Geometric Memory as Trajectory Influence on a Generative Substrate

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September 18, 2025

Abstract

This essay presents a geometric model of memory as trajectories influencing a generative substrate, formalized as a smooth manifold of meaning-states. Unlike static storage, memory is modeled as paths that bias future dynamics via a nonlocal-in-time flow, integrating past influences through a kernel-weighted parallel transport. The substrate evolves under a Riemannian metric, with curvature and torsion shaping convergence and reinterpretation. Plasticity updates the metric and connection based on past trajectories, embedding habitual paths as low-resistance channels. The model ties to the Relativistic Scalar Vector Plenum (RSVP) framework, mapping scalar density (Φ), vector flows ($\vec{v}$), and entropy ($\mathcal{S}$) to memory processes. Testable predictions include geodesic reuse, curvature-habit links, and kernel-driven recall effects. A discrete version aligns with large language models (LLMs), offering a computationally tractable implementation. The model reframes memory as regenerative reconstruction, not retrieval, with implications for cognition, AI, and semantic infrastructures.

1 Substrate and State

Consider a smooth manifold $\mathcal{M}$ representing "meaning-states" (e.g., neural activations, LLM embeddings, or RSVP fields). A system's state at time t is $x(t) \in \mathcal{M}$, with local coordinates x^i and a Riemannian metric $g_{ij}(x)$ quantifying semantic distances. A generative drift field $F : \mathcal{M} \to T\mathcal{M}$ encodes default evolution, reflecting grammar, physics, or policy priors. Formally:

$$\dot{x}(t) = F(x(t)) + \text{additional terms},$$

where F drives the substrate's intrinsic dynamics, akin to autoregressive priors in cognition or LLMs [Vaswani et al., 2017].

2 Memory as Trajectory Influence

Memory is not a static snapshot but a trajectory $x(\tau)$, $\tau \in [0, t]$, that biases future evolution. Recall is a nonlocal-in-time flow:

$$\dot{x}(t) = F(x(t)) + \int_0^t K(t, \tau; x(t), x(\tau))\, U(x(\tau) \to x(t))\, \dot{x}(\tau)\, d\tau + \xi(t),$$

where:

- $K(t, \tau; x(t), x(\tau))$ is an influence kernel weighting past contributions.
- $U(x(\tau) \to x(t)) : T_{x(\tau)}\mathcal{M} \to T_{x(t)}\mathcal{M}$ is parallel transport along a connection Γ^k_{ij}, ensuring coordinate-invariant influence.
- $\xi(t)$ is stochastic innovation, modeling novelty or noise.

Common kernels include:

- Exponential decay: $K(t, \tau) = e^{-\alpha(t-\tau)}$ (fading memory).
- Power-law: $K(t, \tau) = (t - \tau)^{-\beta}$ (long-tail recall).
- Oscillatory-consolidation: $K(t, \tau) = \cos(\omega(t - \tau))e^{-\alpha(t-\tau)}$ (rehearsal rhythms).
- Selective gates: $K(t, \tau) = \sigma(\langle q(x(t)), k(x(\tau))\rangle)$ (content-addressable recall, as in attention [Vaswani et al., 2017]).

3 Geometry: Metric, Curvature, and Torsion

The metric $g_{ij}(x)$ defines semantic proximity. Curvature R^i_{jkl} governs geodesic deviation: high curvature induces convergence (attractors, habits) or divergence (repellors, novelty). A connection with torsion $T^k_{ij} = \Gamma^k_{ij} - \Gamma^k_{ji}$ allows "semantic twist," where past influences are reinterpreted contextually [Penrose, 1989]. Geodesic memory channels emerge where aligned trajectories reduce effective resistance, modeled as a modified connection $\tilde{\Gamma}^k_{ij}$ updated by past usage.

4 Memory-Modulated Geometry (Plasticity)

Past trajectories reshape the substrate:

$$\partial_t g_{ij}(x) = -\eta_g \int_0^t K(t, \tau)\, \Pi_{ij}(x(t), x(\tau))\, d\tau, \quad \partial_t \Gamma^k_{ij} = -\eta_\Gamma \int_0^t K(t, \tau)\, \Psi^k{}_{ij}(x(t), x(\tau))\, d\tau,$$

where Π_{ij} and $\Psi^k{}_{ij}$ are Hebbian-like tensors encoding path reinforcement, and η_g, η_Γ are learning rates. This plasticity embeds habitual paths as low-resistance geodesics, akin to neural synaptic strengthening [Hebb, 1949].

