Beyond RAG for Agent Memory: Retrieval by Decoupling and Aggregation

Zhanghao Hu [1] Qinglin Zhu [1] Hanqi Yan [1] Yulan He [1 2] Lin Gui [1]

Abstract

Agent memory systems often adopt the standard Retrieval-Augmented Generation (RAG) pipeline, yet its underlying assumptions differ in this setting. RAG targets large, heterogeneous corpora where retrieved passages are diverse, whereas agent memory is a bounded, coherent dialogue stream with highly correlated spans that are often duplicates. Under this shift, fixed top-k similarity retrieval tends to return redundant context, and post-hoc pruning can delete temporally linked prerequisites needed for correct reasoning. We argue retrieval should move beyond similarity matching and instead operate over latent components, following *decoupling to aggregation*: disentangle memories into semantic components, organise them into a hierarchy, and use this structure to drive retrieval. We propose xMemory, which builds a hierarchy of intact units and maintains a searchable yet faithful high-level node organisation via a sparsity–semantics objective that guides memory split and merge. At inference, xMemory retrieves top-down, selecting a compact, diverse set of themes and semantics for multi-fact queries, and expanding to episodes and raw messages only when it reduces the reader's uncertainty. Experiments on LoCoMo and PerLTQA across the three latest LLMs show consistent gains in answer quality and token efficiency.

Figure 1. **From similarity top-k to structured retrieval for agent memory.** Agent memory forms a coherent and highly correlated stream, where many spans are near duplicates; similarity top-k retrieval can therefore collapse and retrieve redundant chunks. xMemory organises memories into a hierarchy of intact units and performs structure-aware retrieval to produce a shorter but more answer-sufficient context.

1. Introduction

Large language models (LLMs) are increasingly used as agents that must remain coherent across long, multi-session interactions (Kang et al., 2025; Liu et al., 2024; Wang et al., 2024). To support long trajectory reasoning and personalisation, agent-memory systems store past dialogues and events and retrieve them to answer future queries (Hu et al., 2025). Despite rapid progress, most systems still follow a standard Retrieval-Augmented Generation (RAG) pipeline: embed stored memories, retrieve a fixed top-k by similarity, concatenate them into a context, and generate an answer (Xu et al., 2025; Kang et al., 2025; Fang et al., 2025).

However, this direct adoption is problematic because agent memory does not match the core RAG setting. RAG is designed for large, heterogeneous corpora where retrieved passages are diverse and the main failure mode is irrelevance (Gao et al., 2023). In contrast, an agent's memory is a bounded and coherent stream, so candidate spans are highly correlated and often near duplicates. When retrieval relies on similarity ranking with a fixed top-k, it can collapse into a single dense region, returning redundant evidence and failing to separate what is *needed* from what is merely *similar*. A common reaction is to prune or compress the retrieved

---

[1]Department of Informatics, King's College London, London, United Kingdom [2]The Alan Turing Institute, London, United Kingdom. Correspondence to: Lin Gui <lin.1.gui@kcl.ac.uk>.
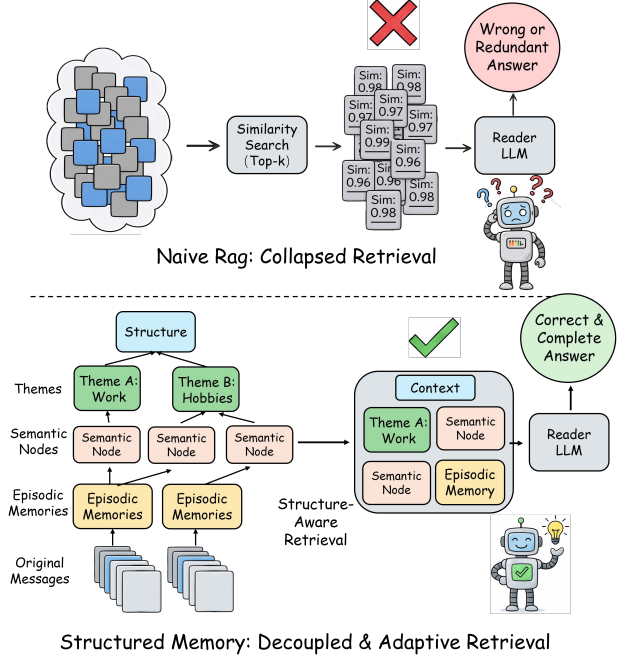
context (Fang et al., 2025), but this is also brittle: pruning modules developed under RAG assumptions depend on local relevance cues (Pan et al., 2024b), whereas conversational evidence is often temporally entangled through co-reference, ellipsis, and timeline dependencies (Hu et al., 2026). As a result, pruning may delete prerequisites within an evidence chain rather than remove redundancy, leaving both fixed top-k retrieval and post-retrieval pruning misaligned with agent memory.

These mismatches call for a different goal: agent memory retrieval should move beyond span matching and instead surface the latent components of a coherent stream, enabling evidence selection at the component level that avoids redundancy by construction, as shown in Fig 1. In other words, memory construction should follow *decoupling to aggregation*: we decompose the stream into semantic components, organise them into higher-level structure, and then invert this structure to drive retrieval. Under this view, *retrieval is not determined by a similarity ranking over raw spans, but by the organisation induced by decomposition and aggregation*. For instance, two spans assigned to different components are unlikely to be retrieved together, even if they are highly similar in embedding space. This perspective raises two questions: how to quantify desirable structural properties, and how to use such signals to guide organisation. Concretely, components should be sufficiently differentiated to prevent redundancy concentration, and aggregations should remain semantically faithful to support reliable evidence reconstruction.

We meet these requirements with xMemory, which couples **memory structure management** with **adaptive retrieval** to control redundancy while preserving evidence integrity. On the management side, we construct a four-level hierarchy from raw messages to abstract units: an *episode* summarises a contiguous message block, *semantics* distil reusable facts from episodes to disentangle highly similar histories, and *themes* group related semantics for high-level access. We further optimise theme–semantic grouping during construction using a guidance objective that balances sparsity and semantic coherence, since overly large themes enlarge the candidate set and slow retrieval, while overly fragmented themes weaken aggregation and reduce evidence coverage when answers span multiple facts.

On the retrieval side, xMemory performs *top-down* retrieval over the hierarchy. At the theme and semantic levels, queries require evidence as a set rather than a single match: some ask for a consolidated description that is distributed across multiple semantics, and multi-hop questions often need several connected semantics for chained reasoning. We therefore select a small, diverse set of query-relevant themes and semantics to broaden recall while staying anchored to the query. At the episode and original message levels, we

control redundancy by admitting finer evidence only when it decreases the reader's uncertainty, and we stop expanding once added detail no longer helps.

Our contributions can be summarised as follows:

1. We introduce a hierarchical memory construction that disentangles highly similar histories into semantic units and organises them into themes. This mitigates collapsed similarity retrieval under RAG pipeline and is guided by a sparsity–semantics objective that shapes the high-level node structure during construction.

2. We propose a top-down retrieval framework that first selects a compact set of relevant theme and semantic units to broaden recall, and then controls fine-grained episode and message expansion to reduce redundancy while preserving intact evidence units.

3. We show consistent gains in answer quality and token efficiency on LoCoMo and PerLTQA across diverse open-source and closed-source LLM backbones, supported by evidence-density and coverage analyses that explain the limitations of standard RAG retrieval and pruning in agent memory.

2. Related Work

Memory Management in LLM Agents. Existing agent memory systems broadly fall into flat context and structured designs. Flat approaches, such as MemGPT (Packer et al., 2023), and MemoryOS (Kang et al., 2025), extend effective context via paging controllers or stream-based storage, but typically log raw dialogue or minimally processed traces, which can accumulate redundancy and incur growing retrieval and processing costs as histories lengthen. Structured systems organise memories into hierarchies or graphs to improve coherence and navigability, e.g., MemoryBank (Zhong et al., 2024), Zep (Rasmussen et al., 2025), and A-Mem (Xu et al., 2025). However, many still rely on raw or minimally processed text as the primary retrieval unit and often expand or retrieve extensively across layers or communities at query time, which can introduce large contexts and high overhead, sometimes offsetting the benefits of structure. In contrast, our memory manager explicitly optimises the structure during construction: a guidance objective jointly promotes node sparsity to control redundant retrieval and semantic organisation to preserve evidence structure and avoid "semantic islands", enabling efficient retrieval without brittle pruning of temporally linked conversational evidence.

