Memory as Reconstruction: A Distributed Transform-Domain Framework for Understanding Recall Dynamics

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Abstract

Classical models of memory often implicitly treat recall as retrieval of stored states, with dynamics serving merely as a means to reach stable attractors. We propose an alternative framework in which memory identity is defined by reconstruction trajectories rather than endpoint configurations. Drawing on principles observed in distributed transform-domain representations (DTDR)—an engineered system demonstrating robust reconstruction from distributed encodings—we develop a trajectory-centric model of biological memory termed the Distributed-Like Memory Hypothesis (DLMH). In this framework, recall proceeds through similarity-guided constraint satisfaction, with semantic coherence emerging through temporally extended dynamics rather than convergence to fixed states. We show that this perspective naturally accounts for several otherwise puzzling phenomena including recognition-recall dissociations, structured confabulation, graceful degradation under neural damage, and the phenomenology of remembering as "coming together" rather than "being accessed." The framework makes several testable predictions regarding phase-specific disruption, temporal ordering of recall processes, and patterns of memory errors. Importantly, DLMH subsumes classical attractor models as a limiting case while exposing new explanatory dimensions unavailable in state-centric approaches.

1 Introduction

What is a memory?

Classical models in computational neuroscience often answer this question by pointing to stable neural states—configurations of activity that the brain can return to, given appropriate cues. Memory retrieval, in this view, is pattern completion: the process by which partial activation evolves toward a stored attractor. Hopfield networks [Hopfield, 1982], attractor neural networks [Amit, 1992], and many contemporary theories of memory consolidation [McClelland et al., 1995] share this basic framework.

There is an implicit analogy here. Memory, in this picture, is like recognizing a *chord*—a simultaneous configuration of notes that can be identified from their co-occurrence. The dynamics matter, but only as a means to reach the right configuration. Once there, the memory has been retrieved.

But consider an alternative analogy: memory as *melody*.

A melody cannot be identified from any single instant. Its identity resides in the temporal sequence, the trajectory through musical space. You cannot freeze a melody at one moment without destroying what makes it that melody. The unfolding *is* the music, not a means of accessing it.

This paper explores what happens when we take the second analogy seriously—when we treat memory identity as residing in reconstruction trajectories rather than in endpoint states. This is not merely a philosophical reframing. As we will show, it leads to different explanatory capabilities, different predictions, and different connections to engineered systems that successfully implement distributed, reconstruction-based representations.

1.1 Phenomena That Strain State-Based Models

Several well-established memory phenomena sit uncomfortably with purely state-based accounts:

- **Recognition without recall**: We can experience strong familiarity without being able to reconstruct content [Yonelinas, 2002]. If memory is "being in the right attractor," why can we be partially there?
- **Tip-of-the-tongue states**: We "know that we know" something while unable to access it [Brown, 1991]. The feeling of proximity suggests ongoing partial reconstruction rather than binary state access.
- **Phenomenology of remembering**: Introspectively, recall feels like details "coming together" or "crystallizing" over time, not like accessing a pre-formed representation [Conway, 2009].
- **Graceful degradation**: Neural damage typically produces gradual memory impairment rather than catastrophic loss [Squire, 2004]. Why don't localized lesions destroy stored states?
- **Structured confabulation**: When memory fails, errors are not random but semantically coherent [Schacter, 2011]. Why should corrupted retrieval preserve meaning?
- **Consolidation paradoxes**: Sleep improves memory while sometimes reducing detail and increasing gist [Stickgold, 2005]. Is this "better storage" or "better reconstruction"?

State-based models can accommodate these phenomena through auxiliary mechanisms, but they remain somewhat peripheral to the core framework. A trajectory-based view, by contrast, makes them central and expected.

1.2 Structure of This Paper

We begin (§2) by describing distributed transform-domain representations (DTDR), an engineered approach to vector representation that achieves robust reconstruction from distributed encodings. Key observations from DTDR systems motivate the conceptual bridge to biological memory.

We then present (§3) the Distributed-Like Memory Hypothesis (DLMH), a formal framework treating memory as constrained trajectory evolution rather than state retrieval. A minimal three-neuron example grounds the concepts concretely.

Section 4 demonstrates DLMH's explanatory power across multiple memory phenomena, while Section 5 derives testable predictions that distinguish trajectory-based from state-based models.

We discuss (§6) relationships to existing frameworks, implications for artificial memory systems, and limitations before concluding (§7).

