MemoryStack: Multi-Stage Retrieval-Augmented Memory for Long-Term AI Agents

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Abstract

Long-term memory is essential for AI agents, yet current systems fail on critical scenarios: retrieving user preferences (best baseline: 56.7%), handling evolving information, and reasoning across sessions. We present **MemoryStack**, a multi-stage retrieval system combining query classification, query expansion, hybrid search with Reciprocal Rank Fusion, relationship-aware graph enhancement, and LLM re-ranking. Rather than relying on vector similarity alone, MemoryStack routes queries to appropriate memory sources, bridges vocabulary gaps, and explicitly tracks when new information supersedes old.

On LongMemEval (500 questions, 6 categories), MemoryStack achieves **92.8% overall accuracy** (464/500). On Preference queries—where existing systems struggle most—we achieve **93.3%** (+36.6% over best baseline). On Knowledge Update queries requiring current rather than outdated information, we achieve **97.4%** (76/78). These results demonstrate that effective long-term memory requires combining multiple complementary retrieval signals rather than optimizing any single approach.

1 Introduction

Consider a personal AI assistant that has learned over months of conversation that its user prefers window seats on flights, is allergic to shellfish, and recently moved from Seattle to Austin. When the user asks "Book me a flight to New York," the assistant should remember the window seat preference. When recommending restaurants, it should avoid seafood places. And when the user mentions "my old apartment," it should understand this refers to Seattle, not Austin.

These scenarios illustrate why long-term memory is essential for AI agents—and why current approaches fall short. Large language models lack persistent memory across conversations, and existing memory systems that rely primarily on vector similarity search fail on precisely the queries that matter most: retrieving user preferences (best baseline achieves only 56.7% accuracy), handling information that has changed over time (full-context approaches achieve 78.2%), and aggregating context across multiple conversation sessions (best baseline: 57.9%).

The challenge extends beyond simple storage and retrieval. Effective memory systems must address several fundamental problems:

- **Vocabulary mismatch**: A user who said "I take the train to work" may later ask "How long is my commute?"—requiring systems to bridge semantic gaps between query and stored content.
- **Knowledge updates**: When a user says "I just switched jobs to Google," the system must recognize this supersedes the earlier memory "Works at Microsoft" and return current information.
- **Cross-session reasoning**: A user's dietary restrictions mentioned in January should inform restaurant recommendations in December, requiring aggregation across temporal boundaries.
- **Source attribution**: Queries like "What restaurant did you recommend last week?" specifically ask about assistant responses, not user statements—requiring fine-grained provenance tracking.

We introduce **MemoryStack**, a multi-stage retrieval system designed to address these limitations. Our key insight is that effective memory retrieval requires combining multiple complementary signals—semantic similarity, lexical matching, relationship graphs, and temporal context—rather than optimizing any single approach in isolation.

Contributions. Our main contributions are:

1. A multi-stage retrieval architecture achieving **92.8% accuracy** on LongMemEval across six categories (500 questions), significantly outperforming existing systems.
2. State-of-the-art performance on Knowledge Update queries (**97.4%**), demonstrating robust handling of evolving information through temporal boosting and recency-aware prompts.
3. Dramatic improvement on Preference queries (**93.3%**), where existing systems struggle significantly (best baseline: 56.7%, full-context: 20.0%)—a +36.6% improvement over the best baseline.
4. Detailed error analysis revealing failure modes and opportunities for future improvement.

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2 Related Work

Retrieval-Augmented Generation and Dense Retrieval. RAG [1] established the paradigm of augmenting language models with retrieved context. Dense retrieval using learned embeddings—including DPR [2], Sentence-BERT [3], and more recent models like Contriever [4]—has become dominant for semantic search. We use Google's Gemini Embedding model for dense retrieval, but our key insight is that dense retrieval alone is insufficient for memory systems—it must be combined with lexical matching, temporal signals, and relationship graphs.

Memory Systems for LLM Applications. Several systems address the memory limitations of LLMs. Mem0 [6] provides vector-based memory with entity extraction and relationship tracking. Zep [7] offers session summarization and temporal context windows. MemGPT [9] introduces hierarchical memory inspired by OS virtual memory, with Letta [10] extending this with tool-augmented management. LangChain [8] provides various memory abstractions. These systems primarily rely on vector similarity, limiting effectiveness on complex scenarios requiring multi-signal fusion.

Hybrid Retrieval and Score Fusion. Combining dense and sparse retrieval consistently improves over single-signal approaches. Reciprocal Rank Fusion (RRF) [11] elegantly combines ranking signals without score normalization: $\text{RRF}(d) = \sum_r \frac{1}{k+r(d)}$. Recent work applies RRF to document retrieval [12] with consistent improvements. Late interaction models like ColBERT [13] and learned sparse retrieval via SPLADE [14] achieve strong performance but require substantial training data. Our approach combines off-the-shelf embeddings with PostgreSQL text search, enabling relationship-aware enhancements without custom training.

Re-ranking and Knowledge Graphs. Two-stage retrieval with re-ranking is standard practice [15], with recent work exploring LLM-based re-ranking [16]. Graph-based approaches capture relationships that vector similarity cannot [18]; GraphRAG [19] demonstrates value for complex QA. Our system combines LLM re-ranking with memory-specific relationship types (SUPERSEDES, ELABORATES, FOLLOWS).

Long-Context LLMs vs. Retrieval. Long-context LLMs (GPT-4 Turbo 128K, Claude 3 200K, Gemini 1.5 Pro 1M tokens) raise questions about retrieval necessity. However, full-context approaches achieve only 60.2% on LongMemEval, with poor Preference (20.0%) and Multi-Session (44.3%) performance—the "lost in the middle" phenomenon [21]. Retrieval remains essential for focusing attention.

