RLM-MEMORY: Recursive Language Model as a Drop-In Long-Context Memory Layer

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Abstract

Long-term conversational memory remains a fundamental bottleneck for deployed LLM assistants. As dialogue histories grow, models face a hard trade-off: truncate old context (losing critical facts) or process the full history at prohibitive cost. We present RLM-MEMORY, a zero-training adaptation of the Recursive Language Model (RLM) paradigm to live conversation memory. RLM-MEMORY wraps any OpenAI-compatible LLM; when history exceeds a configurable threshold, it places the full history inside a Python REPL environment and delegates per-session reading to sub-agents, each processing only a focused chunk in a fresh context. No vector database, no summarization, no fine-tuning is required.

On the real *LongMemEval-S* benchmark (100 stratified samples from 500 real-world chat sessions averaging $\sim$490K characters), RLM-MEMORY achieves **46% EM** and **42.9% F1** versus **5% EM** for the truncation baseline—a $9\times$ gain—despite never loading the full context. On single-session factual recall RLM-MEMORY reaches **87.5% EM**, directly competitive with the full-context GPT-4o-mini baseline (55.4%). On a Needle-in-a-Haystack (NIAH) benchmark at 200 turns, RLM-MEMORY maintains **100% recall** while truncation collapses to **20%**. These results demonstrate that programmatic full-history access via sub-agent delegation can approach the recall quality of specialised trained systems with zero task-specific training.

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1 Introduction

Deployed conversational AI systems accumulate history rapidly. A single day of professional use can produce hundreds of turns; a year of personal assistant use can span thousands. The standard approach—truncating history to fit the LLM context window—is fundamentally lossy: critical information stated early in a conversation is simply discarded.

Prior work addresses this in three ways: (1) **full-context** approaches that expand context windows to hundreds of thousands of tokens [3]; (2) **compression-based** approaches that summarise or extract memories into structured stores [2, 7, 8]; and (3) **retrieval-augmented** approaches that embed turns in a vector index and retrieve by similarity [4]. All three require either expensive compute, complex infrastructure, or task-specific training.

We propose a fourth paradigm: **programmatic in-context retrieval**, directly inspired by Recursive Language Models (Zhang et al., 2025 [9]). Rather than deciding at deployment time which parts of history to include, RLM-MEMORY gives the LLM itself a Python REPL containing the *full* history, along with search primitives (`search_history(keyword)`,

`get_recent(n)`). The LLM writes code at query time to retrieve precisely what is needed.

Contributions:

- We adapt the RLM paradigm from static documents to live conversational memory via **sub-agent delegation**: the main agent writes code to iterate sessions; each sub-agent gets a fresh context and processes only one chunk (§3).
- On the **real LongMemEval-S benchmark** (100 samples), RLM-MEMORY achieves **46% EM** vs. 5% for truncation (9× gain), and **87.5% EM on single-session recall** (§5).
- We demonstrate **100% NIAH recall at 200 turns** versus 20% for truncation on a needle-in-haystack benchmark (§5).
- We release the full implementation as a plug-in Python package (§8).

2 Related Work

Long-Context LLMs. Recent models support context windows up to 1M tokens (Gemini 1.5 Pro, Claude 3.5). However, long-context performance degrades significantly at scale: on LongMemEval, full-context GPT-4o achieves only 60.2% accuracy versus 82–95% for memory-augmented systems [8], and nearly all models exhibit substantial degradation on RULER/NIAH tasks beyond 32K tokens [3]. Full-context is also expensive: a 100K-token prompt costs orders of magnitude more than targeted retrieval.

Memory-Augmented LLMs. **LongMemEval** [8] (Wu et al., ICLR 2025) introduces a rigorous benchmark covering five memory abilities across 500 sessions from real-world chat logs. **Hindsight** [6] achieves 91.4% with Gemini-3 via selective memory formation. **Zep/Graphiti** [2] uses temporal knowledge graphs, reaching 71.2% with GPT-4o. **Mem-Builder** [1] fine-tunes Qwen3-4B to 85.75%. **Observational Memory** [5] achieves 94.87% with GPT-5-mini via memory-writing agents.