Retrieval and Context Management in Agent Memory. Most agent-memory frameworks adopt the standard RAG paradigm and retrieve a fixed top-k set of memories by embedding similarity, which is suited to heterogeneous external
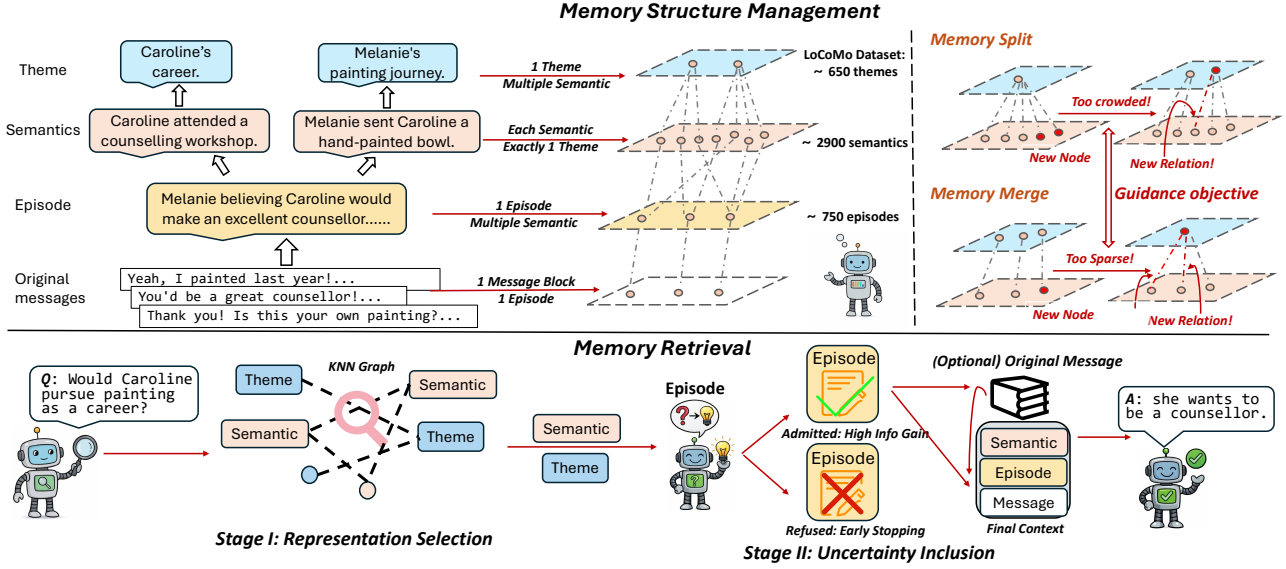
Figure 2. **Overview of xMemory.** xMemory couples memory structuring with top-down retrieval to address the mismatch between agent memory and the RAG pipeline. It organises a coherent stream into a hierarchy that disentangles episodic traces into semantic components while preserving intact units. A sparsity–semantics objective guides split and merge to keep the high-level organisation searchable and faithful. At retrieval, xMemory selects a diverse set of relevant themes and semantics to support aggregation reasoning, then expands to episodes and raw messages only when they decrease the reader's uncertainty, yielding a shorter context with stronger evidence coverage.

corpora but mismatched to conversational memory (Packer et al., 2023; Kang et al., 2025; Xu et al., 2025). In agent memory, the retrieval source is bounded and highly correlated, often from the same character over time; fixed top-k therefore tends to return redundant spans with shared background, inflating context length and distracting the reader LLM. Meanwhile, generic context compression or pruning methods developed for RAG long-context inference can be brittle for chat memory, where key evidence is temporally contiguous and relies on ellipsis; aggressive pruning may fragment evidence chains and exacerbate long-context failures such as lost-in-the-middle (Pan et al., 2024a; Jiang et al., 2024). In contrast, we select a compact evidence skeleton via greedy submodular representative selection on the memory graph to promote relevance and coverage, and apply uncertainty gated adaptive inclusion to control redundancy under a budget without pruning inside evidence units.

3. Methodology

3.1. Problem Description and Overview

Problem Description. We study agent memory with long message histories. Given a history H and a query q, the goal is to construct a context C under a budget that maximises answer quality while preserving evidence structure. Unlike standard RAG, the evidence source is a bounded and coherent stream, where candidate spans are near duplicates, and key facts often rely on neighbouring turns. As a result, similarity top-k retrieval tends to return redundant context,

while post-hoc pruning is prone to breaking prerequisite chains. We formulate retrieval as hierarchical unit selection rather than ranking raw chunks by similarity. This yields more distinguishable semantic units from highly correlated histories and expands to fine-grained evidence only when necessary. The resulting context C is then consumed by a reader LLM to generate the final answer y.

Overview. We propose xMemory, which couples (i) **memory structure management** that disentangles highly correlated histories into reusable components, and (ii) **adaptive retrieval** that selects evidence at the component level and expands to raw text only when necessary. As shown in Figure 2, we first build a four-level hierarchy that preserves intact units while disentangling reusable semantics from redundant episodic traces. We then retrieve *top-down* over this hierarchy: Stage I selects a compact, diverse set of relevant themes and semantics to support queries whose answers require *set-level* evidence or multi-hop reasoning; Stage II admits episodes and original messages only when they measurably improve the reader's certainty, controlling redundancy under a budget.

3.2. Memory Structure Management

Four-level hierarchy and mapping. To avoid collapsed retrieval in a highly correlated stream, we organise memories into a four-level hierarchy that explicitly separates *episodic traces* from *reusable semantic components*: *Original messages → Episode → Semantic → Theme*. An

3

episode summarises a contiguous block of original messages, semantic nodes distil reusable long-term facts from episodes to disentangle similar histories, and themes aggregate related semantics to enable high-level access. This hierarchy keeps intact evidence units at each granularity, which protects temporally linked prerequisites from being pruned away. Under this organisation, each original message block maps to one episode; each episode can yield multiple semantic nodes; each semantic node is assigned to exactly one theme; and each theme can contain multiple semantic nodes.

Guidance function for hierarchical organisation. Given the hierarchy, the remaining question is how to maintain a high-level organisation that is both *searchable* and *faithful*. The problem is: 1) When a **theme becomes too large**, the candidate set expands, retrieval concentrates within a dense neighbourhood, and redundant semantics are repeatedly selected, and 2) When **themes are overly fragmented**, aggregation across semantics weakens and evidence coverage drops for queries whose answers span multiple facts. This motivation has an information-theoretic explanation: any routing step that must choose among a large candidate set under bounded discriminative evidence incurs a non-trivial lower bound on the misrouting probability that grows with the logarithm of the candidate set size (via Fano-type arguments). [1] To balance these failure modes, we introduce a guidance objective that governs theme splitting and merging. Let $\mathcal{P} = \{C_k\}_{k=1}^{K}$ be a partition of N semantic nodes into K themes, where $n_k = |C_k|$. We score the structure by

$$f(\mathcal{P}) = \text{SparsityScore}(\mathcal{P}) + \text{SemScore}(\mathcal{P}). \quad (1)$$

Sparsity. We quantify how balanced the theme partition is via the expected within-theme candidate size. If we uniformly sample a semantic node from all N nodes, it falls into theme k with probability n_k/N. Approximating the within-theme scanning cost by the theme size n_k, the expected cost is $\mathbb{E}[n_{\text{cluster}}] = \sum_{k=1}^{K} (n_k/N) \, n_k = \frac{1}{N} \sum_{k=1}^{K} n_k^2$. We convert this cost into a normalised reward:

$$\text{SparsityScore}(\mathcal{P}) = \frac{N}{K} \cdot \frac{1}{\mathbb{E}[n_{\text{cluster}}]} = \frac{N^2}{K \sum_{k=1}^{K} n_k^2}. \quad (2)$$

This score increases when theme sizes are more balanced, which reduces dense region collapse and improves high-level search efficiency.

Semantic. Beyond sparsity, we encourage semantically coherent themes while avoiding undesirable extremes in inter-theme relations. For intra-theme organisation, we measure cohesion by the average cosine similarity between semantic embeddings and their theme centroid. For inter-theme

relations, we regularise the nearest-neighbour similarity between theme centroids: overly similar themes increase redundancy, while overly dissimilar themes form "semantic islands" that hinder cross-topic navigation (Zhang et al., 2025). Formally,

$$\text{SemScore}(\mathcal{P}) = \frac{1}{K} \sum_{k=1}^{K} \left(\frac{1}{n_k} \sum_{i \in C_k} \cos(\mathbf{x}_i, \boldsymbol{\mu}_k) \right) \cdot g(s_k),$$

$$g(s_k) = \exp\left(-\frac{(s_k - m)^2}{2\sigma^2} \right), \quad (3)$$

where $\mathbf{x}_i$ is the embedding of semantic node i, $\boldsymbol{\mu}_k$ is the centroid embedding of theme k, and $\cos(\cdot, \cdot)$ denotes cosine similarity. We define s_k as the nearest-neighbor similarity of theme k in the centroid space, i.e., $s_k = \max_{j \neq k} \cos(\boldsymbol{\mu}_k, \boldsymbol{\mu}_j)$. We set $m = \text{median}(\{s_k\})$ and use the median absolute deviation as a robust scale, $\sigma = \text{median}(\{|s_k - m|\}) + \varepsilon$, yielding a bell-shaped regularizer that penalises both redundant themes and isolated themes.

Guided attach, split, and merge. When a new semantic node arrives, we attach it to the most similar theme by centroid similarity; otherwise we create a new theme. For an overcrowded theme (n_k exceeding a threshold), we generate candidate splits by clustering its semantic nodes and choose the split that maximises $f(\mathcal{P})$. For tiny themes, we consider merging them into a small set of nearest-neighbour themes and select the merge that maximises $f(\mathcal{P})$.

kNN graph for high-level navigation. To support efficient retrieval without quadratic maintenance, we maintain a k-NN graph among theme and semantic nodes, storing only top-k similarity edges per node. These links mitigate semantic islands and enable efficient traversal during retrieval.

3.3. Adaptive Retrieval

Given a query q, we retrieve top-down over the hierarchy to address the retrieval challenges in agent memory. At the theme and semantic levels, answers often require set-level evidence: queries may draw on multiple complementary facts across semantics, and multi-hop reasoning needs several connected semantics rather than a single best match. At the episode and message levels, the main challenge is to avoid redundant expansion while preserving intact evidence. We therefore use a two-stage procedure: Stage I selects a compact, diverse, and query-relevant high-level node selection; Stage II expands to episodic and raw text only when the added detail is warranted.