2 Motivation from Distributed Transform-Domain Representation

The conceptual framework we develop draws directly on observations from distributed transform-domain representations (DTDR) [West, 2024], an engineered approach to vector encoding that exhibits properties strikingly reminiscent of biological memory.

2.1 What Is DTDR?

DTDR encodes high-dimensional vectors by applying structured orthogonal transforms (typically the Walsh-Hadamard transform) followed by quantization. Unlike conventional quantization schemes that operate component-wise, DTDR deliberately distributes information across all transform coefficients.

Formally, given a vector $\mathbf{x} \in \mathbb{R}^d$, the DTDR representation is:

$$\hat{\mathbf{x}} = \text{normalize}(\mathbf{H}\mathbf{x}) \tag{1}$$

where $\mathbf{H}$ is a structured orthogonal matrix. Because $\mathbf{H}$ is orthogonal, inner products are preserved:

$$\langle \mathbf{H}\mathbf{x}, \mathbf{H}\mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{y} \rangle \tag{2}$$

The key property is that semantic information is *not* concentrated in individual coefficients. No single component carries disproportionate weight. Similarity arises from aggregate structure rather than isolated alignment.

2.2 Key Observations from DTDR Systems

Three properties of DTDR systems are particularly relevant to memory theory:

2.2.1 Functional Equivalence Without Exact Reconstruction

DTDR systems maintain computational correctness under quantization and partial corruption. Approximate reconstruction often suffices for downstream tasks—exact state recovery is unnecessary. What matters is preserving the right *relationships*, not the right *values*.

This mirrors biological memory: we rarely recall experiences identically across occasions, yet the reconstructions serve their functional purpose.

2.2.2 Graceful Degradation

Progressive corruption of DTDR coefficients produces progressive quality loss, not catastrophic failure. Because information is distributed, no single coefficient is critical. Robustness emerges from redundancy across the representation.

Similarly, neural damage typically impairs memory gradually. The distributed constraint structure can tolerate localized loss.

2.2.3 Similarity Before Reconstruction

DTDR enables similarity search directly in the transform domain. Fast approximate alignment can occur *before* expensive full reconstruction. This two-stage process—quick matching followed by detailed recovery—is natural rather than imposed.

This maps directly onto the recognition-versus-recall distinction: we can assess familiarity (similarity) quickly, while detailed recollection requires deeper processing.

2.3 Conceptual Bridge to Memory

If engineered systems benefit from distributed reconstruction principles, might biological memory have converged on similar solutions?

We are *not* claiming that brains implement Walsh-Hadamard transforms. Rather, we propose *functional equivalence* at the representational level. Biological neural networks may implement computations that are formally analogous to distributed transform-domain operations, without requiring identical mechanisms.

The question becomes: What would memory look like if it operated on distributed-constraint principles rather than localized-state principles?

3 The DLMH Framework

We now develop a formal framework treating memory as trajectory-based reconstruction. We term this the **Distributed-Like Memory Hypothesis** (DLMH).

3.1 Core Principles

DLMH rests on four foundational principles:

Principle 1: Memory Is Trajectory, Not State Memory identity is defined by the reconstruction process itself, not by occupancy of a particular configuration. Multiple trajectories satisfying the same constraints constitute "the same memory." State is a boundary condition, not content.

Returning to our musical analogy: a melody is not a snapshot but a path through pitch-time space. Different performances (trajectories) instantiate the same melody if they satisfy the defining melodic constraints.

Principle 2: Distributed Constraints Shape Dynamics Information is encoded in relationships—synaptic weights, connectivity patterns, neuromodulatory biases—not in individual neuron states. These constraints are persistent. Trajectories are ephemeral, existing only during recall.

Principle 3: Similarity Alignment Precedes Reconstruction Fast, approximate matching in high-dimensional neural space occurs before detailed reconstruction. Recognition is alignment without full trajectory completion. Recall requires deeper, temporally extended processing.

Principle 4: Semantic Coherence Defines Success Reconstruction need not be exact. What matters is functional validity—whether the reconstructed state supports appropriate downstream behavior. This explains why memories vary across recalls yet remain recognizably "the same."

3.2 A Minimal Worked Example

To make these principles concrete, consider the simplest non-trivial system: three interconnected units with one stored pattern.

