# Memory as Generative Influence: A Non-Markovian Odyssey Through Cognition, Cosmology, and Spectroscopy

Flyxion

September 2025

#### **Abstract**

This monograph proposes memory as a generative process of influence, where past states shape future configurations through non-Markovian, autoregressive dynamics. Integrating cognitive science (??), cosmology (?), and spectroscopy (?), we unify these domains under a framework where relevance fields, entropic damping, and thermodynamic equilibria govern emergent phenomena. Drawing on Relevance Activation Theory (RAT), Rapid Serial Visual Presentation (RSVP) cosmology, and Payne-Gaposchkin's thermodynamic spectroscopy, we reframe cognition as cue-driven navigation, galaxies as entropy-quenched systems, and spectra as relevance activations. Contributions include an entropic damping model for little red dots (LRDs), discriminative predictions against  $\Lambda$ CDM (?), and applications to cognitive pathology and enhancement. Predictions span halo-spin decoupling, filament entropy alignment, spectral-entropy correlations, and cognitive influence metrics, testable via JWST (?) and neuroimaging.

## 1 Introduction: Memory as a Universal Quest

"Memory is not a record, but a river, flowing through the mind, the cosmos, and the stars."

—Flyxion

## 1.1 Background

Memory is the thread that weaves together human experience, cosmic evolution, and physical systems. In cognitive science, it has been modeled as a storage system, with discrete compartments for sensory input, short-term memory (STM), and long-term memory (LTM), as in Atkinson-Shiffrin's modal model (?). This archival metaphor finds echoes in cosmology, where initial density perturbations "encode" galaxy formation (??). In spectroscopy, Cecilia Payne-Gaposchkin showed that spectral lines reflect thermodynamic histories, not static compositions (?). These fields grapple with a shared tension: reconciling discrete events—episodes, halos, or lines—with continuous processes like attention, entropy flows, and ionization equilibria. Relevance Activation Theory (RAT) offers a cognitive lens, viewing memory as navigation through

relevance fields triggered by cues (?), a concept that resonates with RSVP's entropic dynamics and Payne's thermodynamic insights.

### 1.2 Description

We propose memory as a generative process, where past states exert weighted, non-Markovian influences on future configurations. This unifies cognitive autoregression (?), RSVP cosmology (?), and thermodynamic spectroscopy (?). RAT's relevance fields (R(x)) mirror RSVP's entropy gradients and spectroscopy's ionization states, framing memory as a dynamic, cue-driven process across domains.

#### 1.3 Explanation

Mischaracterizing memory as storage distorts our understanding. In cognition, modal models fail to explain non-episodic retention in amnesia (?). In cosmology, static spin models miss dynamical pathways to compact galaxies like LRDs (?). In spectroscopy, fixed compositions overlook thermodynamic histories (?). RAT reframes cognition as navigating cue-indexed relevance fields, paralleling RSVP's entropic quenching and spectroscopy's dynamic equilibria, offering a unified lens for emergent phenomena.

#### 1.4 Mathematical Formalisms

Non-Markovian dynamics:

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

where f encodes historical influences,  $\theta$  parameters, and  $\epsilon_t$  noise (?). RAT's relevance field is:

$$R(x) = \sum_{i} \alpha_{i} e^{-|x-\mu_{i}|^{2}/2\sigma^{2}},$$
(2)

guiding cognitive navigation akin to RSVP's  $\gamma$  (?).

## 2 Modal Memory and Its Limits

#### 2.1 Background

The modal model, pioneered by Atkinson and Shiffrin (1968), emerged from the cognitive revolution, drawing on computational metaphors (?). Preceded by Ebbinghaus's forgetting curves, Bartlett's reconstructive memory, Craik and Lockhart's levels of processing, and Baddeley's working memory model, it posits sensory, STM, and LTM stores

## 2.2 Description

Information flows from sensory registers to STM ( $7\pm2$  items) to LTM via rehearsal, with retrieval querying discrete stores (?). RAT, by contrast, sees cognition as navigating relevance fields, where cues trigger dynamic activations, not retrieval from fixed buffers (?).