Stage I: Query-aware representative selection on kNN graphs. We begin with embedding-based retrieval to obtain candidate semantic nodes $\mathcal{S}_q$ and their associated themes $\mathcal{T}_q$. To avoid collapsed selection from a single

---

[1]See Appendix B for a concise discussion and its connection to Eq. (1).

dense region while still supporting set-level evidence, we select representatives on the high-level kNN graph via a greedy procedure that trades off *coverage gain* and *query relevance*. Let V be the candidate nodes with neighbours $\mathcal{N}(i)$ and edge similarity $w_{iu} > 0$, and let $R \subseteq V$ be selected representatives. We maintain the covered set $C(R) = \{u \in V \mid \exists r \in R, \ u \in \{r\} \cup \mathcal{N}(r)\}$ and newly covered nodes $\Delta(i; R) = (\{i\} \cup \mathcal{N}(i)) \setminus C(R)$. Each greedy step selects

$$i^{\star} = \arg \max_{i \in V \setminus R} \ \alpha \cdot \frac{\sum_{u \in \Delta(i;R)} w_{iu}}{Z} + (1-\alpha) \cdot \tilde{s}(q, i), \quad (4)$$

where $\tilde{s}(q, i) \in [0, 1]$ is the normalised query–node similarity score, and $\alpha \in [0, 1]$ balances coverage and relevance. $Z > 0$ is a normalisation constant that keeps the coverage term on a comparable scale. We iteratively update $R \leftarrow R \cup \{i^{\star}\}$ and stop when the covered ratio $|C(R)|/|V|$ reaches a target threshold or when $|R|$ hits a budget. We apply Eq. 4 first on theme candidates and then on induced semantic candidates, producing a compact backbone that enables aggregation and multi-hop reasoning while reducing redundant evidence.

Stage II: Uncertainty adaptive evidence inclusion. From the selected semantics, we gather linked episodes as intact evidence units. We rank episodes by combining direct similarity to q with semantic support, and build a coarse context from selected themes and semantic summaries. We then include episodes only when they sufficiently reduce the reader's predictive uncertainty; for included episodes, we optionally expand to original messages when further uncertainty reduction justifies the added tokens. We employ early stopping when additional episodes fail to improve certainty. This stage controls redundancy while preserving temporally linked evidence within intact units, producing a compact final context C for answer generation.

4. Experiments

4.1. Setups

Evaluation datasets. We evaluate long-term agent memory on two complementary benchmarks: LoCoMo (Maharana et al., 2024) and PerLTQA (Du et al., 2024). **LoCoMo** contains 50 multi-session dialogues averaging ∼9K tokens and ∼300 turns (up to 35 sessions), substantially longer than earlier long-term dialogue datasets (Maharana et al., 2024; Xu et al., 2022; Jang et al., 2023). We report results on its four QA categories (single-hop, multi-hop, temporal, open-domain) and follow prior work to omit the adversarial subset. **PerLTQA** evaluates personal long-term memory over a character's life, with QA grounded in profiles, relationships, events, and dialogue history (Du et al., 2024).

Evaluation Metrics. Following common practice on both LoCoMo and PerLTQA (Maharana et al., 2024; Du et al., 2024), we report **BLEU-1** (Papineni et al., 2002) and **token-level F1** as the main QA metrics. Since PerLTQA answers are often full sentences, we additionally report **ROUGE-L** (Lin, 2004), which captures sentence-level overlap via longest common subsequence.

Baselines. We compare against five current baseline methods: **(1) Naive RAG:** We chunk original messages and retrieve the top-20 chunks by vector-based searching to form the context. **(2) A-Mem:** an agentic memory system inspired by Zettelkasten that stores structured notes, dynamically links related memories, and updates the memory network over time for retrieval (Xu et al., 2025). **(3) MemoryOS:** a memory operating system for agents that performs hierarchical memory storage and lifecycle management to support long-horizon personalisation and coherence (Kang et al., 2025). **(4) LightMem:** a lightweight, efficiency-oriented memory framework that filters and organises information in multi-stage memory modules to reduce retrieval overhead while maintaining performance (Fang et al., 2025). **(5) Nemori:** a self-organising agent memory architecture that segments conversational streams into coherent episodes memories under cognitively inspired principles for improved long-term recall (Nan et al., 2025).

Implementation details. We evaluate the frameworks with three backbone LLMs: two recent open-source models, Qwen3-8B (Yang et al., 2025) and Llama-3.1-8B-Instruct (Team, 2024), and a proprietary closed-source model, GPT-5 nano. For answer generation, we use greedy decoding (temperature = 0.0) to eliminate randomness and ensure reproducibility (Sun et al., 2023). All retrieval and memory construction embeddings are computed with `text-embedding-3-small`. Since LoCoMo answers are typically short phrases while PerLTQA answers are often full sentences, we use dataset-specific answer prompts (Appendix C), but keep the final answering prompt *identical across different baselines* within each dataset for fair comparison. Since GPT-5-nano could not return the output logits, we apply GPT-4.1-mini to detect the entropy in our framework when we apply GPT-5-nano. We set the maximum number of semantic nodes per theme to 12[2]. All experiments are done with a NVIDIA A100 80G.

4.2. Main Results

LoCoMo: improved long-range conversational reasoning. Table 1 reports results on LoCoMo. xMemory achieves the best average performance across all three backbones, indicating robust effectiveness across both open-source and closed-source LLMs. With **Qwen3-8B**, xMem-

---

[2]Detailed analysis is in Appendix B.

Table 1. Main results on LoCoMo. We report BLEU and F1 for each question category and the average. Token/query denotes the average total tokens per query (lower is better). Best results within each backbone model are in bold.

Model	Method	Multi-hop		Temporal		Open-domain		Single-hop		Average		Token
		BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	/query
Qwen3-8B	Naive RAG	22.64	34.39	17.03	21.18	12.52	17.01	35.62	45.15	27.92	36.42	6613.17
	Nemori	24.20	36.68	23.60	33.74	12.71	18.48	33.48	45.49	28.51	40.45	7754.66
	LightMem	19.67	26.26	22.62	27.66	7.80	11.78	27.40	34.74	23.77	30.28	5545.35
	A-Mem	9.20	9.06	22.46	32.99	9.01	8.57	23.01	23.28	19.49	21.78	9103.46
	MemoryOS	17.12	21.74	26.84	32.26	14.53	16.25	35.83	40.37	29.20	33.76	7234.66
	xMemory (**Ours**)	**27.24**	**38.57**	**29.58**	**37.46**	**15.55**	**20.69**	**40.94**	**50.94**	**34.48**	**43.98**	**4711.29**
Llama-3.1-8B-Ins	Naive RAG	13.77	19.40	6.20	8.61	6.99	10.22	21.90	35.37	16.21	25.30	11522.60
	Nemori	18.18	26.30	19.23	26.09	9.24	12.06	26.19	40.18	22.21	32.95	14802.69
	LightMem	16.43	23.76	12.44	15.61	9.83	13.70	21.68	25.08	18.05	22.15	5708.11
	A-Mem	15.88	20.90	19.92	24.91	9.92	11.34	24.86	39.90	21.52	31.51	10268.77
	MemoryOS	13.26	17.83	19.88	23.95	11.48	12.92	24.76	28.67	20.81	24.72	7212.07
	xMemory (**Ours**)	**22.21**	**30.99**	**21.20**	**27.42**	**11.58**	**14.61**	**28.43**	**41.15**	**24.73**	**34.77**	**5539.97**
GPT-5 nano	Naive RAG	21.64	32.11	38.43	49.05	22.30	26.42	36.18	46.04	33.12	42.89	7531.46
	Nemori	24.80	37.11	41.56	54.25	22.61	29.29	40.35	51.67	36.65	48.17	9154.76
	LightMem	25.33	34.19	43.37	57.12	23.57	29.45	39.01	45.45	36.45	44.82	6850.04
	A-Mem	14.60	21.31	31.00	38.58	14.27	16.78	24.04	28.59	23.15	28.60	9610.94
	MemoryOS	14.43	18.43	26.76	30.91	17.00	18.74	31.74	35.38	26.57	30.27	7029.02
	xMemory (**Ours**)	**27.56**	**39.97**	**46.10**	**57.62**	**25.53**	**30.92**	**41.14**	**52.63**	**38.71**	**50.00**	**6581.20**

ory improves the average **BLEU** from 28.51 (Nemori) to **34.48** and the average **F1** from 40.45 to **43.98**. The gains are especially evident on long-range reasoning, e.g., **temporal** increases from BLEU 23.60 and F1 33.74 to **29.58** and **37.46**. With **GPT-5 nano**, xMemory improves the average **BLEU** from 36.65 to **38.71** and **F1** from 48.17 to **50.00**, while reducing token usage from 9155 to **6581** per query. These indicate that our framework can provide sufficient evidence without retrieving redundant spans. We also observe limitations of existing agent memory systems. Methods such as A-Mem and MemoryOS rely on LLM-generated structured memory records with *strict schema constraints*, where formatting deviations can cascade into failed updates and unstable reproduction (Xu et al., 2025; Packer et al., 2023; Kang et al., 2025). Methods such as LightMem further integrate generic prompt pruners such as LLMLingua-2 (Pan et al., 2024b), which are developed under the standard RAG assumption that retrieved passages are diverse and noise patterns are separable. In agent memory, however, candidates come from a single coherent dialogue stream and are often nearly duplicated, while key evidence is temporally entangled across adjacent turns. Under this distribution shift, pruning can remove latent prerequisites and fragment evidence chains, which aligns with LightMem trailing xMemory on LoCoMo, especially for multi-hop and temporal questions in Table 1. Overall, the results support our thesis that agent memory needs redundancy control

without breaking evidence into fragmentation.