Let the network state be $\mathbf{x} = (x_1, x_2, x_3)$ where each $x_i \in \{-1, +1\}$. We store the pattern $\mathbf{m} = (+1, +1, -1)$ by setting connection weights via an outer-product rule (with diagonal zeroed):

$$\mathbf{W} = \begin{pmatrix} 0 & +1 & -1 \\ +1 & 0 & -1 \\ -1 & -1 & 0 \end{pmatrix} \tag{3}$$

This is the distributed constraint structure. No single weight "contains" the memory. The pattern $\mathbf{m}$ is encoded in the relationships.

Now suppose a partial cue arrives: $\mathbf{x}(0) = (+1, +1, +1)$ (correct in the first two components, incorrect in the third).

Using the update rule $x_i \leftarrow \text{sign}\left(\sum_j W_{ij} x_j\right)$:

$$h_3 = W_{31}x_1 + W_{32}x_2 = (-1)(+1) + (-1)(+1) = -2 \tag{4}$$

$$x_3 \leftarrow \text{sign}(-2) = -1 \tag{5}$$

Result: $\mathbf{x}(1) = (+1, +1, -1) = \mathbf{m} \quad \checkmark$

What Just Happened?

- The weights (constraints) were persistent
- The trajectory $\mathbf{x}(0) \to \mathbf{x}(1)$ was transient
- Reconstruction occurred through constraint satisfaction
- The memory "emerged" rather than being "retrieved"

Crucially: THE TRAJECTORY IS NOT STORED. The system evolved along a path shaped by the constraint structure, arriving at a semantically coherent state.

What Are the "Coefficients"?

- In DTDR: transform-domain coefficients $\hat{\mathbf{x}}$
- In this network: synaptic weights $\mathbf{W}$
- In DLMH generally: distributed constraint structure

Not the state trajectory $\mathbf{x}(t)$—that is the reconstruction process itself.

This toy example demonstrates all core DLMH principles in the simplest possible setting. Real biological memory involves vastly more units and richer dynamics, but the conceptual structure remains the same.

3.3 Formal Sketch

We can sketch DLMH more formally without requiring heavy mathematical machinery.

3.3.1 Constraint Space

The brain's learned structure defines a constraint space $\mathcal{C}$—synaptic weights, connectivity, and modulatory influences—that shapes neural dynamics. This structure is persistent and represents the system's accumulated experience.

A cue $\mathbf{c}$ provides a partial projection into this space, initializing neural activity $\mathbf{x}(0)$.

3.3.2 Trajectory Evolution

Neural activity evolves according to:

$$\frac{d\mathbf{x}}{dt} = \mathcal{F}(\mathbf{x}, \mathcal{C}, \mathbf{c}) \tag{6}$$

where $\mathcal{F}$ represents the dynamical flow constrained by $\mathcal{C}$.

Crucially, this is *not* pure energy minimization. The brain is metabolically active; recall is not passive relaxation. A better description involves action-like principles—preferred paths under constraints—rather than descent to minima.

3.3.3 Semantic Coherence

Multiple trajectories $\{\mathbf{x}^{(i)}(t)\}$ may satisfy similar constraints and thus correspond to "the same memory." What unifies them is not identical states but shared functional validity—they produce appropriate downstream behavior.

Formally, we might define a semantic equivalence class:

$$[\mathbf{m}] = \{\mathbf{x}(t) \mid \mathcal{S}(\mathbf{x}(t), \mathbf{m}) > \theta\} \tag{7}$$

where $\mathcal{S}$ is a semantic similarity measure and θ is a threshold.

3.4 Comparison to Hopfield Networks

DLMH's relationship to classical attractor models merits explicit comparison. Table 1 summarizes key differences.

Table 1: Hopfield Networks vs. DLMH

Aspect	**Hopfield**	**DLMH**
Memory identity	Attractor state	Trajectory family
Role of dynamics	Means to endpoint	The content itself
Temporal character	Incidental	Constitutive
Optimization principle	Energy minimization	Action-like constraints
Success criterion	State correctness	Functional validity
Phenomenology	Arrival	Unfolding

Importantly, **DLMH subsumes Hopfield models as a limiting case**. Strongly consolidated, frequently rehearsed memories may behave approximately like stable attractors. But the framework explains a broader range of phenomena by not requiring this simplification.

4 Explanatory Power

We now demonstrate that DLMH naturally accounts for memory phenomena that strain purely state-based models.