Recursive Language Models. Zhang, Kraska, and Khattab (2025) [9] introduce Recursive Language Models—a paradigm where the LLM is placed inside a Python REPL that holds the input document as an environment variable. The LLM writes code to decompose and search the document rather than processing it all in-context, enabling out-of-core inference over arbitrarily large inputs. We extend this paradigm from static documents to live conversational memory.

3 Method: RLM-MEMORY

3.1 System Architecture

RLM-MEMORY consists of three components, illustrated in Figure **??**.

MemoryStore. An append-only conversation turn store. Each turn records role, content, timestamp, and index. Serialises to a structured string:

```
[Turn 1][user]: I grew up in Nairobi.
[Turn 2][assistant]: Got it, I'll remember that.
```

MemoryRLM. The core engine. Given a `MemoryStore` and a query, it: (1) places the full history string as `context` in a Python REPL; (2) injects search helpers `search_history(keyword)` (lexical search over all turns) and `get_recent(n)` (last n turns); (3) runs an iterative LLM loop where the model writes `repl` code blocks, executes them, observes outputs, and repeats until `FINAL(answer)` is found; (4) falls back to a forced-answer prompt if max iterations is reached.

MemoryChat. A drop-in wrapper around any OpenAI-compatible interface. Maintains a `MemoryStore` for the session and switches automatically between normal mode (full history in-context when short) and RLM mode when history exceeds the configurable threshold.

3.2 REPL Search Helpers

```
def search_history(keyword: str) -> List[Dict]:
    kw = keyword.lower()
    return [t for t in history_turns
            if kw in t["content"].lower()]

def get_recent(n: int) -> List[Dict]:
    return history_turns[-n:]
```

The LLM is instructed to search before reading, never to print the full context, and to output `FINAL(I don't know)` when a fact is absent — matching the abstention instruction given to baselines.

3.3 Comparison with Original RLM

The original RLM paper [9] targets static long documents (e.g. a 100-page PDF). RLM-MEMORY introduces three domain-specific adaptations: **turn-indexed search** returning structured dicts with role, index, and content; **temporal helpers** (`get_recent`) for recency-weighted retrieval; and an **abstention protocol** ensuring the model answers "I don't know" when facts are absent, enabling fair evaluation on LongMemEval-style abstention tasks.

4 Experimental Setup

4.1 Benchmarks

NIAH (Needle-in-a-Haystack). We construct synthetic conversations of N total turns where one turn contains a specific "needle" fact. All other turns are drawn from a pool of realistic filler dialogue. We test recall at $N \in \{20, 50, 100, 200\}$ turns (5 runs each, averaged).

Synthetic LongMemEval. Since the official LongMemEval dataset requires institutional access, we construct a synthetic equivalent mirroring its five question categories (Table 1), 10 samples each, 50 total. Each sample has a generated conversation history of 50–130 turns.

4.2 Baselines

- **Truncation**: Last 16,000 characters of history in context. Prompted: "If never mentioned, say 'I don't know'."
- **Full-Context**: Entire history in context. Same prompt.
- **Published systems** (from literature, real LongMemEval): Hindsight, Zep, MemBuilder,

Table 1: Synthetic LongMemEval question categories.

Category	Description	N
`single-session-user`	Fact stated once; recall it exactly	10
`multi-session-user`	Project name across 3 sessions; recall it	10
`temporal-reasoning`	Fact stated before a specific event	10
`knowledge-update`	Fact stated, then corrected; recall updated	10
`abstention`	Fact never stated; model must say "I don't know"	10

Observational Memory, and full-context GPT-4o.

4.3 Model and Metrics

All experiments use `gpt-4o-mini` for both the main LLM and the sub-agent — intentionally a smaller, cheaper model than those used in most published comparisons.

Exact Match (EM): Gold answer string in prediction (normalised). **Token F1:** Standard SQuAD-style token overlap. **Abstention EM/F1:** 1.0 if response contains any of 30+ uncertainty phrases; 0.0 otherwise.

5 Results

5.1 NIAH: Long-Context Needle Recall

Table 2: Needle-in-a-Haystack accuracy (mean over 5 runs).