PerLTQA: generalisation to personal long-term memory. Table 2 reports results on PerLTQA, which requires reasoning over richer, lifelong memories and typically expects sentence-level answers. xMemory remains effective in this setting across different backbones. With **Qwen3-8B**, xMemory achieves an average **BLEU** of **36.24**, **F1** of **47.08**, and **ROUGE-L** of **42.50**, while using **5087** tokens per query; it surpasses strong structured-memory baselines such as MemoryOS with BLEU 35.14, F1 42.35, and ROUGE-L 38.48. With **GPT-5 nano**, xMemory further reaches **F1 46.23** and **ROUGE-L 41.25**, improving over Nemori with BLEU F1 41.79 and ROUGE-L 38.43. These results suggest that the xMemory retrieval principles transfer beyond dialogue recall to broader personal memory reasoning.

Efficiency. We report *tokens per query* as the average end-to-end token consumption per query during inference, including retrieval, final answer generation, and any auxiliary calls. Across both open-source and closed-source backbones, xMemory improves accuracy while reducing token usage (Tables 1 and 2). On **LoCoMo** with **Qwen3-8B**, xMemory lowers tokens per query from the most expensive baseline **A-Mem 9103**) to **4711**, while achieving the best overall performance. The same trend holds for **GPT-5 nano**, from **9155** to **6581**, suggesting that xMem-

Table 2. Main results on PerLTQA. We report BLEU, F1, ROUGE-L, and token usage per query (lower is better). Best results within each backbone model are in bold.

Model	Method	BLEU	F1	ROUGE-L	Token/query
Qwen3-8B	Naive RAG	32.08	41.37	35.95	6274.38
	Nemori	32.55	42.80	38.05	9091.72
	LightMem	16.97	32.41	29.87	7692.05
	A-Mem	28.62	34.99	33.54	9864.32
	MemoryOS	35.14	42.35	38.48	6499.47
	xMemory	**36.24**	**47.08**	**42.50**	**5087.18**
Llama-3.1-8B-Ins	Naive RAG	33.67	44.84	39.65	9531.30
	Nemori	41.01	49.62	44.65	11440.04
	LightMem	23.47	35.93	33.65	**5452.49**
	A-Mem	11.40	13.28	15.90	7707.40
	MemoryOS	35.14	42.35	38.48	6511.11
	xMemory	**42.68**	**52.37**	**47.84**	6066.40
GPT-5 nano	Naive RAG	27.35	37.76	32.35	10756.39
	Nemori	33.44	41.79	38.43	11882.70
	LightMem	14.04	28.30	26.11	7579.27
	A-Mem	33.12	41.17	37.94	14717.77
	MemoryOS	27.66	33.83	31.44	12669.39
	xMemory	**36.79**	**46.23**	**41.25**	**7307.30**

ory retrieval pipeline mitigates the redundancy induced by fixed top-k retrieval in RAG pipeline without harming answer quality. On **PerLTQA**, we observe similar efficiency gains on both open-source and closed-source LLMs. While xMemory is not always the cheapest option, e.g., LightMem with pruning model uses fewer tokens than xMemory under Llama-3.1-8B-Instruct on PerLTQA. This comes with a large performance drop, such as BLEU decreasing from **42.68** to **23.47** (Table 2), consistent with our earlier discussion that RAG-trained pruning can be brittle when evidence is entangled in agent memory.

5. Analysis

5.1. Ablation Studies

We conduct an ablation study to quantify the contribution of each component. Figure 3 reports five settings on Lo-CoMo with Qwen3-8B: (i) **Naive RAG** chunks raw messages and retrieves top-k chunks; (ii) **Memory-only** uses our hierarchical memory structure but applies basic similarity retrieval without our search framework; (iii) **+RepSel** adds Stage I (query-aware representative selection on the high-level node kNN graph) to improve relevance and diversity; (iv) **+UncSion** adds Stage II (uncertainty adaptive evidence inclusion) to control low-level node expansion; and (v) **Ours (Full)** combines both modules (Full performance shown in Appendix A.1). Using the hierarchical memory alone already yields a large gain over Naive RAG;
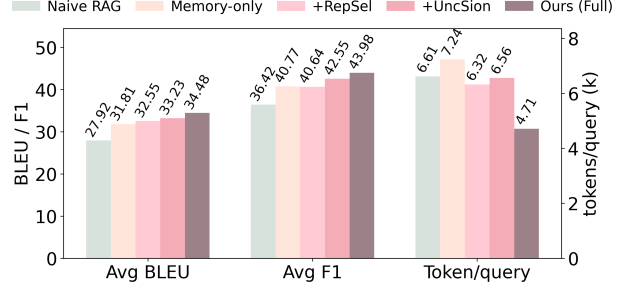

Figure 3. **Ablation on LoCoMo with Qwen3-8B.** We report BLEU and F1 on the left axis and Token/query on the right axis (lower is better). **Memory-only** uses our hierarchical memory structure with a simple similarity retriever, but disables both adaptive retrieval stages. **+RepSel** adds Stage I, which selects representative theme and semantic nodes on the high-level kNN graph. **+UncSion** adds Stage II, which admits episodic and original evidence only when it reduces the reader's uncertainty. **Ours (Full)** combines both stages.

for example, average BLEU increases from 27.92 to 31.81 and F1 from 36.42 to 40.77, indicating that structured, intact units are more evidence managed than chunked passages. Adding either RepSel or UncSion further improves performance, and combining both performs best, suggesting the two stages are complementary: RepSel improves semantic alignment and coverage at the high level node, while UncSion refines low-level evidence inclusion. In terms of efficiency, the Memory-only variant is the most expensive among our variants, with 7.24k tokens per query, consistent with over-fetching redundant evidence under RAG similarity retrieval; RepSel reduces cost by selecting representative high-level nodes (6.32k tokens per query), while UncSion adaptively halts expansion when uncertainty reduces. The full system achieves the trade-off, reducing token usage to the least while also improving accuracy over all ablations.

5.2. Evidence Density under RAG and Pruning Effect

We compare three settings: (i) naive RAG with top-20 retrieved passage chunks, (ii) RAG augmented with the LLMLingua-2 pruning module (Pan et al., 2024b) as in LightMem (Fang et al., 2025), and (iii) our structured memory retrieval. For each query, we remove stopwords from the reference answer and treat the remaining content words as minimal evidence units. A retrieved block is **1-hit** if it contains exactly one distinct answer token, **2-hit** if it contains two, and **multi-hit** if it contains at least three.

Figure 4 shows that xMemory yields more evidence-dense retrieval across categories, with substantially higher 2-hit and multi-hit proportions than both RAG baselines. In contrast, pruning tends to shift mass from 2-hit and multi-hit to 1-hit, indicating that compression often removes answer-bearing details even when the retrieved context is broadly relevant. For example, on multi-hop questions (Cat. 1), prun-
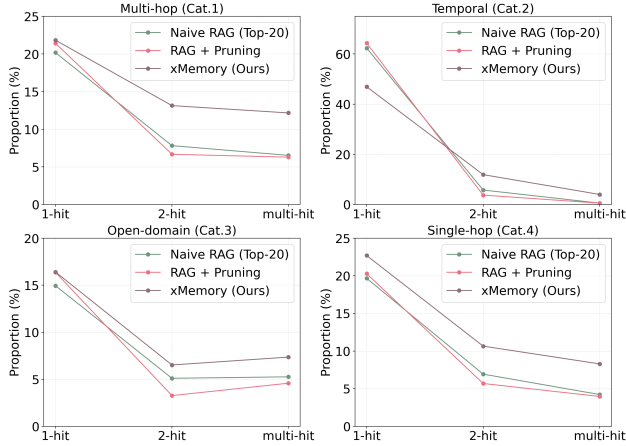
Figure 4. Evidence hit distribution by question category. Each subplot shows the proportions of retrieved blocks that are 1-hit, 2-hit, or multi-hit with respect to answer content tokens, comparing Naive RAG, RAG with pruning, and xMemory. Higher 2-hit and multi-hit indicate more evidence-dense retrieval under xMemory.

Table 3. **Performance and evidence coverage efficiency.** *Perf.* reports end-to-end BLEU-1/F1. *Avg. blocks for coverage* is the average number of retrieved blocks required to cover all answer content tokens, and *Avg. tokens for coverage* is the token cost.

Method	Perf. (BLEU/F1)	Avg. blocks↓ for coverage	Avg. tokens↓ for coverage
Naive RAG	27.92 / 36.42	10.81	1979.26
RAG + Pruning	26.55 / 34.58	13.31	1587.99
Ours	34.48 / 43.98	5.66	974.56

ing reduces the 2-hit and multi-hit proportions from 7.82% and 6.53% (Naive RAG) to 6.67% and 6.29%, whereas xMemory increases them to 13.14% and 12.19%.