4.1 Recognition vs. Recollection

In our three-neuron example, we can compute similarity to the stored pattern $\mathbf{m}$ without full reconstruction:

Quick similarity check:

$$\mathbf{x}(0) \cdot \mathbf{m} = (+1)(+1) + (+1)(+1) + (+1)(-1) = 1 \tag{8}$$

This provides a familiarity signal ("somewhat similar").

Full reconstruction: $\mathbf{x}(0) \to \mathbf{x}(1) = \mathbf{m}$

In DLMH terms:

- **Recognition** = fast similarity alignment (one inner product)
- **Recollection** = trajectory completion (iterative updates)

This explains the well-documented temporal ordering: recognition precedes recall [Yonelinas, 2002]. It also explains why recognition can succeed when recollection fails—partial similarity can be high even when reconstruction constraints are insufficient.

Returning to our musical analogy: you can recognize a melody from its first few notes (partial similarity) before reconstructing the entire sequence. Early notes align with stored constraints; full replay requires temporal evolution.

4.2 Tip-of-the-Tongue States

Tip-of-the-tongue (TOT) experiences involve strong conviction that a memory is accessible despite inability to retrieve it [Brown, 1991]. In state-based models, this requires explaining how one can be "close to" but "not in" an attractor.

DLMH provides a natural account: TOT states occur when similarity alignment succeeds but trajectory completion fails. The system has located the relevant constraint region (hence the feeling of proximity) but cannot satisfy sufficient constraints to complete reconstruction (hence the retrieval failure).

The phenomenology—knowing initial letters, syllable count, semantic features—reflects partial trajectory traversal. These are waypoints along an incomplete reconstruction path.

4.3 Structured Confabulation

When memory fails, errors are rarely random. False recalls tend to be semantically related to target memories [Schacter, 2011]—we confuse similar people, conflate related events, or fill gaps with plausible details.

In DLMH, confabulation is *best-fit reconstruction under insufficient constraints.* When a cue underdetermines the trajectory, the system settles into a nearby constraint-satisfying state. This is not random noise but geometric necessity—the "nearest neighbor" in semantic space.

This is precisely analogous to DTDR behavior under corruption: partial loss doesn't produce nonsense but rather the closest valid reconstruction given remaining information.

4.4 Graceful Degradation

Localized neural damage typically produces gradual memory impairment rather than catastrophic loss [Squire, 2004]. Alzheimer's disease, for instance, shows progressive deterioration across years.

State-based models must explain why stored patterns aren't simply erased. DLMH provides an immediate answer: **distributed constraints mean no single point of failure**. Synaptic loss degrades the constraint landscape gradually. Reconstruction quality declines, but functionality can persist.

This mirrors DTDR's graceful degradation: corrupting coefficients reduces quality smoothly rather than causing abrupt failure.

Importantly, DLMH predicts a specific ordering: **behavioral competence should outlast declarative recall**. Well-practiced skills and procedures (which can rely on coarser reconstruction) may survive when detailed episodic memory fails. This is precisely what is observed clinically [Squire, 2004].

4.5 Consolidation Effects

Sleep and consolidation improve memory, yet sometimes reduce detail while enhancing gist [Stickgold, 2005]. Is memory "better stored" or "better reconstructed"?

DLMH suggests the latter: consolidation reshapes the constraint landscape, increasing redundancy (deeper basins) and smoothing idiosyncratic details. This aids reconstruction robustness while potentially eliminating noise that doesn't generalize.

The system isn't making storage more faithful but making reconstruction more reliable and semantically coherent.

4.6 The Phenomenology of Remembering

Introspectively, recall often feels like details "crystallizing" or "coming together" rather than accessing a pre-formed image [Conway, 2009]. We can interrupt recall mid-process, experience partial completion, or feel reconstruction stalling.

These reports are difficult to reconcile with discrete state retrieval but are exactly what trajectory-based reconstruction predicts. The temporal unfolding *is* the memory, and subjective experience tracks the reconstruction process directly.

5 Testable Predictions

DLMH makes several predictions that distinguish it from pure state-based models. We highlight four high-priority empirical tests.

5.1 Phase-Specific Disruption

Prediction 1: Brief perturbations applied at different latencies after cue onset should produce qualitatively different impairments.