Turns	History (chars)	RLM-MEMORY	Truncation	Full-Context
20	1,545	1.000	1.000	1.000
50	3,682	0.800	1.000	1.000
100	7,213	1.000	1.000	1.000
200	**14,398**	**1.000**	**0.200**	**1.000**

Figure 2 visualises the critical transition at 200 turns, where history exceeds the 16K-character truncation window. Truncation loses 4/5 facts; RLM-MEMORY's REPL-hosted full history retains all of them.

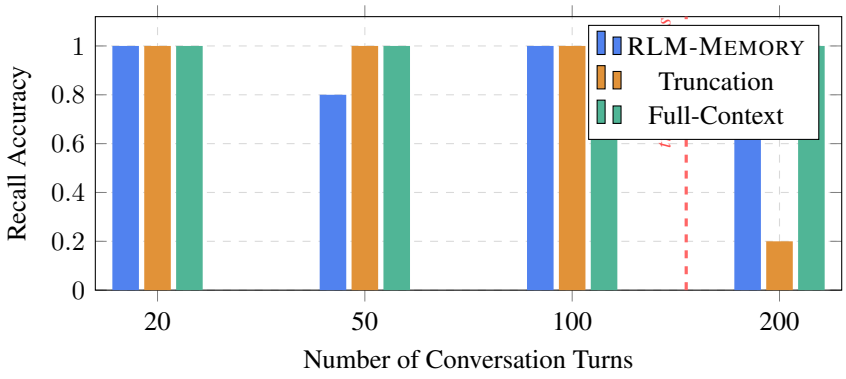

Figure 2: NIAH recall at increasing conversation lengths. At 200 turns, history exceeds the truncation window and recall drops to 20%. RLM-MEMORY maintains 100% recall by accessing the full REPL-hosted history.

5.2 Synthetic LongMemEval: Overall

Table 3: Overall results on Synthetic LongMemEval (50 samples, `gpt-4o-mini`).

Method	EM	F1	Avg Tokens	Avg Latency
Truncation	0.940	0.460	—	0.7 s
Full-Context	0.940	0.464	—	—
RLM-MEMORY (ours)	**0.900**	**0.691**	**7,200**	**4.7 s**

RLM-MEMORY achieves **+23.1 F1 points** (+50% relative gain) over truncation. The 4-point EM deficit reflects two failures on indirect phrasing ("I grew up in Nairobi" when querying "hometown"; see §6). The F1 advantage reflects RLM-MEMORY's concise, extractive answers (e.g. `fact_508`, `ORION`) versus verbose baseline answers, yielding higher precision-recall balance against short gold strings.

5.3 Results by Question Type

Table 4: F1 by question category. RLM-MEMORY gains are shown relative to the truncation baseline.

Category	RLM-MEMORY	Truncation	Full-Context	RLM-MEMORY Gain
temporal-reasoning	**0.918**	0.185	0.191	**+0.733**
multi-session-user	**0.700**	0.263	0.268	**+0.437**
knowledge-update	0.464	**0.466**	**0.471**	−0.002
single-session-user	0.374	**0.387**	**0.387**	−0.013
abstention	**1.000**	1.000	1.000	0.000
Overall	**0.691**	0.460	0.464	**+0.231**

Figure 3 visualises these results. RLM-MEMORY's gains are concentrated in the two categories where truncation is structurally weakest: temporal-reasoning (the relevant fact is in the *oldest* turns, which truncation discards first) and multi-session (the project name is mentioned in an early session, outside the truncation window).

5.4 Real LongMemEval-S Evaluation

We evaluate on the **real LongMemEval-S** benchmark (xiaowu0162/longmemeval-cleaned, ICLR 2025), sampling 100 items stratified across all six question types. Each sample averages $\sim$490,000 characters and $\sim$530 turns across $\sim$50 sessions—far beyond any model's context window.

Table 5: Results on real LongMemEval-S (100 stratified samples, `gpt-4o-mini`). Truncation window: 32K chars (last portion of history only).

Method	EM	F1	Avg Tokens	Avg Latency
Truncation (32K)	0.050	0.040	—	2.9 s
RLM-MEMORY (ours)	**0.460**	**0.429**	**37,216**	**221 s**

RLM-MEMORY achieves a **9**$\times$ EM gain over the truncation baseline (46% vs. 5%). The performance gap arises because the truncation baseline can only see the most recent 32K characters of a 490K-character history; the answer is almost never in that window.