We further evaluate *evidence coverage efficiency* by measuring the minimum number of retrieved blocks required to cover all answer content tokens, together with their token cost for each query (Full Performance shown on Appendix A.2). Table 3 confirms the same trend. Pruning reduces the token cost for coverage, but requires more blocks and yields lower accuracy than Naive RAG, consistent with losing evidence density. In contrast, xMemory achieves higher accuracy while covering the evidence with fewer blocks and about half the tokens, indicating more answer-sufficient retrieval under a tighter budget.

5.3. Retroactive Restructuring in Memory Construction

Agent memory differs from standard RAG in that its evidence source evolves over time: facts and relations can be updated as new interactions occur, rather than remaining static as in most retrieval corpora under RAG settings. Therefore, memory construction should support revising the high-level structure, updating node relations to reflect newly
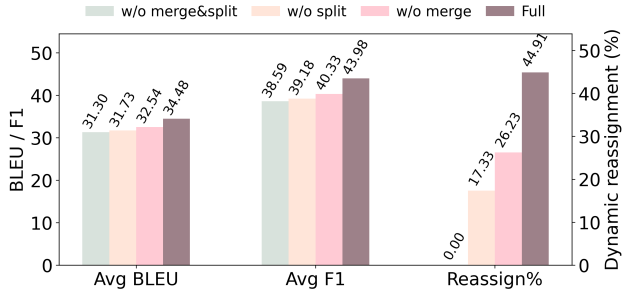

Figure 5. **Structural plasticity vs. downstream QA.** We report Avg. BLEU/F1 (left axis) and the *dynamic reassignment ratio* (right axis) for four construction settings. Freezing high-level restructuring (w/o merge&split) yields 0% reassignment and lower accuracy, while the full system performs substantial reassignment (44.91%) and achieves the best Avg. BLEU/F1.

revealed or corrected information. Our memory manager enables such retroactive restructuring: previously stored semantic nodes can be reassigned to different themes when subsequent insertions trigger theme *split* or *merge* (Sec. 3.2). We measure this effect using the **dynamic reassignment ratio**, defined as the fraction of semantic nodes whose theme assignment changes during construction.

Figure 5 shows that retroactive restructuring improves downstream performance. Disabling both *split* and *merge* freezes the high-level structure, yields 0% reassignment, and reduces the average F1 to 38.59. Enabling restructuring substantially increases reassignment and accuracy, and the full system achieves both the highest reassignment ratio (44.91%) and the best average F1 (43.98). Moreover, *split* induces more reassignment than *merge*, indicating that splitting overcrowded themes is the primary source of structural revision. However, *merge* remains important for forming a stable high-level structure: without merge, the hierarchy retains far more themes (1122 vs. 642 in the full system) despite a similar scale of semantic nodes, whereas enabling merge consolidates redundant themes and yields a more compact organisation for retrieval (Table 7). Detailed results and structure statistics are reported in Appendix A.3.

6. Conclusion

We presented xMemory, a retrieval framework that uses hierarchical organisation to address the mismatch between agent memory and standard RAG assumptions. By disentangling highly correlated memories into semantic components and retrieving top-down over the resulting hierarchy, xMemory reduces redundancy while preserving temporally linked evidence. Across LoCoMo and PerLTQA, xMemory improves answer quality with lower token cost and retrieves more evidence-dense contexts than RAG baselines.

Impact Statement

The paper advances agent-memory retrieval for long-horizon interactions by reducing redundant context while preserving temporally linked evidence. The techniques may improve reliability and efficiency in applications such as personal assistants and multi-session decision support, and can reduce compute cost by lowering inference token usage.

Potential risks include privacy leakage or unintended retention of sensitive user information if deployed with real user data, as well as amplified harm if an agent retrieves and reinforces outdated or incorrect memories. Our method does not introduce new data collection and is model-agnostic, but practical deployments should incorporate consent, data minimisation, access control, and deletion policies, and should provide mechanisms to correct or override stored memories. Overall, we do not anticipate societal impacts beyond those commonly associated with retrieval-augmented LLM systems, but responsible use requires careful privacy and safety safeguards.

References

Du, Y., Wang, H., Zhao, Z., Liang, B., Wang, B., Zhong, W., Wang, Z., and Wong, K.-F. PerLTQA: A personal long-term memory dataset for memory classification, retrieval, and fusion in question answering. In Wong, K.-F., Zhang, M., Xu, R., Li, J., Wei, Z., Gui, L., Liang, B., and Zhao, R. (eds.), *Proceedings of the 10th SIGHAN Workshop on Chinese Language Processing (SIGHAN-10)*, pp. 152–164, Bangkok, Thailand, August 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.sighan-1.18/.

Fang, J., Deng, X., Xu, H., Jiang, Z., Tang, Y., Xu, Z., Deng, S., Yao, Y., Wang, M., Qiao, S., Chen, H., and Zhang, N. Lightmem: Lightweight and efficient memory-augmented generation. *CoRR*, abs/2510.18866, 2025. doi: 10.48550/ARXIV.2510.18866. URL https://doi.org/10.48550/arXiv.2510.18866.

Gao, Y., Xiong, Y., Gao, X., Jia, K., Pan, J., Bi, Y., Dai, Y., Sun, J., Guo, Q., Wang, M., and Wang, H. Retrieval-augmented generation for large language models: A survey. *CoRR*, abs/2312.10997, 2023. doi: 10.48550/ARXIV.2312.10997. URL https://doi.org/10.48550/arXiv.2312.10997.

Hu, C., Gao, X., Zhou, Z., Xu, D., Bai, Y., Li, X., Zhang, H., Li, T., Zhang, C., Bing, L., et al. Evermemos: A self-organizing memory operating system for structured long-horizon reasoning. *arXiv preprint arXiv:2601.02163*, 2026.

Hu, Y., Liu, S., Yue, Y., Zhang, G., Liu, B., Zhu, F., Lin, J.,

Guo, H., Dou, S., Xi, Z., et al. Memory in the age of ai agents. *arXiv preprint arXiv:2512.13564*, 2025.

Jang, J., Boo, M., and Kim, H. Conversation chronicles: Towards diverse temporal and relational dynamics in multi-session conversations. In Bouamor, H., Pino, J., and Bali, K. (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023*, pp. 13584–13606. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.EMNLP-MAIN.838. URL https://doi.org/10.18653/v1/2023.emnlp-main.838.

Jiang, H., Wu, Q., Luo, X., Li, D., Lin, C., Yang, Y., and Qiu, L. Longllmlingua: Accelerating and enhancing llms in long context scenarios via prompt compression. In Ku, L., Martins, A., and Srikumar, V. (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2024, Bangkok, Thailand, August 11-16, 2024*, pp. 1658–1677. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.ACL-LONG.91. URL https://doi.org/10.18653/v1/2024.acl-long.91.

Kang, J., Ji, M., Zhao, Z., and Bai, T. Memory OS of AI agent. In Christodoulopoulos, C., Chakraborty, T., Rose, C., and Peng, V. (eds.), *Proceedings of the 2025 Conference on Empirical Methods in Natural Language Processing*, pp. 25961–25970, Suzhou, China, November 2025. Association for Computational Linguistics. ISBN 979-8-89176-332-6. doi: 10.18653/v1/2025.emnlp-main.1318. URL https://aclanthology.org/2025.emnlp-main.1318/.

Langley, P. Crafting papers on machine learning. In Langley, P. (ed.), *Proceedings of the 17th International Conference on Machine Learning (ICML 2000)*, pp. 1207–1216, Stanford, CA, 2000. Morgan Kaufmann.

Lin, C.-Y. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pp. 74–81, Barcelona, Spain, July 2004. Association for Computational Linguistics. URL https://aclanthology.org/W04-1013/.

Liu, N. F., Lin, K., Hewitt, J., Paranjape, A., Bevilacqua, M., Petroni, F., and Liang, P. Lost in the middle: How language models use long contexts. *Transactions of the Association for Computational Linguistics*, 12:157–173, 2024. doi: 10.1162/tacl_a_00638. URL https://aclanthology.org/2024.tacl-1.9/.

Maharana, A., Lee, D., Tulyakov, S., Bansal, M., Barbieri, F., and Fang, Y. Evaluating very long-term conversational memory of LLM agents. In Ku, L., Martins, A., and Srikumar, V. (eds.), *Proceedings of the 62nd Annual*

Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2024, Bangkok, Thailand, August 11-16, 2024, pp. 13851–13870. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.ACL-LONG.747. URL https://doi.org/10.18653/v1/2024.acl-long.747.

Nan, J., Ma, W., Wu, W., and Chen, Y. Nemori: Self-organizing agent memory inspired by cognitive science. *CoRR*, abs/2508.03341, 2025. doi: 10.48550/ARXIV.2508.03341. URL https://doi.org/10.48550/arXiv.2508.03341.

Packer, C., Fang, V., Patil, S. G., Lin, K., Wooders, S., and Gonzalez, J. E. Memgpt: Towards llms as operating systems. *CoRR*, abs/2310.08560, 2023. doi: 10.48550/ARXIV.2310.08560. URL https://doi.org/10.48550/arXiv.2310.08560.

Pan, Z., Wu, Q., Jiang, H., Xia, M., Luo, X., Zhang, J., Lin, Q., Rühle, V., Yang, Y., Lin, C., Zhao, H. V., Qiu, L., and Zhang, D. Llmlingua-2: Data distillation for efficient and faithful task-agnostic prompt compression. In Ku, L., Martins, A., and Srikumar, V. (eds.), *Findings of the Association for Computational Linguistics, ACL 2024, Bangkok, Thailand and virtual meeting, August 11-16, 2024*, pp. 963–981. Association for Computational Linguistics, 2024a. doi: 10.18653/V1/2024.FINDINGS-ACL.57. URL https://doi.org/10.18653/v1/2024.findings-acl.57.