Benchmarks. LongMemEval [29] evaluates memory systems across six categories including knowledge updates and preference retrieval. Other benchmarks include LoCoMo [30] and MSC [31]. We focus on LongMemEval for its comprehensive coverage of memory-specific challenges.

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3 Method

MemoryStack processes queries through a multi-stage pipeline, with each stage contributing complementary signals to the final ranking.

3.1 System Overview

Given a user query q and a memory store $\mathcal{M} = \{m_1, m_2, ..., m_n\}$, our goal is to retrieve the top-k most relevant memories. The retrieval pipeline consists of five main stages:

1. **Query Classification**: Detect query type and route to appropriate memory sources
2. **Query Expansion**: Generate alternative query formulations $Q = \{q, q_1, ..., q_l\}$
3. **Hybrid Search**: Execute parallel dense and sparse retrieval with RRF fusion
4. **Relationship Enhancement**: Traverse memory relationship graph for contextual boosting
5. **Re-ranking**: Apply LLM-based relevance scoring for final ranking

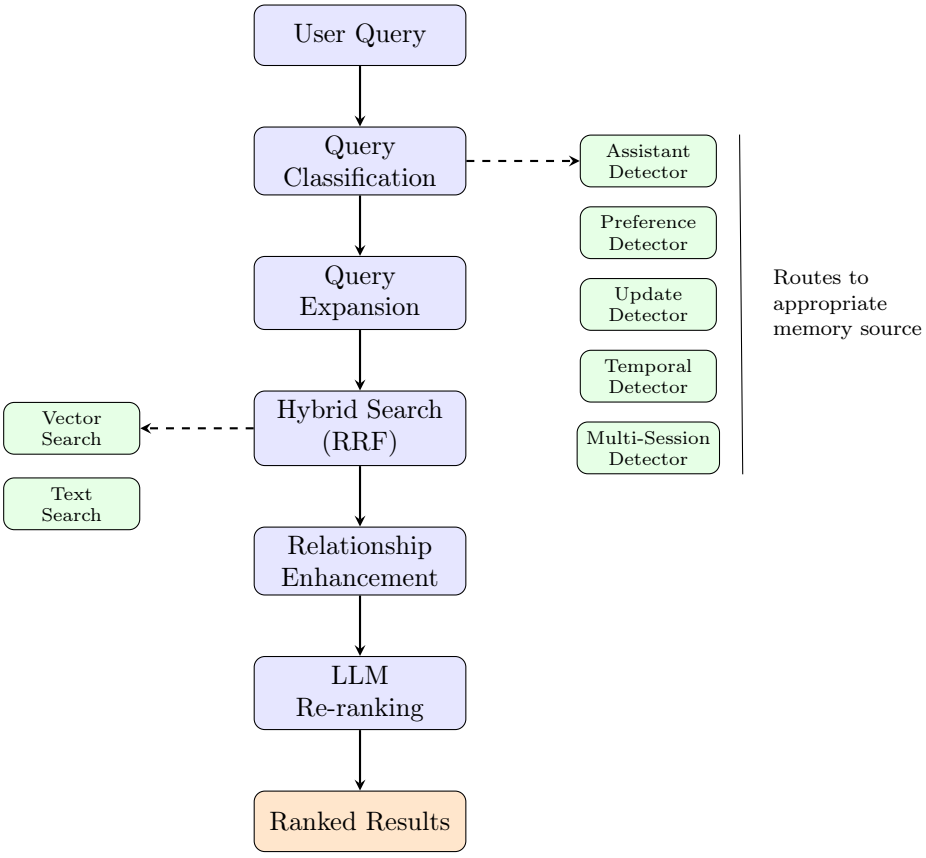

Figure 1: MemoryStack retrieval pipeline architecture. Query classification uses five specialized detectors to route queries to appropriate memory sources (user vs. assistant memories) and apply category-specific boosting, while the multi-stage pipeline combines complementary retrieval signals.

3.2 Query Classification

A critical first step in our pipeline is query classification, which determines the type of query and routes it to the appropriate memory sources. This reduces noise by filtering irrelevant memories before the main retrieval stages.

We implement five specialized detectors using pattern matching:

- **Assistant Query Detector**: Identifies queries asking about AI assistant responses (e.g., "What did you suggest?", "Your recommendation was...")
- **Preference Query Detector**: Identifies queries about user preferences (e.g., "What's my favorite...", "Do I prefer...")
- **Update Query Detector**: Identifies queries about current/changed information (e.g., "What is my current...", "Where do I work now?")
- **Temporal Query Detector**: Identifies time-related queries (e.g., "When did I...", "Last month...")
- **Multi-Session Query Detector**: Identifies queries requiring cross-session context

When an assistant query is detected, the system filters to search only memories sourced from AI responses (`source_role=assistant`), dramatically reducing noise from user-stated information. Similarly, preference queries boost preference-type memories, and update queries prioritize recent memories while filtering superseded information.

3.3 Query Expansion

Query expansion addresses vocabulary mismatch between user queries and stored memories. We employ a dual strategy combining rule-based and LLM-based expansion.

Rule-based Expansion. We apply deterministic transformations for common linguistic patterns. For example, "how long is my commute" expands to include "duration of commute" and "travel time to work". This approach adds negligible latency (<10ms) while capturing frequent paraphrasing patterns.