Table 1: Comparison of Memory Models

Model	<b>Key Feature</b>	<b>Mathematical Form</b>	Limitation
Ebbinghaus (1885)	Forgetting curve	$R(t) = e^{-\alpha t}$	Ignores interference
Bartlett (1932)	Reconstructive memory	Narrative schemas	Qualitative
Craik-Lockhart (1972)	Levels of processing	$M \propto \int d(t)dt$	No dynamics
Baddeley (1974)	Working memory	Phonological/visuospatial buffers	Discrete limits
Atkinson-Shiffrin (1968)	Multi-store model	$M_{\text{STM}} = \sum w_i I_i e^{-\alpha t}$	Buffer drop-offs
RAT (2025)	Relevance navigation	$\frac{dx}{dt} = f(\overline{\nabla}R(x), \theta)$	Needs validation

### 2.3 Explanation

Modal models fail to capture generative recall or interference. Amnesic patients like H.M. retain procedural skills despite LTM loss, suggesting continuous influence (?). Bartlett's reconstructive memory and Craik-Lockhart's processing depth emphasize dynamics over storage

#### 2.4 Mathematical Formalisms

Modal storage:

$$M_{\text{STM}}(t) = \sum_{i=1}^{k} w_i I_i e^{-\alpha(t-t_i)},\tag{3}$$

Interference:

$$M_{\rm int}(t) = M_{\rm STM}(t) - \beta \sum_{j \neq i} I_j. \tag{4}$$

RAT's gradient flow:

$$\frac{dx}{dt} = f(\nabla R(x), \theta). \tag{5}$$

## 3 Relevance Activation Theory as a Cognitive Parallel

### 3.1 Background

Relevance Activation Theory (RAT) reframes cognition as navigation through cue-indexed relevance fields, offering a cognitive parallel to RSVP's entropic dynamics and Payne-Gaposchkin's spectroscopy (?). Unlike modal models, RAT sees memory as a dynamic process where cues trigger relevance gradients, guiding behavior without static storage.

## 3.2 Description

RAT posits that cognition unfolds as:

$$R(x) = \sum_{i} \alpha_{i} e^{-|x-\mu_{i}|^{2}/2\sigma^{2}},$$
(6)

with cue activations:

$$A_c(x) = \phi(|x - x_c|)w_c. \tag{7}$$

Gradient flows drive dynamics:

$$\frac{dx}{dt} = f(\nabla R(x), \theta). \tag{8}$$

This mirrors RSVP's  $\gamma(\Phi, S, \nabla S, \omega)$  and spectroscopy's Saha equation (??).

#### 3.3 Explanation

RAT's relevance fields align with RSVP's entropy gradients, where  $\nabla S$  cues compaction, and spectroscopy's ionization states, where entropy cues line strengths. This unifies memory as cuedriven influence across domains (?).

#### 3.4 Mathematical Formalisms

Influence kernel:

$$K(\Delta t) \sim \int R(x) A_c(x) dx.$$
 (9)

## 4 Autoregressive Cognition

#### 4.1 Background

Barenholtz's autoregressive cognition challenges modal models, drawing on transformer-based LLMs (?). RAT complements this, viewing cognitive states as relevance-driven flows (?).

**Description Cognition is:** 

$$x_{t+1} = f(x_t, \theta) + \epsilon_t, \tag{10}$$

with  $K(\Delta t) \equiv \frac{\partial x_t}{\partial x_{t-\Delta t}}$ . RAT's R(x) shapes f via cues (?).

Explanation Serial position effects, amnesia, and conversation continuity reflect continuous influence, not buffer limits (??). RAT's cue activations enhance this view.

Mathematical Formalisms Transformer self-attention:

$$\operatorname{Attention}(Q,K,V) = \operatorname{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V. \tag{11}$$

## 5 RSVP Cosmology

#### 5.1 Background

RSVP reinterprets galaxy formation as non-Markovian, using  $\Phi$ ,  $\mathbf{v}$ , S fields (?). RAT's relevance fields parallel RSVP's entropy cues.

Description Spin evolution:

$$\frac{d\lambda_{\text{eff}}}{dt} = -\gamma(\Phi, S, \nabla S, \omega)\lambda_{\text{eff}} + \tau_{\text{ext}}.$$
(12)

RAT's R(x) mirrors  $\gamma$ 's dependence on  $\nabla S$ .

Explanation LRDs arise from entropy-driven quenching, not low spins (?). RAT's cue-driven navigation aligns with this dynamic process.