Pan, Z., Wu, Q., Jiang, H., Xia, M., Luo, X., Zhang, J., Lin, Q., Rühle, V., Yang, Y., Lin, C.-Y., Zhao, H. V., Qiu, L., and Zhang, D. LLMLingua-2: Data distillation for efficient and faithful task-agnostic prompt compression. In Ku, L.-W., Martins, A., and Srikumar, V. (eds.), *Findings of the Association for Computational Linguistics: ACL 2024*, pp. 963–981, Bangkok, Thailand, August 2024b. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.57. URL https://aclanthology.org/2024.findings-acl.57/.

Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. Bleu: a method for automatic evaluation of machine translation. In Isabelle, P., Charniak, E., and Lin, D. (eds.), *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pp. 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073135. URL https://aclanthology.org/P02-1040/.

Rasmussen, P., Paliychuk, P., Beauvais, T., Ryan, J., and Chalef, D. Zep: A temporal knowledge graph architecture for agent memory. *CoRR*, abs/2501.13956, 2025. doi: 10.48550/ARXIV.2501.13956. URL https://doi.org/10.48550/arXiv.2501.13956.

Sun, W., Yan, L., Ma, X., Wang, S., Ren, P., Chen, Z., Yin, D., and Ren, Z. Is chatgpt good at search? investigating large language models as re-ranking agents. In Bouamor, H., Pino, J., and Bali, K. (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing, EMNLP 2023, Singapore, December 6-10, 2023*, pp. 14918–14937. Association for Computational Linguistics, 2023. doi: 10.18653/V1/2023.EMNLP-MAIN.923. URL https://doi.org/10.18653/v1/2023.emnlp-main.923.

Team, L. The llama 3 herd of models. *CoRR*, abs/2407.21783, 2024. doi: 10.48550/ARXIV.2407.21783. URL https://doi.org/10.48550/arXiv.2407.21783.

Wang, T., Tao, M., Fang, R., Wang, H., Wang, S., Jiang, Y. E., and Zhou, W. AI PERSONA: towards life-long personalization of llms. *CoRR*, abs/2412.13103, 2024. doi: 10.48550/ARXIV.2412.13103. URL https://doi.org/10.48550/arXiv.2412.13103.

Xu, J., Szlam, A., and Weston, J. Beyond goldfish memory: Long-term open-domain conversation. In Muresan, S., Nakov, P., and Villavicencio, A. (eds.), *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), ACL 2022, Dublin, Ireland, May 22-27, 2022*, pp. 5180–5197. Association for Computational Linguistics, 2022. doi: 10.18653/V1/2022.ACL-LONG.356. URL https://doi.org/10.18653/v1/2022.acl-long.356.

Xu, W., Liang, Z., Mei, K., Gao, H., Tan, J., and Zhang, Y. A-mem: Agentic memory for LLM agents. In *The Thirty-ninth Annual Conference on Neural Information Processing Systems*, 2025. URL https://openreview.net/forum?id=FiM0M8gcct.

Yang, A., Li, A., Yang, B., Zhang, B., Hui, B., Zheng, B., Yu, B., Gao, C., Huang, C., Lv, C., Zheng, C., Liu, D., Zhou, F., Huang, F., Hu, F., Ge, H., Wei, H., Lin, H., Tang, J., Yang, J., Tu, J., Zhang, J., Yang, J., Yang, J., Zhou, J., Lin, J., Dang, K., Bao, K., Yang, K., Yu, L., Deng, L., Li, M., Xue, M., Li, M., Zhang, P., Wang, P., Zhu, Q., Men, R., Gao, R., Liu, S., Luo, S., Li, T., Tang, T., Yin, W., Ren, X., Wang, X., Zhang, X., Ren, X., Fan, Y., Su, Y., Zhang, Y., Zhang, Y., Wan, Y., Liu, Y., Wang, Z., Cui, Z., Zhang, Z., Zhou, Z., and Qiu, Z. Qwen3 technical report. *CoRR*, abs/2505.09388, 2025. doi: 10.48550/ARXIV.2505.09388. URL https://doi.org/10.48550/arXiv.2505.09388.

Zhang, Y., Wu, R., Cai, P., Wang, X., Yan, G., Mao, S., Wang, D., and Shi, B. Leanrag: Knowledge-graph-based generation with semantic aggregation and hierarchical retrieval. *arXiv preprint arXiv:2508.10391*, 2025.

Zhong, W., Guo, L., Gao, Q., Ye, H., and Wang, Y. Memorybank: Enhancing large language models with long-term memory. In Wooldridge, M. J., Dy, J. G., and Natarajan, S. (eds.), *Thirty-Eighth AAAI Conference on Artificial Intelligence, AAAI 2024, Thirty-Sixth Conference on Innovative Applications of Artificial Intelligence, IAAI 2024, Fourteenth Symposium on Educational Advances in Artificial Intelligence, EAAI 2014, February 20-27, 2024, Vancouver, Canada*, pp. 19724–19731. AAAI Press, 2024. doi: 10.1609/AAAI.V38I17.29946. URL https://doi.org/10.1609/aaai.v38i17.29946.

Table 4. **Detailed ablation results on LoCoMo with Qwen3-8B.** We report BLEU and F1 for each question category and the average. Token/query denotes the average total tokens per query (lower is better).

Setting	Multi-hop		Temporal		Open-domain		Single-hop		Average		Token
	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	/query
Naive RAG	22.64	34.39	17.03	21.18	12.52	17.01	35.62	45.15	27.92	36.42	6613.17
Memory-only	24.48	35.41	27.28	34.14	13.20	17.75	38.19	47.73	31.81	40.77	7235.56
+RepSel	26.55	38.02	28.08	35.72	14.30	19.75	38.36	45.79	32.55	40.64	6320.72
+UncSion	26.64	37.03	28.92	37.09	14.10	20.43	39.28	49.01	33.23	42.55	6556.58
xMemory (Full)	**27.24**	**38.57**	**29.58**	**37.46**	**15.55**	**20.69**	**40.94**	**50.94**	**34.48**	**43.98**	**4711.29**

Table 5. **Expanded results for evidence density and coverage efficiency on LoCoMo (Qwen3-8B).** We report BLEU and F1 for each question category and the average. *Avg. blocks for coverage* is the average number of retrieved blocks required to cover all answer content tokens, and *Cover token cost/query* is the corresponding token cost (lower is better).

Framework	Multi-hop		Temporal		Open-domain		Single-hop		Average		Avg. blocks↓ for coverage	Avg. tokens↓ for coverage
	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1		
Naive RAG	22.64	34.39	17.03	21.18	12.52	17.01	35.62	45.15	27.92	36.42	10.81	1979.26
RAG + Pruning	23.81	33.58	16.53	23.33	12.92	16.22	32.85	41.23	26.55	34.58	13.31	1587.99
xMemory (Ours)	**27.24**	**38.57**	**29.58**	**37.46**	**15.55**	**20.69**	**40.94**	**50.94**	**34.48**	**43.98**	**5.66**	**974.56**

A. More Experiment Results

A.1. Ablation Study Full Results and Observations

Table 4 reports category-level results for the five ablation settings on LoCoMo with Qwen3-8B. Moving from Naive RAG to Memory-only yields consistent gains across all categories, with the largest improvements on temporal and single-hop questions, suggesting that storing intact hierarchical units already improves evidence accessibility compared to chunked retrieval. Adding RepSel mainly benefits multi-hop and open-domain questions, where selecting representative high-level nodes improves coverage and reduces redundancy from dense neighbourhood retrieval. Adding UncSion provides broader gains, especially on temporal and single-hop questions, indicating that uncertainty-based inclusion helps admit fine-grained evidence only when it is useful, while avoiding unnecessary expansion. Combining both modules achieves the best results in every category, improving the average from 31.81/40.77 (Memory-only) to 34.48/43.98 on BLEU/F1, and substantially reducing token cost from 7236 to 4711 tokens per query. Overall, the two stages are complementary: RepSel improves high-level selection and coverage, while UncSion refines low-level inclusion and budget usage.

A.2. Full Performance in Evidence Density under RAG and Pruning Effect

Table 5 provides the detailed performance and coverage statistics for the three settings on LoCoMo with Qwen3-8B. RAG with pruning shows mixed behaviour across categories: while it slightly improves BLEU on multi-hop and open-domain questions, it reduces F1 and consistently underperforms Naive RAG on single-hop and the overall average. This is consistent with Figure 4, where pruning shifts retrieved blocks from 2-hit and multi-hit toward 1-hit, suggesting that compression often discards answer-bearing details. In contrast, xMemory improves both BLEU and F1 in every category, with particularly large gains on temporal and single-hop questions, and achieves the highest overall average. It also covers answer evidence more efficiently, requiring fewer blocks for full coverage (5.66 vs. 10.81 and 13.31) and substantially lower coverage token cost (974.56 vs. 1979.26 and 1587.99), indicating more answer-sufficient retrieval under a tighter budget.

A.3. Full Performance of Retroactive Restructuring in Memory Construction

Extended results. Table 6 provides category-level QA results together with the dynamic reassignment ratio for different construction settings. Table 7 reports the resulting numbers of themes and semantic nodes.