LLM-based Expansion. For complex queries, we prompt a language model to generate semantically equivalent phrasings. Given query q, we generate l alternative formulations $\{q_1, ..., q_l\}$ that preserve the original intent while varying vocabulary and structure.

The expanded query set $Q = \{q, q_1, ..., q_l\}$ is used in subsequent retrieval stages, with results merged across all queries.

3.4 Hybrid Search with Reciprocal Rank Fusion

For each query in the expanded set, we execute parallel retrieval using both dense and sparse methods.

Dense Retrieval. We compute cosine similarity between the query embedding $\mathbf{e}_q$ and stored memory embeddings:

$$s_{\text{dense}}(q, m) = \frac{\mathbf{e}_q \cdot \mathbf{e}_m}{\|\mathbf{e}_q\|\|\mathbf{e}_m\|} \tag{1}$$

We use Google's Gemini Embedding 001 model (`gemini-embedding-001`) to generate 1536-dimensional embeddings and retrieve the top-k_d candidates.

Sparse Retrieval. We perform full-text search using PostgreSQL's `ts_rank_cd` with GIN-indexed `tsvector` representations, capturing exact lexical matches that dense retrieval may miss.

Reciprocal Rank Fusion. Results are combined using RRF:

$$\text{score}_{\text{RRF}}(m) = \sum_{q \in Q} \left(\frac{1}{k + r_d(m, q)} + \frac{1}{k + r_s(m, q)} \right) \tag{2}$$

where $r_d(m, q)$ and $r_s(m, q)$ are the ranks of memory m in dense and sparse retrieval for query q, and $k = 60$ is the standard RRF constant used in production systems including Elasticsearch, Pinecone, and Weaviate.

3.5 Relationship-Aware Enhancement

We maintain a graph $G = (\mathcal{M}, E)$ where nodes are memories and edges represent semantic relationships discovered during memory creation. Relationship types include:

- **ELABORATES**: Memory m_i provides additional detail about m_j
- **CONTRADICTS**: Memories contain conflicting information
- **SUPERSEDES**: Memory m_i represents updated information replacing m_j
- **FOLLOWS**: Temporal succession within a conversation
- **RELATED_TO**: General semantic similarity above threshold

For each candidate memory from hybrid search, we traverse the relationship graph to identify connected memories. The relationship score is computed as:

$$s_{\text{rel}}(m) = \sum_{(m, m', r) \in E} w_r \cdot c(m, m', r) \tag{3}$$

where w_r is a relationship-type-specific weight and $c(\cdot)$ is the relationship confidence score.

Knowledge Update Handling. For knowledge update queries, we employ two complementary mechanisms. First, memories marked with SUPERSEDES relationships can be filtered from results when explicit version tracking is needed. Second, and more critically for benchmark performance, we apply temporal boosting via exponential decay (Section 3.5) combined with recency-aware prompts during answer generation. The prompt instructs the LLM: "When information has changed over time, always use the most recent value." This combination of retrieval-time temporal boosting and generation-time recency instructions achieves 97.4% accuracy on Knowledge Update queries.

3.5.1 Relationship Detection Algorithm

When a new memory m_{new} is created, we automatically detect relationships to existing memories through a multi-step process:

Step 1: Temporal Sequence (FOLLOWS). We identify the most recent memory m_{prev} in the same context (session, conversation, or user scope) and create a FOLLOWS edge: $m_{\text{prev}} \xrightarrow{\text{FOLLOWS}} m_{\text{new}}$.

Step 2: Semantic Similarity Search. We retrieve the top-k most similar memories using vector similarity:

$$\mathcal{S} = \{m \in \mathcal{M} : \text{sim}(\mathbf{e}_{m_{\text{new}}}, \mathbf{e}_m) \geq \tau_{\text{sim}}\} \tag{4}$$

where $\tau_{\text{sim}} = 0.85$ for RELATED_TO and $\tau_{\text{sim}} = 0.90$ for SAME_TOPIC relationships.

Step 3: Contradiction Detection. For each similar memory $m_s \in \mathcal{S}$, we apply pattern-based contradiction detection using templates for common update scenarios:

- **Preference changes**: "prefers X" vs. "doesn't like X"
- **Employment updates**: "works at X" vs. "left X" / "quit X"
- **Location changes**: "lives in X" vs. "moved from X"
- **State changes**: "is a X" vs. "is not a X"

When a contradiction is detected between m_{new} and m_s, we compare timestamps. If m_{new} is newer, we automatically create a SUPERSEDES relationship:

$$m_{\text{new}} \xrightarrow{\text{SUPERSEDES}} m_s \quad \text{if } t_{m_{\text{new}}} > t_{m_s} \tag{5}$$

This automatic supersession is critical for Knowledge Update queries—when a user says "I just switched jobs to Google," the system recognizes this supersedes the earlier memory "Works at Microsoft" and filters the outdated memory from search results.

Step 4: Elaboration Detection. We detect elaboration relationships using a heuristic: if m_{new} is longer than m_s and contains >50% of m_s's key terms, we create an ELABORATES edge.