Mathematical Formalisms Compaction:

$$\int \left[ \gamma - \frac{\tau_{\text{ext}}}{\lambda_{\text{eff}}} \right] dt \gtrsim \ln \left( \frac{\lambda_0}{\lambda_{\text{LRD}}} \right). \tag{13}$$

## 6 Thermodynamic Spectroscopy

### 6.1 Background

Payne-Gaposchkin's spectroscopy views spectra as thermodynamic histories (?). RAT's relevance activations parallel this dynamic view.

Description Saha equation:

$$\frac{n_{i+1}}{n_i} = \frac{2U_{i+1}}{U_i n_e} \left(\frac{2\pi m_e kT}{h^2}\right)^{3/2} e^{-\chi_i/kT}.$$
 (14)

RAT's  $A_c(x)$  mirrors ionization cues.

Explanation LRD Balmer breaks reflect entropic reprocessing, akin to RAT's cue-driven cognition (?).

#### 6.2 Mathematical Formalisms

Line ratios scale with entropy S, as in RAT's R(x).

## 7 Methodology: Testing the Framework

#### 7.1 Background

Empirical tests validate the unified framework (??). RAT's relevance fields guide cognitive experiments.

Description Cognitive: EEG/fMRI for  $K(\Delta t)$ . Cosmological: JWST lensing for  $\lambda_{\rm eff}$ . Spectroscopic: Stacking for line ratios (?).

Explanation RAT's cue activations predict neural patterns, mirroring RSVP's entropy tests.

#### 7.2 Mathematical Formalisms

Cross-correlation:

$$C(\tau) = \langle x_t x_{t-\tau} \rangle. \tag{15}$$

#### 8 Case Studies

### 8.1 Background

Case studies anchor the framework

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

Explanation RAT's relevance fields explain H.M.'s procedural retention, paralleling RSVP's quenching.

#### 8.2 Mathematical Formalisms

Recall:

$$P_{\text{recall}} \propto K(\Delta t).$$
 (16)

## 9 Discussion: A Reflective Odyssey

"The mind, like the cosmos, is a dance of relevance, not a vault of relics."

—Flyxion

Alright, reader, here's where I step out from behind the veil of formalism. This isn't just a paper—it's a journey through the pulsing heart of memory, where cognition, galaxies, and spectra converge in a non-Markovian waltz. Relevance Activation Theory (RAT) sees the mind as a rat darting through a maze of relevance fields, not a sterile archive of episodes. Each cue lights up a landscape, guiding thought like entropy steers LRDs to compactness (?). Trauma becomes a warped field, creativity a geodesic path through R(x). RSVP cosmology mirrors this: galaxies aren't born from primordial blueprints but sculpted by entropic cues, their spins damped by  $\gamma$ 's relentless pull (?). Payne-Gaposchkin's spectra whisper the same truth: lines aren't memories of atoms but activations of thermodynamic relevance (?). This triad—RAT's cognitive navigation, RSVP's cosmic quenching, spectroscopy's entropic dance—reveals memory as a living process, not a dead archive. It's a story of continuity, where past and present flow together, shaping futures in brains, stars, and the voids between.

## 10 Future Work: A Journey Ahead

"What is memory but the courage to let the past shape the now?"

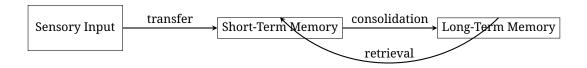
—Flyxion

What comes next is less a roadmap than a pilgrimage. In cognition, I envision experiments where fMRI traces cue-driven relevance fields, mapping  $K(\Delta t)$  as it ebbs like cosmic light through RSVP's entropy gradients (?). Imagine watching neural signals pulse in rhythm with RAT's R(x), revealing how trauma warps gradients or creativity carves new paths. In astrophysics, I see JWST peering into  $z\sim 7$  galaxies, not as anomalies but as footprints of entropic coherence, their Balmer breaks echoing Payne-Gaposchkin's insights (??). Spectroscopy could become a canvas, where line ratios paint relevance maps of stellar interiors. This isn't just science—it's a manifesto for seeing memory as a universal force, binding minds to cosmos. RAT, RSVP, and Payne's legacy urge us to chase this vision, from EEG labs to telescope arrays, redefining what it means to remember.