Table 6. **Extended results for retroactive restructuring on LoCoMo (Qwen3-8B).** We report BLEU/F1 by question category and the average, together with the dynamic reassignment ratio under each construction setting.

Setting	Multi-hop		Temporal		Open-domain		Single-hop		Average		Reassign ratio
	BLEU	**F1**	**BLEU**	**F1**	**BLEU**	**F1**	**BLEU**	**F1**	**BLEU**	**F1**	
w/o merge&split	24.01	34.35	28.24	34.90	10.97	14.04	37.24	44.23	31.30	38.59	0.00%
w/o split	24.46	35.46	28.55	34.77	11.61	15.75	37.69	44.79	31.73	39.18	17.33%
w/o merge	24.81	35.46	29.68	35.99	13.09	18.09	38.45	46.16	32.54	40.33	26.23%
xMemory (Full)	**27.24**	**38.57**	**29.58**	**37.46**	**15.55**	**20.69**	**40.94**	**50.94**	**34.48**	**43.98**	**44.91**%

Table 7. **Structure statistics under different construction settings.** We report the resulting numbers of themes and semantic nodes.

Setting	#Themes	#Semantics
w/o merge&split	1114	2876
w/o split	651	2897
w/o merge	1122	2928
Full	642	2879

Summary. Disabling both operators yields a static hierarchy with 0% reassignment and the lowest overall accuracy. Allowing split or merge enables retroactive reassignment and improves QA, while the full system achieves the highest reassignment ratio and the best accuracy across all categories. Split accounts for a larger share of reassignment, whereas merge is important for consolidating redundant themes and producing a compact high-level organisation, as reflected by the reduced number of themes under the full setting.

B. Theoretical Analysis of Branching Factor in Hierarchical Dialogue Summarization

B.1. Motivation and Fano Inequality

Our hierarchy performs top-down retrieval, where key subroutines repeatedly *route* to a relevant unit by choosing from a candidate set (e.g., selecting a theme/semantic relevant to the current query context). In high-similarity dialogue streams, the observable signal used for routing (summaries/embeddings/LLM scores) can be inherently weak in its ability to discriminate among many near-duplicate candidates. This subsection summarizes a standard information-theoretic implication: with bounded discriminative information, the error of a multi-way routing decision cannot be made arbitrarily small as the candidate set grows.

Consider one such routing decision that must identify the correct option among n_k candidates on semantic-theme level. Let $Z \in \{1, ..., n_k\}$ be the (unknown) index of the correct candidate (It is binary label indicates whether this semantic is correctly linked with the theme, and n_k is the number of semantics under the theme) and let O denote the observable evidence (summarized theme based on semantics) used for routing (e.g., derived from the query context and stored representations). Any routing rule outputs $\hat{Z}(O)$ with error probability $p_e = \Pr[\hat{Z} \neq Z]$. A classical result (Fano's inequality) implies

$$p_e \geq 1 - \frac{I(Z;O) + 1}{\log_2 n_k}, \tag{5}$$

where $I(Z;O)$ denotes the mutual information between the routing evidence O (derived from the query/context and stored representations) and the correct candidate index Z. In our setting, candidates within the same theme are often near-duplicates, and the evidence is produced from compressed LLM representations (with additional noise from imperfect assignments). As a result, the *discriminative* information available for distinguishing among candidates is bounded, i.e., $I(Z;O)$ is small. By Fano's inequality, a bounded $I(Z;O)$ implies a non-trivial lower bound on the routing error that increases with $\log n_k$. Therefore, to achieve a low misrouting rate (small p_e), it is necessary to control the candidate set size n_k. This aligns with the practical intuition: when many candidates are highly similar, identifying the source becomes close to guessing unless we reduce the arity of the routing problem.

Table 8. **Effect of the theme size cap on LoCoMo (Qwen3-8B).** We vary the upper bound of semantic nodes per theme and report BLEU/F1 by question category and the average, together with resulting structure statistics.

Upper bound	Multi-hop		Temporal		Open-domain		Single-hop		Average		# Sem.	# Themes	Avg. sem. per theme
	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1	BLEU	F1			
14	25.32	36.23	27.68	35.21	12.88	17.89	38.56	47.32	32.26	40.93	2867	385	7.45
12	**27.24**	**38.57**	**29.58**	**37.46**	**15.55**	**20.69**	**40.94**	**50.94**	**34.48**	**43.98**	2897	642	4.48
10	25.62	35.80	27.56	35.66	13.22	18.12	38.67	46.26	32.37	40.38	2945	818	3.60
8	23.58	34.25	26.34	33.62	10.83	13.81	37.22	44.08	30.81	38.21	2856	1109	2.57

B.2. Connection to Metric Designing

Equation (5) shows that if $I(Z;O)$ is bounded (as expected when many candidates are highly similar), then increasing n_k necessarily increases a lower bound on the misrouting probability.

In our theme partition $P = \{C_k\}_{k=1}^{K}$ of N semantic nodes with $n_k = |C_k|$, the typical within-theme candidate set size directly governs the arity of routing within a theme. Eq. (2) estimates the expected within-theme scanning cost as $E[n_{\text{cluster}}] = \frac{1}{N} \sum_{k=1}^{K} n_k^2$, and defines $\text{SparsityScore}(P) = \frac{N^2}{K \sum_{k=1}^{K} n_k^2}$. Maximizing $\text{SparsityScore}(P)$ thus controls the typical within-theme candidate size (and prevents extremely large themes), which is precisely the regime where the lower bound in Eq. (5) becomes prohibitive. This provides a theoretical motivation for balancing theme sizes: it limits unavoidable routing errors under bounded discriminative evidence in high-similarity dialogue memory.

B.3. Fano-style Lower Bound and optimal n_k in hirachical structure.

In this subsection, we use Fano-style lower bound to guide us to find the optimal n_k.

Theorem B.1. *Let $Z \in \{1, \ldots, n_k\}$ denote the (unknown) correct index and let O be the observable evidence used to infer Z. For any estimator $\hat{Z} = g(O)$ with error probability $p_e = \Pr[\hat{Z} \neq Z]$,*

$$H(Z \mid O) \leq h(p_e) + p_e \log_2(n_k - 1), \tag{6}$$

where $h(\cdot)$ is the binary entropy function. In particular, if Z is uniform on $\{1, \ldots, k\}$, then

$$p_e \geq 1 - \frac{I(Z;O) + 1}{\log_2 n_k}. \tag{7}$$

Proof. Equation (6) is the standard form of Fano's inequality. Using $I(Z;O) = H(Z) - H(Z \mid O)$ and rearranging yields

$$H(Z) - I(Z;O) \leq h(p_e) + p_e \log_2(n_k - 1).$$

Since $h(p_e) \leq 1$ and $\log_2(n_k - 1) \leq \log_2 n_k$, we have

$$H(Z) - I(Z;O) \leq 1 + p_e \log_2 n_k.$$

If Z is uniform, then $H(Z) = \log_2 n_k$, hence

$$\log_2 n_k - I(Z;O) \leq 1 + p_e \log_2 n_k \quad \Rightarrow \quad p_e \geq 1 - \frac{I(Z;O) + 1}{\log_2 n_k},$$

which is (7). $\square$

Corollary B.2 (Admissible candidate set size under bounded discriminability). *Assume the routing evidence has bounded discriminative information $I(Z;O) \leq B$ (in bits). If we require $p_e \leq \varepsilon$ for some $\varepsilon \in (0,1)$, then any feasible n_k must satisfy*

$$\log_2 n_k \leq \frac{B+1}{1-\varepsilon} \quad \Longrightarrow \quad n_k \leq 2^{\frac{B+1}{1-\varepsilon}}. \tag{8}$$

Proof. Rearrange (7) and substitute $I(Z;O) \leq B$. □

To determine an appropriate branching factor, we need a reasonable upper bound B on the mutual information between the (local) source index and the observed summary. In practice, summaries are not perfectly non-informative even they might be extremely similar in our setup, so we assume a conservative bound

$$I(Z;O) \leq B,$$

where B includes a safety margin for estimation noise and distribution shift. That means B, in practise, should be small to ensure the routing error is bounded (We take $B = 2$ bits in our implementation, which is able to perfectly index 4 documents if the indexing is independent from the content).

Plugging this bound into our design inequality (derived from the routing accuracy requirement)

$$n_k \leq 2^{\frac{B+1}{\alpha}},$$

where α denotes the target routing accuracy (e.g., $\alpha = 0.85$ for at least 85% accuracy), yields a practical threshold. For example, taking $B = 2$ bits and $\alpha = 0.85$ gives

$$n_k \leq 2^{\frac{2+1}{0.85}} = 2^{3.529} \approx 11.5,$$

which motivates setting the split threshold to $n_k = 12$ in our implementation (see able 8). Interestingly, although this is a loose (worst-case) bound, the algorithm typically yields an average branching factor of about 4.5 in practice. This gap suggests that, even when we allow a 15% routing error budget, the summaries still provide enough signal to separate children *without* additional side information, and the construction procedure naturally enforces a conservative split policy. Empirically, the extra 2-bit margin translates into indexing only ≈ 4.5 semantic groups per parent on average, indicating (i) our method tends to impose a strict partitioning criterion from an information-theoretic perspective, and (ii) items within the same cluster are indeed highly similar, making fine-grained discrimination difficult.