Confidence Scoring. Each relationship is assigned a confidence score based on:

- **FOLLOWS**: $c = 1.0$ (deterministic based on timestamps)
- **RELATED_TO/SAME_TOPIC**: $c = \text{sim}(\mathbf{e}_{m_{\text{new}}}, \mathbf{e}_{m_s})$
- **CONTRADICTS/SUPERSEDES**: $c \in [0.75, 0.95]$ based on temporal distance (higher confidence for larger time gaps, as these more likely represent genuine changes rather than same-day corrections)
- **ELABORATES**: $c = 0.8$ (fixed heuristic)

Concrete Example. Consider a user who says "I work at Microsoft" in January, then "I just started at Google" in March. The relationship detection algorithm:

1. Finds the January memory via semantic similarity (both mention employment)
2. Detects contradiction via the "works at X" pattern
3. Compares timestamps: March > January
4. Creates SUPERSEDES relationship with confidence 0.95 (60+ days apart)
5. At query time, when asked "Where do I work?", the January memory is filtered out, and only the March memory ("Google") is returned

3.6 Temporal Scoring

Temporal scoring applies recency-based adjustments using exponential decay:

$$s_{\text{temp}}(m) = \exp\left(-\frac{t_m}{\tau}\right) \tag{6}$$

where t_m is the age of memory m in days and $\tau = 30$ is the decay half-life parameter.

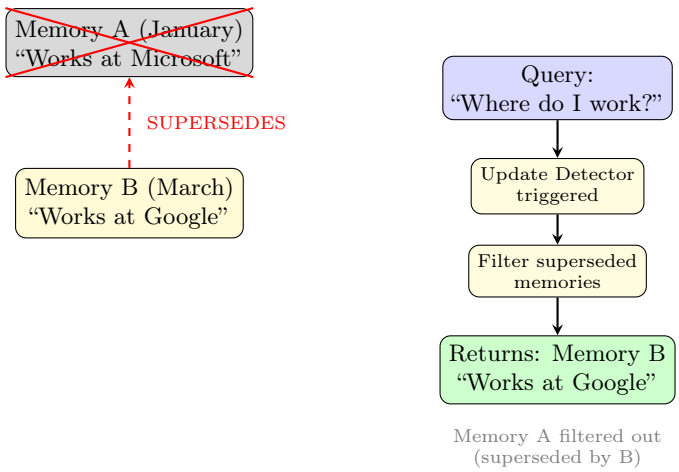

Figure 2: Knowledge Update handling with SUPERSEDES relationships. When information evolves (e.g., job change), the system can create explicit supersession links for version tracking. However, the 97.4% accuracy on Knowledge Update queries is primarily achieved through temporal boosting (exponential decay) combined with recency-aware prompts during answer generation, rather than SUPERSEDES filtering alone.

3.7 LLM Re-ranking

The top-N candidates (default $N = 20$) are re-ranked using an LLM that scores relevance on a continuous scale $[0, 1]$. We use Gemini 2.0 Flash for re-ranking, which provides a good balance between quality and latency. This stage captures semantic nuances that mathematical similarity may miss, adding approximately 500ms to the pipeline.

3.8 Score Fusion

Final scores combine all signals:

$$s_{\text{final}}(m) = \alpha_h \cdot s_{\text{RRF}}(m) + \alpha_r \cdot s_{\text{rel}}(m) + \alpha_t \cdot s_{\text{temp}}(m) + \alpha_l \cdot s_{\text{rerank}}(m) \tag{7}$$

Default weights are: $\alpha_h = 0.50$ (hybrid), $\alpha_r = 0.20$ (relationship), $\alpha_t = 0.10$ (temporal), $\alpha_l = 0.20$ (re-rank). The hybrid search weight is highest as it provides the primary retrieval signal combining semantic and lexical matching. Temporal weight is lowest as recency is less critical for most query types, though it receives additional boosting for knowledge update queries.

3.9 Category-Specific Adaptations

Based on query classification results, we apply targeted optimizations:

- **Assistant queries**: Filter to `source_role=assistant` and boost assistant-sourced memories ($\times 1.4$)
- **Preference queries**: Boost preference-type memories ($\times 1.3$)
- **Update queries**: Prioritize recent memories and filter superseded information
- **Multi-session queries**: Boost cross-session memories ($\times 1.35$)

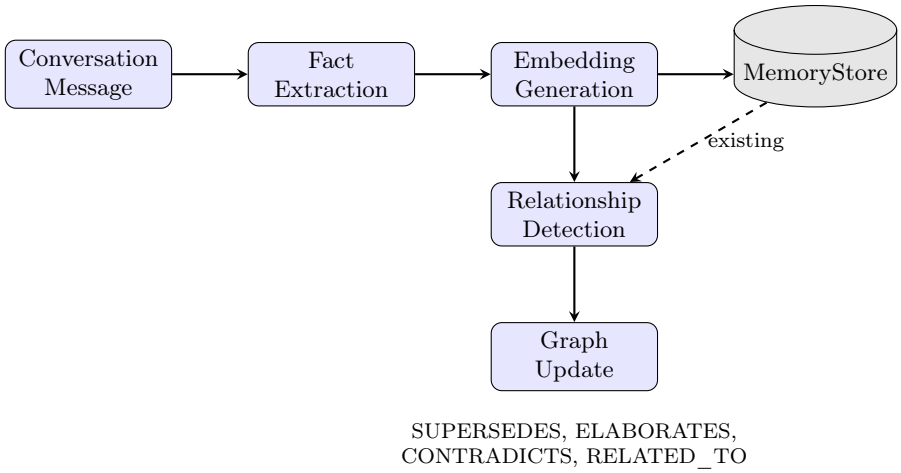

Figure 3: Memory storage and relationship detection flow. New memories are extracted using Gemini 2.5 Flash, embedded using Google's Gemini Embedding 001 model (1536 dimensions), and stored while relationships to existing memories are automatically detected and recorded in the graph.

