9\ \text{cm}^{-3}$, $T \sim 10^4$ K yield V-shaped SEDs (**?**).

6 Cross-Domain Mapping

6.1 Background

RAT, RSVP, and spectroscopy share autoregressive cores (**???**).

6.2 Description

Table 2 maps domains:

6.3 Mathematical Formalism

Unified kernel:

$$x_t = \int K(t,s) x_s ds + \epsilon_t. \tag{18}$$

7 Methodology

7.1 Background

Empirical tests contrast RSVP with ΛCDM (**??**).

Description Tests include JWST lensing, CGM tomography, and spectral stacking (**??**).

7.2 Mathematical Formalism

Vorticity spectrum:

$$P_\omega(k) \propto k^{-\alpha}, \quad \alpha \sim 2 \text{ (RSVP)}. \tag{19}$$

8 Case Studies

8.1 Background

Case studies anchor the framework (**???**).

Description H.M., Clive Wearing, LRDs at $z \sim 7$, and Payne's atmospheres illustrate generative influence.

8.2 Mathematical Formalism

Recall probability:

$$P_{\text{recall}} \propto K(\Delta t). \tag{20}$$

9 Implications

9.1 Background

The framework connects to predictive coding (**?**), IIT (**?**), and Bergson's duration (**?**).

9.2 Description

Memory as constraint enables applications in AI (RAG) and cosmology (CMB anomalies) (**??**).

9.3 Mathematical Formalism

Free energy:

$$F = \mathbb{E}[\ln p(x|\theta) - \ln q(x)]. \tag{21}$$

10 Conclusion

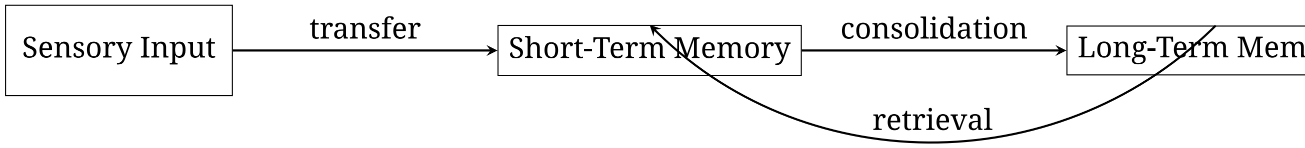
This framework unifies cognition, cosmology, and spectroscopy via non-Markovian autoregression, with testable predictions (**??**).

A Stability of RSVP Damping

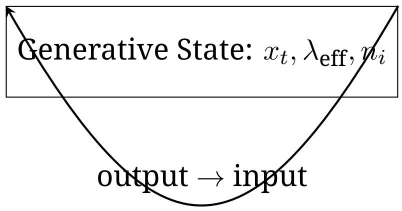
Linearize:

$$\frac{d\delta\lambda}{dt} = -\gamma\delta\lambda. \tag{22}$$

Solution: $\delta\lambda(t) = \delta\lambda_0 e^{-\gamma t}$.



(a) Modal Storage Model



(b) Autoregressive Dynamics

Figure 1: (a) Modal model (**?**). (b) Autoregressive dynamics for RAT, RSVP, and spectroscopy (**???**).

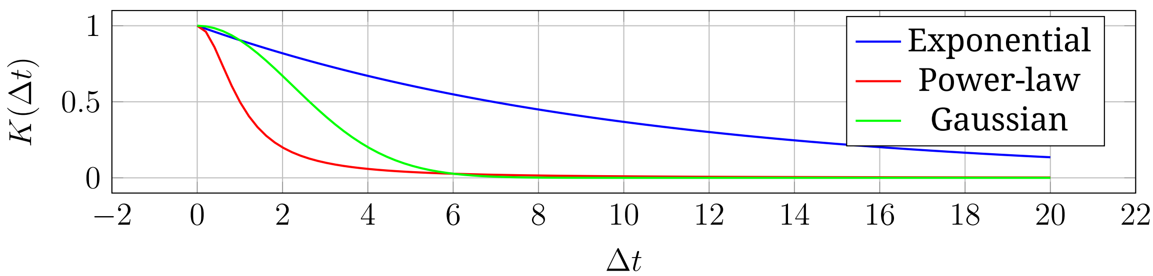


Figure 2: Influence kernels (**?**).

B Influence Kernels

Kernels: exponential, power-law, Gaussian. Spectral density:

$$S(f) = \int K(\Delta t)e^{-i2\pi f\Delta t}d\Delta t. \tag{23}$$

C RAT Formalism

Relevance fields and cue activations drive $K(\Delta t)$ **(?)**.

D Cross-Domain Example

For LRDs: $\gamma_0 = 5\,\mathrm{Gyr}^{-1}$, $\lambda_{\mathrm{LRD}} = 0.015$. For RAT: $\tau_{\mathrm{mem}} = 10$.

E Markov vs. Non-Markov

Non-Markovian:

$$x(t) = \int_0^t K(t-s)\xi(s)ds. \tag{24}$$