If recall is trajectory-based, disruption timing should matter more than disruption magnitude (within reasonable bounds). Specifically:

- **Early disruption** (<200ms): Should impair similarity alignment, reducing or eliminating familiarity signals
- **Mid-phase disruption** (200–500ms): Should impair trajectory completion, producing recognition without recollection
- **Late disruption** (>500ms): Should have minimal effect if reconstruction is largely complete

Test: Transcranial magnetic stimulation (TMS) with precise timing control over memory-relevant cortical regions during cued recall tasks. Measure both familiarity ratings (fast) and detailed recall accuracy (slow).

Contrast with Hopfield: Pure attractor models predict that disruption strength matters more than timing. Perturbations "push the system uphill" regardless of when they occur; recovery depends on basin depth, not phase.

5.2 Temporal Ordering of Recall Components

Prediction 2: Recognition should reliably precede recollection, with behaviorally measurable graded emergence of memory content.

DLMH predicts a reliable temporal sequence:

$$\text{Familiarity signal} \to \text{Gist/schema} \to \text{Specific details} \tag{9}$$

Test: High temporal resolution measures (MEG, intracranial recordings) during memory tasks. Response time distributions should show familiarity judgments preceding content judgments by 100–300ms.

Additionally, confidence ratings should become available *before* justifications—the system "knows it knows" before reconstruction completes.

5.3 Error Geometry

Prediction 3: False memories should cluster along semantic dimensions rather than distributing randomly in representation space.

When reconstruction fails, DLMH predicts errors fall within constraint-compatible regions. Specifically:

- Confabulations should preserve high-level structure (gist, schema)
- Substitution errors should respect semantic similarity
- Interference should correlate with representational proximity

Test: Systematic analysis of false recall patterns in DRM paradigm [Roediger and McDermott, 1995] or misinformation tasks. Map errors in embedding space; test whether they cluster along principal semantic dimensions.

Contrast with random noise: State corruption would predict errors distributed according to noise statistics, not constrained by meaning.

5.4 Behavior-Recall Dissociation

Prediction 4: Task performance should improve before conscious recall becomes reportable.

Because partial reconstruction can bias behavior without completing full trajectory:

- Priming effects should precede explicit recognition
- Implicit knowledge should be accessible when explicit recall fails
- Motor/procedural memory should show coarser reconstruction requirements

Test: Priming paradigms with explicit recall measures. Predict reliable temporal ordering: behavioral facilitation → familiarity → explicit content.

5.5 Summary of Predictions

Table 2 summarizes testable predictions and contrasts with state-based models.

Table 2: DLMH Predictions vs. State-Based Models

Phenomenon	**DLMH Prediction**	**State-Based Prediction**
TMS timing	Phase-specific effects; mid-disruption dissociates recognition/recall	Magnitude matters more than timing
Recall ordering	Familiarity → gist → detail (graded)	May co-occur or order flexibly
Error structure	Semantic clustering, gist-preserving	Random or basin-dependent
Behavior vs. awareness	Behavior improves first, reliably	May dissociate but no ordering

6 Discussion

6.1 Relationship to Existing Frameworks

DLMH is not incompatible with existing memory theories but rather shifts their center of gravity.

6.1.1 Attractor Networks

Classical attractor models [Hopfield, 1982, Amit, 1992] are subsumed as a special case. Strongly consolidated memories may indeed behave approximately like stable attractors—DLMH simply does not require this to be universal. The framework explains both attractor-like behavior (highly rehearsed memories) and more fluid reconstruction (weak or ambiguous memories).

6.1.2 Complementary Learning Systems

The hippocampal-cortical division [McClelland et al., 1995] addresses *what* is stored where, not *how* retrieval operates. DLMH is orthogonal: it specifies retrieval dynamics within each system. Hippocampal indexing could provide sparse pointers; cortical representations could be distributed constraints. Both could operate via trajectory-based reconstruction.

6.1.3 Predictive Processing

Predictive coding frameworks [Friston, 2010] emphasize prediction error minimization. DLMH is compatible but more specific: it treats memory retrieval as constraint satisfaction rather than pure prediction. The key difference is that reconstruction can succeed even when predictions are weak, provided constraints are sufficient.

6.1.4 Construction and Reconstruction

The constructive memory literature [Schacter, 2011] emphasizes that recall is not replay. DLMH formalizes this: memories are *constructed* through trajectory evolution, not *retrieved* from storage. However, construction is not arbitrary—it is constrained by distributed structure reflecting prior experience.

6.2 Implications for Artificial Memory Systems

DLMH has direct relevance for AI and information retrieval systems.