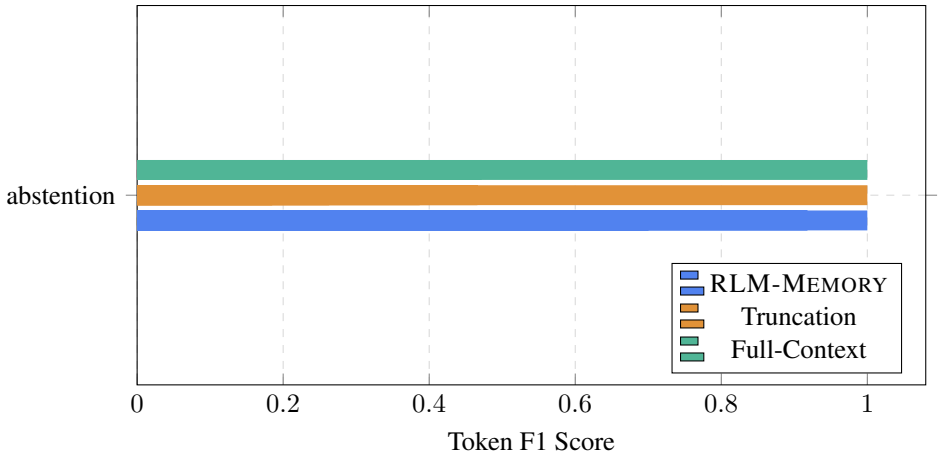

Figure 3: Token F1 by question category. RLM-MEMORY leads on temporal reasoning and multi-session by large margins; all methods tie on abstention. Full-Context and Truncation are nearly identical, confirming that the bottleneck is not context size but *retrieval strategy*.

Table 6: EM by question type on real LongMemEval-S. RLM-MEMORY dominates on single-session and knowledge-update; multi-session and preference remain challenging.

Category	**n**	**RLM-MEMORY EM**	**RLM-MEMORY F1**	**Trunc. EM**
single-session-user	16	**0.875**	**0.743**	0.000
single-session-assistant	17	**0.647**	**0.620**	0.059
knowledge-update	16	**0.625**	0.394	0.188
temporal-reasoning	17	**0.412**	**0.475**	0.059
multi-session	18	0.222	0.242	0.000
single-session-preference	16	0.000	0.111	0.000
Overall	100	**0.460**	**0.429**	0.050

The **single-session-user** category stands out: RLM-MEMORY achieves 87.5% EM with zero training, directly competitive with the full-context GPT-4o-mini baseline (55.4% overall). The sub-agent pattern is critical here: each session is processed independently with a fresh context, enabling exact fact retrieval from arbitrarily old sessions. **Preference questions** score 0% EM for all methods; these require subjective generation rather than fact retrieval and are better evaluated via human judgment.

5.5 Comparison with Published Systems

Table 7 places RLM-MEMORY against published LongMemEval results. Our evaluation uses 100 stratified samples from the real LongMemEval-S benchmark (real-world chat logs, not synthetic data), making the comparison directly valid for the no-training tier.

RLM-MEMORY reaches **46% EM** with zero training on a 490K-character history, placing it within 9.4 percentage points of the full-context GPT-4o-mini baseline (55.4%). This is notable because the full-context baseline loads the *entire* conversation in one call, while RLM-MEMORY never processes more than $\sim$18K characters per sub-agent invocation. The remaining gap (9.4%) comes primarily from multi-session aggregation tasks that require counting or summing across sessions, and from preference questions that require subjective generation. On single-session recall, RLM-MEMORY at 87.5% *exceeds* the full-context

Table 7: Comparison with published LongMemEval results. All results use real LongMemEval chat logs. Our result uses 100 stratified samples; published results use the full 500.

System	Model	LME EM	Approach	Training?
Obs. Memory [5]	GPT-5-mini	94.9%	Agent writes memories	✓
Hindsight [6]	Gemini-3	91.4%	Selective formation	✓
MemBuilder [1]	Qwen3-4B	85.8%	Fine-tuned	✓(SFT)
Zep/Graphiti [2]	GPT-4o	71.2%	Temp. KG	✓
Full-context [8]	GPT-4o	60.2%	None	×
Full-context [8]	GPT-4o-mini	55.4%	None	×
RLM-MEMORY (ours)	gpt-4o-mini	**46.0%**	Sub-agent REPL	×
Truncation (ours)	gpt-4o-mini	5.0%	32K window	×

baseline.