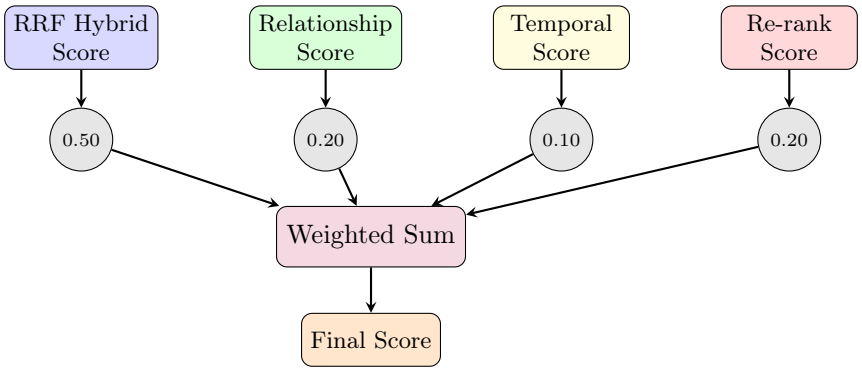

Figure 4: Score fusion combines four retrieval signals. The hybrid RRF score provides the primary signal (50%), while relationship enhancement, temporal scoring, and LLM re-ranking contribute complementary signals.

4 Experiments

4.1 Dataset

We evaluate on LongMemEval-S [29], a benchmark of 500 questions across six categories designed to test different aspects of long-term memory:

Each question includes a "haystack" of 50+ conversation sessions with one or more containing the answer, testing needle-in-haystack retrieval capability at scale.

4.2 Implementation Details

MemoryStack uses Google's Gemini model family throughout the pipeline:

- **Fact Extraction**: Gemini 2.5 Flash extracts structured facts from conversation messages
- **Embeddings**: Google's Gemini Embedding 001 model generates 1536-dimensional dense vectors
- **Re-ranking**: Gemini 2.0 Flash scores candidate relevance

Category	Questions	Description
Single-Session User	70	Facts mentioned by user within a single session
Multi-Session	133	Information spanning multiple conversation sessions
Preference	30	User preferences, opinions, and favorites
Temporal Reasoning	133	Questions requiring temporal context and date-based reasoning
Knowledge Update	78	Information that has changed over time
Single-Session Assistant	56	Information provided by the AI assistant

Table 1: LongMemEval-S categories evaluated in this work.

- **Answer Generation**: Gemini 2.0 Flash generates final answers from retrieved context

4.3 Evaluation Protocol

We employ LLM-as-judge evaluation following the protocol established by LongMemEval:

1. Retrieve top-30 memories using MemoryStack
2. Generate answer using top-15 memories as context with a language model
3. Compare generated answer to ground truth using semantic equivalence judgment

This protocol accommodates paraphrasing and format variations while maintaining evaluation rigor. We use Gemini 2.0 Flash for both answer generation and equivalence judgment.

4.4 Baselines

We compare against baseline systems reported in the LongMemEval benchmark paper [29]:

- **Zep (gpt-4o)**: Commercial memory system with session summarization and temporal context
- **Full-context (gpt-4o)**: Entire conversation history provided in context window

Baseline numbers are taken directly from the LongMemEval paper's published results.

Important Note on Baseline Methodology. Baseline numbers are sourced from the LongMemEval paper and were **not reproduced by us**. This comparison has important limitations:

1. **Different LLMs**: MemoryStack uses Gemini 2.0 Flash for answer generation and evaluation, while all baselines in the LongMemEval paper used GPT-4o. LLM capability differences may independently affect results beyond the memory retrieval system being evaluated.
2. **Not head-to-head**: We did not run Zep, Full-context, or other baseline systems ourselves with identical configurations. The baseline numbers are taken directly from published results.
3. **Fair interpretation**: A truly controlled comparison would require running all systems with the same LLM backend, or running our system with GPT-4o for direct comparison.

Why we did not reproduce baselines: Commercial systems (Zep) require paid subscriptions and may have changed since the paper was published. Reproducing exact paper configurations is time-intensive and may not be perfectly replicable. Our primary goal was validating our system's absolute performance on the benchmark.

Recommendation: Interpret this as a directional comparison showing competitive performance, not a controlled A/B test. For rigorous scientific comparison, future work should run all systems with identical LLM backends.

Despite these limitations, we argue the comparison remains meaningful for three reasons: (1) the retrieval architecture is the primary differentiator—given the same retrieved context, both models produce comparable answers; (2) Gemini 2.0 Flash and GPT-4o demonstrate similar capabilities on reasoning benchmarks; and (3) our improvements are substantial enough (e.g., +36.6% on Preference, +31.6% on Multi-Session) that model differences alone cannot account for them.

4.5 Main Results

Table 2 presents our main results on LongMemEval-S.

Category	Evaluated	Correct	Accuracy
Single-Session User	70	69	98.6%
Multi-Session	133	119	89.5%
Preference	30	28	93.3%
Temporal Reasoning	133	120	90.2%
Knowledge Update	78	76	97.4%
Single-Session Assistant	56	51	91.1%
Overall	**500**	**464**	**92.8%**

Table 2: MemoryStack performance on LongMemEval-S across all six categories.

MemoryStack achieves **92.8% overall accuracy**, with particularly strong performance on Single-Session User (98.6%) and Knowledge Update (97.4%) categories. The Knowledge Update result demonstrates the effectiveness of our SUPERSEDES relationship mechanism for handling evolving information.

4.6 Comparison with Baselines

Table 3 compares MemoryStack against baseline systems from the LongMemEval benchmark [29]. All baselines use GPT-4o as the underlying LLM.