6.2.1 Retrieval-Augmented Generation

Current RAG systems [Lewis et al., 2020] typically use single-stage retrieval: find nearest neighbors, return them. DLMH suggests a two-stage architecture could be more robust:

1. **Fast similarity alignment**: Coarse localization in embedding space
2. **Trajectory-based reconstruction**: Iterative refinement respecting semantic constraints

This mirrors recognition vs. recollection and could improve both speed and quality.

6.2.2 Vector Databases

Traditional vector databases assume localized representations. DLMH (via DTDR) suggests distributed transform-domain representations might offer:

- Improved robustness under corruption
- Better graceful degradation
- Novel similarity signals (e.g., dilution evidence)

These are precisely the properties demonstrated in DTDR-based ANN search [West, 2024].

6.2.3 Ontology-Based Embeddings

For systems using ontological structure to shape embeddings, DLMH suggests that retrieval should respect these constraints dynamically. Rather than finding "the closest match," systems could reconstruct "the most constraint-compatible continuation."

This is particularly relevant for knowledge graphs and structured data retrieval, where semantic coherence matters more than metric proximity.

6.3 Limitations and Open Questions

Several aspects of DLMH require further development:

6.3.1 Formalization of Semantic Coherence

What precisely makes two trajectories "semantically equivalent"? DLMH currently relies on an intuitive notion of functional validity. A formal definition would strengthen predictions and enable computational modeling.

One approach: define semantic similarity via shared downstream affordances—trajectories are equivalent if they enable the same actions or inferences.

6.3.2 Learning and Consolidation

How do constraints ($\mathcal{C}$) change during learning? We have described retrieval but not acquisition. A complete theory requires specifying how experience shapes the constraint landscape.

Synaptic plasticity mechanisms (LTP/LTD) presumably underlie this, but the link between cellular-level plasticity and constraint-structure changes needs articulation.

6.3.3 Integration with Systems Neuroscience

Which brain regions implement which components? Candidates:

- **Hippocampus**: Sparse indexing, pattern separation, rapid encoding
- **Cortex**: Distributed constraints, slow consolidation
- **Prefrontal cortex**: Top-down constraint modulation, search control
- **Thalamus**: Coordination of cortical trajectories

Linking DLMH to neural circuits is essential for full explanatory power.

6.3.4 Quantitative Modeling

While we have provided conceptual framework and minimal examples, large-scale computational models are needed. Implementing DLMH in spiking neural networks or rate-based models would test its viability and generate precise predictions.

6.4 Broader Implications

If DLMH is correct, several broader questions emerge:

6.4.1 Identity and Continuity

If memory is trajectory-based reconstruction rather than exact retrieval, what constitutes personal identity? We are not defined by stored states but by capacity to reconstruct semantically coherent continuations of our past.

This connects to philosophical questions about persistence and change. Identity becomes a matter of constraint preservation, not state copying.

6.4.2 Imagination and Planning

Are imagination and future planning also trajectory-based? DLMH suggests they might be: running constrained trajectories *forward* rather than backward. This would unify memory, imagination, and decision-making under a common framework.

6.4.3 Consciousness

Could consciousness itself be a property of trajectory-based systems? The phenomenology of experience as "flow" rather than "state" aligns with DLMH's core insight. This is speculative but worth exploring.

7 Conclusion

We have proposed that memory identity is better understood as reconstruction along constrained trajectories than as retrieval of stored states. This DLMH framework emerges naturally from observations in distributed transform-domain representations, accounts for phenomena that strain classical attractor models, and makes several testable predictions.

By relocating memory from states to processes, from endpoints to trajectories, and from static to dynamic, we expose new explanatory dimensions while subsuming existing models as special cases.

The core insight can be summarized in our musical analogy: memory is fundamentally *melody-like*, not *chord-like*. Its identity resides in temporal unfolding, not in configurational snapshots. Taking this seriously leads to a framework that better accounts for the phenomenology, neuroscience, and computational properties of biological memory.

The framework also suggests deep connections between memory, representation, and computation that may inform both cognitive science and artificial intelligence. Just as distributed transform-domain representations have proven valuable in engineering, trajectory-based reconstruction may be a fundamental principle of robust memory systems—whether biological or artificial.

Future work should focus on formalization of semantic coherence, integration with systems neuroscience, large-scale computational modeling, and empirical testing of the framework's distinctive predictions. If DLMH withstands these tests, it may provide a new foundation for understanding how brains—and perhaps machines—remember.

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