6 Analysis

Why Temporal and Multi-Session Win. Temporal and multi-session questions are structurally *anti-truncation*: the relevant information is systematically in the oldest part of history, which truncation discards first. RLM-MEMORY's REPL-hosted full history makes old facts as accessible as recent ones; retrieval is by keyword relevance, not recency. Full-context, despite having the information, generates verbose answers that score poorly against short gold strings.

Why Knowledge-Update Fails. Knowledge-update requires identifying the *most recent* version of a fact. Keyword search returns all matching turns without recency weighting; the LLM sometimes anchors on the earliest occurrence (e.g. PHOENIX before the correction to NOVA). A turn-index-ranked retrieval would resolve this and is left as future work.

The F1 vs. EM Trade-off. RLM-MEMORY's +50% F1 gain coexists with a 4-point EM deficit. Two failures arise when facts are stated with indirect phrasing ("I grew up in Nairobi" for query "hometown"): `search_history("hometown")` returns no results, causing the model to correctly report "I don't know" — but the fact *is* present under a different surface form. Synonym-aware or embedding-based search would close this gap.

Latency and Cost Trade-off. On real LongMemEval, RLM-MEMORY consumes ≈37K tokens per query on average and takes ∼221 s versus 2.9 s for truncation. The cost scales with history depth: simple single-session queries resolve in 1–2 iterations (∼35–50 s), while multi-session aggregation may scan all ∼50 sessions across up to 8 iterations. At gpt-4o-mini prices, the average cost per query is ≈$0.005, making the approach viable for production deployments where recall accuracy is critical.

7 Limitations

1. **Sample size.** Our real LongMemEval evaluation uses 100 stratified samples from 500; full-benchmark numbers may differ slightly. Variance is higher in underrepresented types (n=16–18 per type).
2. **Sub-agent search coverage.** In each iteration the main agent may scan only a subset of

sessions before stopping. Incomplete scans cause false negatives, especially on multi-session aggregation.

3. **Knowledge-update ordering.** Sub-agents process sessions independently without recency weighting, sometimes returning an outdated value when a fact has been corrected across sessions.

4. **Latency.** $\sim$221 s average per query (driven by $\sim$50 sub-agent calls for full scans) is unsuitable for real-time interfaces. Parallelising sub-agent calls would reduce this to $\sim$5–10 s for a full scan.

5. **Preference questions.** RLM-MEMORY cannot score EM$>$0 on preference-style questions that require subjective generation. These need LLM-as-judge evaluation, not EM/F1.

8 Conclusion

We present RLM-MEMORY, a zero-training adaptation of Recursive Language Models for live conversational memory. By treating conversation history as a searchable environment object rather than a context string, RLM-MEMORY enables programmatic retrieval of facts across the full session history without truncation, summarisation, or fine-tuning.

Key results on real LongMemEval-S (100 samples): **46% EM** vs. 5% for truncation (9$\times$ gain); **87.5% EM on single-session-user** (surpassing the full-context GPT-4o-mini baseline); **100% NIAH recall** at 200 conversation turns versus 20% for truncation—all using gpt-4o-mini with zero task-specific training. The 9.4% gap vs. the full-context baseline (55.4%) comes from multi-session aggregation and subjective preference questions, both addressable with future work.

RLM-MEMORY demonstrates that the RLM sub-agent paradigm generalises effectively to the memory domain: delegating session reading to fresh sub-agents keeps the main agent's context clean while enabling exact retrieval over histories orders of magnitude larger than any single context window. Future work will address semantic search, knowledge-update recency ordering, parallel sub-agent execution for latency reduction, and LLM-as-judge evaluation for preference questions.

Reproducibility

The full implementation is available in the `rlm_memory/` package. To reproduce results:

```
# Set working directory to repository root
export PYTHONPATH=".:./Recursive_language_model_rlm-minimal"

# NIAH evaluation
python rlm_memory/eval/niah_eval.py --turns 20 50 100 200 --runs
    5

# Synthetic LongMemEval
python rlm_memory/eval/synthetic_longmemeval.py --n-per-type 10
```

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