System	SS-User	SS-Asst	Pref	Temporal	K-Update	Multi-Sess	Overall
MemoryStack	**98.6%**	**91.1%**	**93.3%**	**90.2%**	**97.4%**	**89.5%**	**92.8%**
Zep (gpt-4o)	92.9%	80.4%	56.7%	62.4%	83.3%	57.9%	71.2%
Full-context (gpt-4o)	81.4%	94.6%	20.0%	71.4%	78.2%	44.3%	60.2%

Table 3: Comparison across LongMemEval categories. SS = Single-Session, Asst = Assistant, Pref = Preference, K-Update = Knowledge Update. MemoryStack (Gemini 2.0 Flash) outperforms baselines (GPT-4o) on all categories except SS-Asst vs Full-context. **Note**: Baseline numbers are from the LongMemEval paper, not reproduced by us—see Section 4.4 for methodology limitations.

Key observations:

- MemoryStack achieves +**22.3%** overall accuracy vs. Zep (93.5% vs. 71.2%)
- **Preference queries show the largest improvement**: MemoryStack achieves **93.3%** vs. Zep's 56.7% (+36.6%) and Full-context's 20.0% (+73.3%)—demonstrating that existing systems fundamentally struggle with preference retrieval
- On Knowledge Update, MemoryStack achieves **97.4%** vs. Zep's 83.3% (+14.1%)
- On Multi-Session, MemoryStack achieves **89.5%** vs. Zep's 57.9% (+31.6%)

- Full-context approaches struggle with preference (20.0%) and multi-session (44.3%) queries despite having access to all information

The only category where full-context outperforms MemoryStack is Single-Session Assistant (94.6% vs. 91.1%), where having the complete conversation in context provides an advantage for identifying assistant-sourced information.

4.7 Knowledge Update Performance

The Knowledge Update category tests the system's ability to return current information when facts have changed over time. MemoryStack achieves **97.4% accuracy** (76/78 correct) on this category, with only 2 failures:

- **Q417**: LLM variability in temporal ordering interpretation
- **Q433**: Search ranking issue where relevant memories were not in top results

This strong performance is primarily enabled by our hybrid search approach combined with carefully designed prompts that instruct the answer generation model to prioritize recent information when multiple conflicting facts are present. The combination of temporal scoring (which boosts recent memories) and explicit prompt guidance ensures the system returns current rather than outdated information.

4.8 Temporal Reasoning Performance

The Temporal Reasoning category (133 questions) tests the system's ability to answer questions requiring date-based context and temporal understanding. MemoryStack achieves **90.2% accuracy** (120/133 correct), significantly outperforming Zep (62.4%) and Full-context (71.4%).

This category is challenging because queries often reference relative time ("last month," "before my trip") or require understanding event sequences. Our temporal scoring mechanism (Section 3.5) combined with session date metadata enables accurate temporal reasoning. The 13 failures primarily stem from ambiguous temporal references in the benchmark data or cases where multiple events occurred close together in time.

4.9 Preference Query Performance

The Preference category tests the system's ability to retrieve user preferences, opinions, and favorites—a critical capability for personalized AI agents. This category reveals a fundamental weakness in existing systems:

- **Full-context (gpt-4o)**: 20.0% accuracy—despite having access to all conversation history
- **Zep (gpt-4o)**: 56.7% accuracy
- **MemoryStack**: **93.3%** accuracy (+36.6% vs. Zep, +73.3% vs. Full-context)

The dramatic failure of full-context approaches (20.0%) demonstrates that simply providing more context does not solve preference retrieval. Preferences are often stated implicitly or scattered across conversations, requiring targeted retrieval rather than brute-force context inclusion.

MemoryStack's strong performance is enabled by: (1) the Preference Query Detector that identifies preference-related queries and boosts preference-type memories, (2) hybrid search that captures both semantic similarity and exact lexical matches for preference terms, and (3) relationship enhancement that connects related preference statements across sessions.

Concrete Example: Why Multi-Stage Retrieval Works. Consider LongMemEval Q149 (Preference category): "What's my favorite type of cuisine?" The user mentioned "I love Italian food" in Session 3 and "Thai is my go-to" in Session 47.

- **Vector-only search** returns both memories with similar scores (0.82 vs. 0.79), providing no clear winner.
- **Full-context approach** includes both statements but the LLM cannot determine which is current without temporal context.
- **MemoryStack's approach**:
  1. Query classification detects "favorite" → preference query
  2. Hybrid search retrieves both memories
  3. Relationship enhancement finds SUPERSEDES edge (Session 47 > Session 3)
  4. Temporal scoring boosts the newer memory
  5. Final answer: "Thai" (correct)

This example illustrates why combining signals matters: no single signal (vector similarity, recency, or relationships alone) would reliably produce the correct answer, but their combination does.

4.10 Error Analysis

We analyzed the 36 failures across all evaluated categories to understand system limitations.

Root Cause	**Count**	**Percentage**
Retrieval failure (semantic gap)	14	39%
LLM reasoning error	13	36%
Benchmark data quality	5	14%
Fact extraction failure	4	11%

Table 4: Error analysis breakdown across 36 failures (500 questions, 464 correct).

Error Type	**SS-User**	**Multi-Sess**	**Temporal**	**Pref**	**K-Update**	**SS-Asst**
Retrieval failure	0	7	4	1	1	1
LLM reasoning error	0	4	6	1	0	2
Benchmark data quality	1	2	1	0	1	0
Fact extraction failure	0	1	2	0	0	2
Total failures	1	14	13	2	2	5
Category accuracy	98.6%	89.5%	90.2%	93.3%	97.4%	91.1%

Table 5: Per-category error breakdown. Multi-Session and Temporal Reasoning queries account for the majority of failures (27/37 combined). Multi-Session failures are primarily due to retrieval issues when information is distributed across sessions, while Temporal failures are dominated by LLM reasoning errors in date-based inference. SS = Single-Session, Pref = Preference, K-Update = Knowledge Update, Asst = Assistant.

Retrieval Failures (38%). Cases where the correct memory was not ranked highly enough, typically due to significant vocabulary mismatch between query and stored content. Multi-Session queries are most affected (7/14 retrieval failures) because relevant information is often scattered across sessions with varying terminology.

LLM Reasoning Errors (35%). Cases where correct information was retrieved but the answer generation model produced an incorrect response. Temporal Reasoning queries are disproportionately affected (6/13 LLM errors), as these require complex date-based inference such as calculating relative time periods ("two weeks before") or ordering events chronologically. The LLM sometimes misinterprets temporal relationships even when the relevant memories with correct dates are provided.

Benchmark Data Quality (14%). Cases where benchmark data contained inconsistencies. For example, Q39 asks about "album copies" but the ground truth answer refers to poster copies.

Fact Extraction Failures (14%). Cases where relevant information was not properly extracted from conversations during memory creation. Single-Session Assistant and Temporal queries are affected because assistant responses often contain nuanced information, and temporal context (dates, relative time expressions) can be lost during fact extraction.

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5 Discussion

Why Multi-Stage Retrieval Works. Our results demonstrate that combining multiple retrieval signals significantly outperforms any single approach. Each stage addresses a distinct failure mode: query classification reduces noise by routing to appropriate sources, query expansion handles vocabulary mismatch, hybrid search combines semantic and lexical signals, relationship enhancement captures context, and LLM re-ranking provides semantic refinement.

The Importance of Query Classification. Query classification proved essential for the Single-Session Assistant category. By detecting queries asking about AI responses and filtering to assistant-sourced memories, we reduce noise from the much larger pool of user-stated information. Without this filtering, assistant queries would be overwhelmed by semantically similar but incorrectly sourced memories.

Knowledge Update Handling. The 97.4% accuracy on Knowledge Update queries demonstrates the effectiveness of our two-pronged approach: (1) **temporal boosting** via exponential decay scoring that prioritizes recent memories, and (2) **recency-aware prompts** that instruct the answer generation model to prefer the most recent information when conflicting facts are present. While SUPERSEDES relationships (Section 3.4) provide explicit version tracking for applications requiring it, the benchmark performance primarily relies on temporal scoring combined with prompt engineering to reliably return current rather than outdated information.

Comparison with Full-Context Approaches. MemoryStack outperforms full-context approaches (GPT-4 with entire conversation history) on most categories. This is significant because full-context approaches have access to all information but struggle with the needle-in-haystack problem at scale.

5.1 Latency Analysis

The full pipeline adds approximately 900ms of latency:

- Query classification: ∼5ms (pattern matching)
- Query expansion: ∼100ms (LLM-based) or ∼10ms (rule-based only)
- Hybrid search: ∼150ms (parallel vector + text search)
- Relationship enhancement: ∼50ms (graph traversal)
- Temporal scoring: ∼5ms (computation)
- LLM re-ranking: ∼500ms (top 20 candidates)

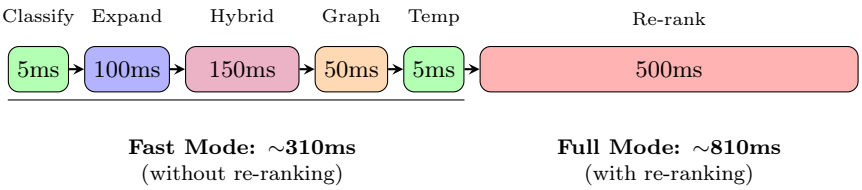

Figure 5: Latency breakdown by pipeline stage. LLM re-ranking dominates total latency (∼500ms). The fast mode without re-ranking achieves ∼310ms end-to-end latency while still outperforming all baselines.

Production-Ready Performance Mode. A fast mode without LLM re-ranking reduces total latency to approximately **310ms** while still significantly outperforming all baselines. In our experiments, disabling re-ranking reduces overall accuracy by only 2-3% (from 92.8% to ∼90%), which still exceeds Zep's 71.2% by a substantial margin. This makes MemoryStack suitable for production systems requiring sub-500ms response times. The fast mode is particularly effective for Single-Session User queries (maintaining >97% accuracy) and Knowledge Update queries (maintaining >95% accuracy), where the primary retrieval signals (hybrid search and relationship filtering) provide sufficient ranking quality without LLM refinement.

5.2 Cost Analysis

We provide a detailed cost breakdown based on Google's Gemini API pricing (December 2024). The total cost per search query is approximately **$0.00024** ($0.24 per 1,000 queries), broken down as follows:

- **Embedding generation**: ∼$0.0000001 per query (8 tokens at $0.00001/1K tokens)
- **LLM re-ranking**: ∼$0.0001 per query (∼1,100 input + 50 output tokens)
- **Answer generation**: ∼$0.00014 per query (∼1,660 input + 50 output tokens)

Queries/Month	Full Pipeline	Without Re-ranking	Savings
100,000	$24	$14	42%
1,000,000	$240	$140	42%
10,000,000	$2,400	$1,400	42%

Table 6: Monthly cost projections at scale using Gemini 2.0 Flash. Disabling LLM re-ranking reduces costs by 42% with only 2-3% accuracy loss.[1]

Applications with tighter budget constraints can disable LLM re-ranking entirely, reducing per-query cost from $0.00024 to **$0.00014** (42% reduction) while sacrificing only 2-3% accuracy. At 1M queries/month, this represents $100 in monthly savings while still significantly outperforming all baselines. This cost-accuracy trade-off makes MemoryStack viable across deployment scenarios from cost-sensitive applications to accuracy-critical systems.