5 Energy/Lyapunov View

Define a reconstruction functional:

$$\mathrm{E}[x(\cdot)] = \int_0^T \left\{ \frac{1}{2} \langle \dot{x}(t) - F(x(t)), \dot{x}(t) - F(x(t)) \rangle_g + \int_0^t \mathcal{L}(x(t), x(\tau))\, K(t, \tau)\, d\tau \right\} dt,$$

where $\mathcal{L}$ penalizes deviation from past trajectories. Dynamics minimize E, balancing fidelity to prior paths and generative drift [Friston, 2010].

6 Discrete (Sequence) Version

For LLMs or sequence models, let states be $x_t \in \mathbb{R}^d$ with learned metric g_t. The dynamics are:

$$x_{t+1} = f(x_t) + \sum_{s=0}^{t} \alpha_{t,s}\, P_{t\leftarrow s}\,(x_{s+1} - x_s) + \epsilon_t,$$

where $P_{t\leftarrow s}$ is a transport map (e.g., Jacobian of f or learned linear map), $\alpha_{t,s} = K(t,s) \cdot \sigma(\langle q(x_t), k(x_s)\rangle)$ combines temporal and content-based attention, and ϵ_t is noise. Plasticity updates g_t and $P_{t\leftarrow s}$ via Hebbian rules weighted by $\alpha_{t,s}$.

7 RSVP Tie-In

In RSVP [Flyxion, 2025]:

- Φ: Capacity density, measuring reliable paths per region.
- $\vec{v}$: Average flow field, reflecting habitual trajectories.
- $\mathcal{S}$: Entropy, high for exploratory novelty, low for stabilized recall.

Memory consolidation reduces $\mathcal{S}$ along practiced channels, increasing Φ locally. This aligns with RSVP's semantic infrastructure, preserving $\mathcal{S}$ for generativity [Lurie, 2009].

8 Testable Predictions

1. **Geodesic Reuse**: Trained transport $P_{t\leftarrow s}$ aligns with future steps; measure cosine similarity between $P_{t\leftarrow s}(x_{s+1} - x_s)$ and $x_{t+1} - x_t$.
2. **Curvature–Habit Link**: High-recall regions show reduced sectional curvature in practiced directions; detect via PCA spectra or fMRI/EEG manifold learning.
3. **Kernel Manipulations**: Perturbing K (e.g., via sleep rhythms) shifts recency/primacy effects in recall.
4. **Torsion and Reinterpretation**: Ambiguous cues yield path-dependent decoding; context rotates transported vectors, detectable as non-commuting transport loops.
5. **Energy Descent**: Recall loss follows E; noise flattening $\mathcal{L}$ increases creative confabulations.

9 Minimal Implementation Sketch

- **State**: Latent $x_t \in \mathbb{R}^d$, metric $g_t = I + W_t W_t^\top$.
- **Transport**: $P_{t\leftarrow s} = \exp(-\gamma(t-s))I$ or learned matrix.
- **Kernel**: $K(t,s) = e^{-\alpha(t-s)}$ or $\sigma(\langle q(x_t), k(x_s)\rangle)$.
- **Update**: $x_{t+1} = f(x_t) + \sum_s \alpha_{t,s} P_{t\leftarrow s}(x_{s+1} - x_s)$.
- **Plasticity**: $W_{t+1} = W_t + \eta \sum_s \alpha_{t,s}(x_s x_s^\top)$.

- **Evaluation**: Measure recall fidelity (MSE to target sequence) vs. creativity (divergence from training data).

10 Intuition

Memory is a landscape of meanings—a manifold—where past journeys carve paths. Each step you take is pulled by those prior routes, smoothed by frequent travel and twisted by context. Recall isn't replaying a tape; it's regenerating a path, guided by worn trails yet free to find shortcuts, balancing fidelity with discovery.

References

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