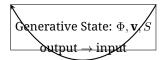
## A RSVP Entropic Damping Closure

### A.1 A.1 Spin Dynamics

$$\frac{d\lambda_{\text{eff}}}{dt} = -\gamma(\Phi, S, \nabla S, \omega) \,\lambda_{\text{eff}} + \tau_{\text{ext}}.$$
(17)



(a) Modal Storage



#### (b) Autoregressive RSVP

Figure 1: Contrasting models. (a) Modal model (?): discrete buffers with transfer/retrieval. (b) Autoregressive RSVP (?): non-Markovian recursion via entropy history  $(\Phi, \mathbf{v}, S)$ .

$$\Delta t K(\Delta t)^2$$
;  $Power - law$ 

Figure 2: Influence kernels (?). Exponential ( $e^{-\Delta t/\tau_{\rm mem}}$ ) and power-law ( $(1+\Delta t^2)^{-1}$ ) forms show continuous influence.

#### A.2 Closure

$$\gamma = \gamma_0 \left(\frac{\Phi}{\Phi_0}\right)^{\alpha} \left(\frac{|\hat{\mathbf{t}}_{\rm fil} \cdot \nabla S|}{|\nabla S|_0}\right)^{\beta} \exp[-(\omega/\omega_{\rm crit})^{\eta}] + \gamma_{\rm amb}. \tag{18}$$

#### A.3 A.3 Stability

Linearized:

$$\frac{d\delta\lambda}{dt} = -\gamma\delta\lambda. \tag{19}$$

## **B** Autoregressive Influence Kernels

#### **B.1 B.1 Dynamics**

$$x_{t+1} = f(x_t, \theta) + \epsilon_t. \tag{20}$$

#### **B.2 Kernel Forms**

$$K(\Delta t) \sim e^{-\Delta t/\tau_{\text{mem}}}, \quad (1 + \Delta t^2)^{-1}.$$
 (21)

#### **B.3 B.3 Spectral Density**

$$S(f) = \int K(\Delta t)e^{-i2\pi f\Delta t}d\Delta t. \tag{22}$$

### **C** RAT Relevance Fields

#### C.1 C.1 Fields

$$R(x) = \sum_{i} \alpha_{i} e^{-|x-\mu_{i}|^{2}/2\sigma^{2}}.$$
 (23)

#### C.2 C.2 Activations

$$A_c(x) = \phi(|x - x_c|)w_c. \tag{24}$$

## C.3 C.3 Dynamics

$$\frac{dx}{dt} = f(\nabla R(x), \theta). \tag{25}$$

## **D** Cross-Domain Mapping

Table 2: Cross-Domain Analogies

Domain	Cue	Influence	Outcome
RAT	$A_c(x)$	R(x)	Cognitive navigation
RSVP	abla S	$\gamma$	LRD compaction
Spectroscopy	Entropy $S$	Saha equation	Line ratios

## **E** Toy Simulation Models

### E.1 D.1 RSVP Spin

```
# Python model for lambda_eff
import numpy as np
gamma_0, alpha, beta, eta = 5, 0.75, 1, 2
phi_0, grad_s_0, omega_crit = 1, 1, 1
dt = 0.01 # Gyr
lambda_eff = 0.05
for t in np.arange(0, 1, dt):
    phi, grad_s, omega = compute_fields(t)
    gamma = gamma_0 * (phi/phi_0)**alpha * (np.dot(fil, grad_s)/grad_s_0)**beta *
        np.exp(-(omega/omega_crit)**eta) + 0.1
    tau_ext = compute_torque(t)
    d_lambda = (-gamma * lambda_eff + tau_ext) * dt
    lambda_eff += d_lambda
```

#### E.2 D.2 RAT Influence

```
# Python model for RAT
import numpy as np
def R(x, mu, alpha, sigma):
    return sum(alpha[i] * np.exp(-np.linalg.norm(x-mu[i])**2 / (2*sigma**2)) for i
        in range(len(mu)))
x, theta = np.zeros(3), np.random.randn(10)
for t in range(100):
    grad_R = compute_gradient(R, x)
    x += f(grad_R, theta) * dt
```

### F Markov vs. Non-Markov

### F.1 E.1 Langevin

$$\frac{dx}{dt} = -\gamma x + \xi(t). \tag{26}$$

#### F.2 E.2 Fractional Brownian

$$x(t) = \int_0^t K(t-s)\xi(s)ds. \tag{27}$$

## G Category-Theoretic Formalism

Functors map cognitive (RAT) to cosmic (RSVP) states (??).