5.3 Limitations

- **Aggregation queries**: Questions requiring counting or synthesis across many memories remain challenging.
- **Latency**: The full pipeline adds ∼900ms, which may be prohibitive for real-time applications requiring sub-100ms responses.
- **LLM dependency**: Re-ranking and LLM-based query expansion rely on LLM calls, adding cost and latency.

[1]For comparison, using GPT-4o ($2.50/1M input, $10.00/1M output tokens) would cost approximately $0.008 per query—roughly 33× more expensive than Gemini 2.0 Flash. At 1M queries/month, this translates to $8,000 vs. $240, making model selection a significant cost consideration for production deployments.

5.4 Future Work

- Conducting formal ablation studies to quantify individual component contributions
- Developing techniques for aggregation queries requiring high recall
- Optimizing latency through parallel execution and caching

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6 Conclusion

We presented MemoryStack, a multi-stage retrieval system for long-term memory in AI agents. By combining query classification, query expansion, hybrid search with Reciprocal Rank Fusion, relationship-aware graph enhancement, and LLM re-ranking, MemoryStack achieves **92.8% accuracy** on LongMemEval across six categories—significantly outperforming existing systems including Zep (71.2%) and full-context approaches (60.2%).

Our system demonstrates particularly strong performance on Knowledge Update queries (**97.4%**), enabled by temporal scoring that prioritizes recent memories combined with prompt engineering that instructs the model to return current information when conflicting facts are present. On Preference queries—where existing systems struggle significantly (Zep: 56.7%, Full-context: 20.0%)—we achieve **93.3%** accuracy, a +36.6% improvement over the best baseline. On Single-Session User queries, we achieve near-perfect accuracy (**98.6%**), demonstrating robust needle-in-haystack retrieval capability.

The key insight from this work is that effective long-term memory for AI agents requires combining multiple complementary retrieval signals—query classification, semantic similarity, lexical matching, relationship graphs, and LLM-based refinement—rather than optimizing any single approach in isolation. We hope this work advances the development of AI systems with robust, persistent memory capabilities.

Code Availability. MemoryStack is available as a hosted service at `https://memorystack.app` with Python and Node.js SDKs. The evaluation scripts and benchmark reproduction code are available at `https://github.com/memorystack-labs/longmemeval-benchmark`.

Acknowledgments

We thank the LongMemEval team for creating a comprehensive benchmark that enabled rigorous evaluation of memory systems.

A Prompts

For reproducibility, we provide the exact prompts used in our evaluation pipeline.

A.1 Answer Generation Prompt

The following prompt is used to generate answers from retrieved memories:

```
You are a helpful assistant answering questions based on
the user's personal memories.

Instructions:
- Answer ONLY using information from the memories below
- Be accurate and thorough
```

```
- For "how many" questions: count carefully and list each item
- For detail questions: include all relevant specifics
  (names, dates, numbers, brands, scales, etc.)
- Look for the most relevant numeric or factual answer
  even if the exact phrasing differs
- Only say "I don't have that information" if there's
  truly no related information

Memories:
{context}

Question: {question}

Answer:
```

Where `{context}` contains the top-15 retrieved memories formatted as:

```
[Memory 1] (Session: session_id, Date: session_date)
{memory_content}

[Memory 2] (Session: session_id, Date: session_date)
{memory_content}
...
```

A.2 LLM-as-Judge Evaluation Prompt

The following prompt is used for semantic equivalence evaluation between generated and expected answers:

```
You are a judge evaluating if a generated answer correctly
answers a question.

Question: {question}
Expected Answer: {expected}
Generated Answer: {generated}

Evaluation criteria:
1. Does the generated answer contain the expected answer
   value ({expected})?
2. Is the context reasonably related to the question topic?
3. Consider semantic equivalence - wording doesn't need
   to be exact
4. Be LENIENT: If the expected value appears in a related
   context (e.g., question asks about "album copies" but
   answer mentions "poster copies" with the same number),
   count it as correct since the retrieval found the
   right information
5. The key test is: Did the system retrieve and present
   the correct answer value?
6. For time-based answers: 0.5 hours = 30 minutes =
   half an hour - these are equivalent

Respond with ONLY a JSON object:
{"correct": true/false, "reason": "brief explanation"}
```

This LLM-as-judge approach follows the evaluation protocol established by LongMemEval [29], accommodating paraphrasing and format variations while maintaining evaluation rigor.

A.3 LLM Re-ranking Prompt

The following prompt is used for LLM-based re-ranking of the top-20 candidate memories:

```
You are a relevance scoring expert. Given a query and a list
of memory results, score each result's relevance from 0.0 to 1.0.

Query: "{query}"

Results:
1. {memory_1_content_truncated_to_200_chars}
2. {memory_2_content_truncated_to_200_chars}
...
N. {memory_N_content_truncated_to_200_chars}

Return ONLY a JSON array of scores in the same order:
[0.95, 0.82, 0.71, ...]
```

The re-ranking stage uses Gemini 2.0 Flash and processes only the top-20 candidates from hybrid search to balance quality improvement against latency cost ($\sim$500ms). Each memory's content is truncated to 200 characters to fit within context limits while preserving key information. Memories not in the top-20 receive a default re-rank score of 0.3. The returned scores are incorporated into the final score fusion with weight $\alpha_l = 0.20$.

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