C. Prompt Design

In this section, we present the specific prompts used for the experiments in Section 4.1.

C.1. Memory Structure Managment

This appendix lists the prompts used to construct our hierarchical memory from fine to coarse granularity. We first apply a boundary detector to segment the dialogue stream into coherent episodes. For each episode, we generate an episodic memory record with a title, third-person narrative content, and an explicit timestamp. We then distill high-value, persistent semantic memories from accumulated episodes to form reusable long-term knowledge, filtering out transient conversation details. Finally, we summarise clusters of related semantic statements into concise theme descriptions that serve as stable high-level indices for structure management and retrieval.

C.2. Answer Generation

We provide dataset-specific answer generation prompts to match the distinct answer formats and evaluation protocols of LoCoMo and PerLTQA. For LoCoMo, the prompt enforces short phrase-style outputs and explicit handling of temporal reasoning by resolving relative time expressions using memory timestamps. For PerLTQA, the prompt requests a single complete sentence and prioritises explicit factual attributes from the memory store, resolving conflicts by recency. Importantly, to ensure fair comparison, we keep the final answer prompt identical across different baselines within each dataset.

Prompt for Boundary Detect

You are a dialogue boundary detection expert. You need to determine if the newly added dialogue should end the current episode and start a new one.

Current conversation history: {*conversation history*}

Newly added messages: {*new messages*}

Please carefully analyze the following aspects to determine if a new episode should begin:

1. **Topic Change** (Highest Priority): - Do the new messages introduce a completely different topic? - Is there a shift from one specific event to another? - Has the conversation moved from one question to an unrelated new question?

2. **Intent Transition**: - Has the purpose of the conversation changed? (e.g., from casual chat to seeking help, from discussing work to discussing personal life) - Has the core question or issue of the current topic been answered or fully discussed?

3. **Temporal Markers**: - Are there temporal transition markers ("earlier", "before", "by the way", "oh right", "also", etc.)? - Is the time gap between messages more than 30 minutes?

4. **Structural Signals**: - Are there explicit topic transition phrases ("changing topics", "speaking of which", "quick question", etc.)? - Are there concluding statements indicating the current topic is finished?

5. **Content Relevance**: - How related is the new message to the previous discussion? (Consider splitting if relevance ¡ 30- Does it involve completely different people, places, or events?

Decision Principles: - **Prioritize topic independence**: Each episode should revolve around one core topic or event - **When in doubt, split**: When uncertain, lean towards starting a new episode - **Maintain reasonable length**: A single episode typically shouldn't exceed 10-15 messages

Note: - If conversation history is empty, this is the first message, return false - When a clear topic change is detected, split even if the conversation flows naturally - Each episode should be a self-contained conversational unit that can be understood independently

---

Prompt for Episodic Generation

You are an episodic memory generation expert. Please convert the following conversation into an episodic memory.

Conversation content: *conversation*

Boundary detection reason: *boundary reason*

Please analyze the conversation to extract time information and generate a structured episodic memory. Return containing the following three fields: "title": "A concise, descriptive title that accurately summarises the theme (10-20 words)", "content": "A detailed description of the conversation in third-person narrative. It must include all important information: who participated in the conversation at what time, what was discussed, what decisions were made, what emotions were expressed, and what plans or outcomes were formed. Write it as a coherent story so that the reader can clearly understand what happened. Ensure that time information is precise to the hour, including year, month, day, and hour.", "timestamp": "YYYY-MM-DDTHH:MM:SS format timestamp representing when this episode occurred (analyse from message timestamps or content)"

Time Analysis Instructions: 1. **Primary Source**: Look for explicit timestamps in the message metadata or content 2. **Secondary Source**: Analyze temporal references in the conversation content ("yesterday", "last week", "this morning", etc.) 3. **Fallback**: If no time information is available, use a reasonable estimate based on context 4. **Format**: Always return timestamp in ISO format: "2024-01-15T14:30:00"

Requirements: 1. The title should be specific and easy to search (including key topics/activities). 2. The content must include all important information from the conversation. 3. Convert the dialogue format into a narrative description. 4. Maintain chronological order and causal relationships. 5. Use third-person unless explicitly first-person. 6. Include specific details that aid keyword search. 7. Notice the time information, and write the time information in the content. 8. When relative times (e.g., last week, next month, etc.) are mentioned in the conversation, you need to convert them to absolute dates (year, month, day). Write the converted time in parentheses after the original time reference. 9. **IMPORTANT**: Analyze the actual time when the conversation happened from the message timestamps or content, not the current time.

Example: If the conversation is about someone planning to go hiking and the messages have timestamps from March 14, 2024 at 3:00 PM: "title": "Weekend Hiking Plan March 16, 2024: Sunrise Trip to Mount Rainier", "content": "On March 14, 2024 at 3:00 PM, the user expressed interest in going hiking on the upcoming weekend (March 16, 2024) and sought advice. They particularly wanted to see the sunrise at Mount Rainier, having heard the scenery is beautiful. When asked about gear, they received suggestions including hiking boots, warm clothing (as it's cold at the summit), a flashlight, water, and high-energy food. The user decided to leave at 4:00 AM on Saturday, March 16, 2024 to catch the sunrise and planned to invite friends for the adventure. They were very excited about the trip, hoping to connect with nature.", "timestamp": "2024-03-14T15:00:00"

Prompt for Semantic Generation

You are an AI memory system. Extract HIGH-VALUE, PERSISTENT semantic memories from the following episodes.
CRITICAL: Focus on extracting LONG-TERM VALUABLE KNOWLEDGE, not temporary conversation details.
Episodes to analyze: episodes
HIGH-VALUE Knowledge Criteria
Extract ONLY knowledge that passes these tests: - **Persistence Test**: Will this still be true in 6 months? - **Specificity Test**: Does it contain concrete, searchable information? - **Utility Test**: Can this help predict future user needs? - **Independence Test**: Can be understood without conversation context?
HIGH-VALUE Categories (FOCUS ON THESE):
1. **Identity & Professional** - Names, titles, companies, roles - Education, qualifications, skills
2. **Persistent Preferences** - Favorite books, movies, music, tools - Technology preferences with reasons - Long-term likes and dislikes
3. **Technical Knowledge** - Technologies used (with versions) - Architectures, methodologies - Technical decisions and rationales
4. **Relationships** - Names of family, colleagues, friends - Team structure, reporting lines - Professional networks
5. **Goals & Plans** - Career objectives - Learning goals - Project plans
6. **Patterns & Habits** - Regular activities - Workflows, schedules - Recurring challenges
Examples:
HIGH-VALUE (Extract these): - "Caroline's favorite book is 'Becoming Nicole' by Amy Ellis Nutt" - "The user works at ByteDance as a senior ML engineer" - "The user prefers PyTorch over TensorFlow for debugging" - "The user's team lead is named Sarah" - "The user is learning Rust for systems programming" - "The user has been practicing yoga since March 2021" - "The user joined Amazon in August 2020 as a data scientist" - "The user plans to relocate to Seattle in January 2025"
LOW-VALUE (Skip these): - "The user thanked the assistant" - "The user was confused about X" - "The user appreciated the help" - "The conversation was productive" - Any temporary emotions or reactions
Quality over quantity - extract only knowledge that truly helps understand the user long-term.

Prompt for Theme Generation

"You are building a stable high-level theme summary that captures recurring facts." "Given the following factual statements, write a concise abstract theme that names the topic:" f"joined" "Return only the summary."

Prompt for Answer Generation in LOCOMO Dataset

You are an intelligent memory assistant tasked with retrieving accurate information from conversation memories.
CONTEXT: You have access to memories from two speakers in a conversation. These memories contain timestamped information that may be relevant to answering the question.
INSTRUCTIONS: 1. Carefully analyze all provided memories from both speakers 2. Pay special attention to the timestamps to determine the answer 3. If the question asks about a specific event or fact, look for direct evidence in the memories 4. If the memories contain contradictory information, prioritize the most recent memory 5. If there is a question about time references (like "last year", "two months ago", etc.), calculate the actual date based on the memory timestamp. For example, if a memory from 4 May 2022 mentions "went to India last year," then the trip occurred in 2021. 6. Always convert relative time references to specific dates, months, or years. For example, convert "last year" to "2022" or "two months ago" to "March 2023" based on the memory timestamp. Ignore the reference while answering the question. Do not answer temporal questions in timestamp such as "2023-05-08", but answer naturally such as "7 May 2023" or "The week before 6 July 2023"! 7. Focus only on the content of the memories from both speakers. Do not confuse character names mentioned in memories with the actual users who created those memories. 8. The answer should be less than 5-8 words.
Semantic Memories: semantic
Episodic Memories: episodic
Question: question
Answer:

Prompt for Answer Generation in PerLTQA Dataset

You are a memory question-answering assistant. Answer the question using ONLY the information in the provided memories. Memories may contain profiles, events, and relationship descriptions. Prefer explicit facts (e.g., "Gender: female", "Nationality: China", dates, numbers, names). If multiple memories conflict, choose the most recent one by timestamp.
OUTPUT RULES (VERY IMPORTANT): - Write ONE concise, complete sentence. - Preserve the key value EXACTLY as stated in the memories (names, numbers, dates, gender terms, nationality words). - Do NOT add extra explanation. - Do NOT include quotes, bullet points, or prefixes like "Answer:".
Episodic Memories: episodic
Semantic Memories: semantic
Question: question
Answer: