PLUGMEM: A TASK-AGNOSTIC PLUGIN MEMORY MODULE FOR LLM AGENTS

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ABSTRACT

Long-term memory is essential for large language model (LLM) agents operating in complex environments, yet existing memory designs are either task-specific and non-transferable, or task-agnostic but less effective due to low task-relevance and context explosion from raw memory retrieval. We propose PLUGMEM, a task-agnostic plugin memory module that can be attached to arbitrary LLM agents without task-specific redesign. Motivated by the fact that decision-relevant information is concentrated as abstract knowledge rather than raw experience, we draw on cognitive science to structure episodic memories into a compact, extensible knowledge-centric memory graph that explicitly represents propositional and prescriptive knowledge. This representation enables efficient memory retrieval and reasoning over task-relevant knowledge, rather than verbose raw trajectories, and departs from other graph-based methods like GraphRAG by treating *knowledge* as the unit of memory access and organization instead of entities or text chunks. We evaluate PLUGMEM unchanged across three heterogeneous benchmarks (long-horizon conversational question answering, multi-hop knowledge retrieval, and web agent tasks). The results show that PLUGMEM consistently outperforms task-agnostic baselines and exceeds task-specific memory designs, while also achieving the highest information density under a unified information-theoretic analysis.

1 INTRODUCTION

Large language model (LLM) agents increasingly operate in settings that require long-term memory, where relevant information is distributed across long interaction histories and must be reused to support future decisions (Wang et al., 2024a; Park et al., 2023). However, naively accumulating past interactions as raw context quickly leads to unbounded memory growth, high computational cost, and degraded performance (Packer et al., 2024; Liu et al., 2023). To address this, many agent architectures rely on external memory modules to store and retrieve past experience. Yet most existing memory designs tightly couple memory representation and retrieval to specific tasks or benchmarks, relying on hand-crafted heuristics for what to store and how to use it (Wang et al., 2024b; Gutiérrez et al., 2025). While effective in narrow settings, such task-specific memory modules fail to generalize: a mem-

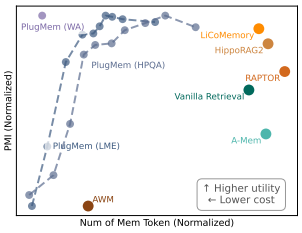

Figure 1: A utility–cost visualization of agentic memory approaches. [1] **PLUGMEM, evaluated unchanged across heterogeneous benchmarks requiring processing multiple memory types, achieves the highest decision-making utility of memory at the lowest agent-side memory cost.**

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[1]Each point corresponds to a memory method evaluated on at least one of three benchmarks, i.e., LongMemEval (Wu et al., 2024), HotpotQA (Yang et al., 2018) and WebArena (Zhou et al., 2024), plotted in a normalized utility–cost space to enable cross-task visualization and to accommodate baselines that are not applicable to all benchmarks. Both axes are min–max normalized, scaled linearly to be within $[0, 1]$ while preserving relative ordering across methods. Curves are obtained by sweeping the memory token budget. Detailed benchmark-specific analyses using raw PMI values and token numbers are reported in Section 4 and Figure 5.

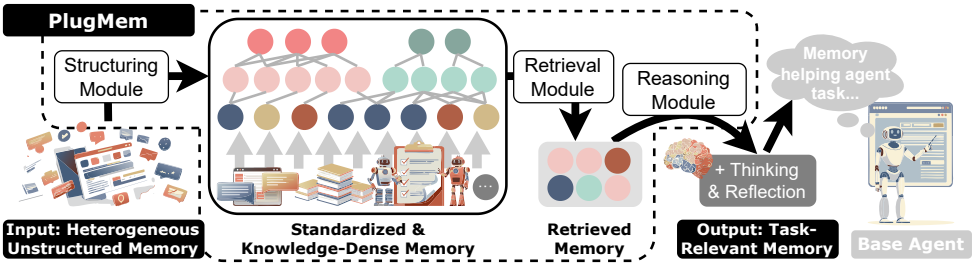


Figure 2: PLUGMEM organizes raw memory and outputs refined memory tokens to help the base agent's decision-making.

ory system optimized for long-horizon conversations does not readily transfer to web navigation, and vice versa. This limitation motivates the need for a *task-agnostic plug-and-play* memory module that can be attached to arbitrary LLM agents without task-specific redesign, reducing per-task engineering overhead and enabling a single memory module to be reused across diverse agentic settings.

Designing such a general plugin memory module is challenging. The most straightforward task-agnostic approach is retrieval-based memory, where all past experiences are stored as raw text chunks and retrieved by relevance (optionally augmented with reasoning, as in RAG). However, this paradigm often fails in practice due to *knowledge sparsity*. Memories that are truly useful for decision-making are typically condensed and abstract forms of knowledge, whereas raw memories are verbose, episodic, and dominated by low-level information. For example, when recommending recipes, an agent benefits from knowing a user's dietary preferences and restrictions, which are compact factual propositions distilled from many interactions, rather than re-reading long conversation histories. Similarly, when shopping on a previously unseen web interface, an agent needs generalizable procedural knowledge, i.e., how to search, filter, and check out, not raw trajectories containing full-page observations with thousands of irrelevant tokens. Treating raw episodic memory as directly usable knowledge therefore imposes an unnecessary context burden and obscures the information most relevant for decision-making.

Prior work has attempted to bridge this gap by compressing or summarizing memory, but largely in task-specific ways. Memory modules are often engineered to perform well on a particular benchmark, such as conversational long-term memory or web-based agents, implicitly assuming a single dominant type of memory (Wang et al., 2024b; Gutiérrez et al., 2025). When applied to a different task domain, these designs rarely transfer without significant task-specific modifications. This raises a key challenge: how can we design a general-purpose memory module that simultaneously supports multiple memory types and adapts to the diverse demands of agentic tasks, and evaluate it in a way that jointly reflects decision utility and agent-side cost, while allowing cross-task comparability?

To address the design side of this challenge, we ground our approach in a principled account of memory organization from cognitive science. Decades of research suggest that the human brain makes a fundamental distinction between episodic memory (detailed records of experience) and knowledge-level memory, which can be further divided into semantic memory (knowing that; factual *propositions*) and procedural memory (knowing how; action-oriented *prescriptions*) (Tulving, 1972; Squire, 2004). Episodic memory serves as the source from which propositional and prescriptive knowledge are abstracted, while the latter forms are most directly useful for reasoning and decision-making. This perspective suggests that effective agent memory should not merely retrieve past experiences, but actively transform raw episodic memory into structured, knowledge-dense representations.

Based on these principles, we introduce a novel plugin memory module PLUGMEM, that performs *memory-to-knowledge abstraction* and supports the unified management of multiple key memory types across agentic tasks. As shown in Figure 2, our approach consists of: *i)* a *structuring module* that standardizes heterogeneous raw memories and extracts propositional and prescriptive knowledge through hierarchical abstraction, organizing them into a memory graph; *ii)* a *retrieval module* that selects task-relevant subgraphs; and *iii)* a *reasoning module* that further adapts and compresses retrieved knowledge for the base agent. Unlike conventional knowledge graphs that operate on entities and relations, our memory graph operates on *knowledge units* (i.e., propositions and prescriptions) which form the fundamental units of memory access and manipulation. PLUGMEM can be viewed as a knowledge-centric form of GraphRAG (Edge et al., 2025) tailored for memory management, where graph nodes are knowledge rather than entities or text chunks.

Complementary to the design of a general-purpose memory module, we contribute a novel utility-cost analysis framework that enables fair comparison between different memory designs

across tasks, capturing both performance improvements and memory efficiency. Specifically, we measure the *information density* of memory, defined as the decision-relevant information gain provided to the base agent per memory token. We implement PLUGMEM and evaluate it on three heterogeneous and challenging benchmarks: long-horizon conversational question answering (Wu et al., 2024), multi-hop knowledge retrieval over Wikipedia (Yang et al., 2018), and web-based agent tasks (Zhou et al., 2024). *Using the same memory module implementation across all settings*, we demonstrate consistent performance gains over vanilla task-agnostic baselines and task-specific memory modules, while incurring lower agent-side memory cost, as illustrated in Figure 1. Ablation studies further clarify the roles of different components. Since agentic memory ultimately serves decision-making, task performance is primarily determined by whether retrieval brings the most useful memory to bear at decision time. Our structuring module incrementally enhances retrieval by organizing heterogeneous experience into knowledge-centric memory units, yielding additional performance gains. Meanwhile, the reasoning module substantially improves efficiency, reducing memory token usage by one to two orders of magnitude through task-adaptive condensation. We provide illustrative benchmark examples in Appendix A.

In summary, our contributions are fourfold:

- **Design principles:** cognitively motivated principles for task-agnostic memory in LLM agents.
- **Evaluation framework:** an information-theoretic measure of memory utility and efficiency.
- **General memory module:** a plugin memory system applicable across heterogeneous agentic benchmarks.
- **Reproducibility:** released code and experimental results.

2 RELATED WORK

Cognitive Science Based Agent Memory Cognitive science characterizes long-term memory as persistent storage, and distinguishing episodic, semantic, and procedural memory (Atkinson & Shiffrin, 1968; Tulving, 1972; Squire, 2004). In agentic settings, interactions are naturally episodic, from which reusable abstractions can be derived, e.g., factual information such as user preferences can be distilled into semantic memory (Li et al., 2025), while action strategies can be abstracted as procedural memory (Wang et al., 2024b). These abstractions align with more general knowledge notions: propositional knowledge as factual statements and prescriptive knowledge as generalized goal-directed procedures (Diebolt & Perrin, 2013).

Table 1: Comparison of representative agentic memory systems. **M2K** indicates if a system transforms working memories into *reusable, abstract knowledge* that's generalizable across tasks. **KaU** means if it adopts knowledge as the memory unit. **Mech.** characterizes the design of the memory modules, including **Str.** (structured memory representations), **Ret.** (refined retrieval strategies), and **Rea.** (post-retrieval reasoning or compression). **Mem.** denotes the memory type that the system supports, including **E**pisodic, **S**emantic, and **P**rocedural memory. **Agn.** indicates whether the memory design is task-agnostic.

Meth.	M2K	KaU	Mech.			Mem.			Agn.
			Str.	Ret.	Rea.	E	S	P	
Vanilla Retrieval	✗	✗	✗	✗	✓	✓	✗	✗	✓
Vanilla RAG	✗	✗	✗	✗	✗	✓	✗	✗	✓
GraphRAG	✓	✗	✓	✓	✓	✗	✓	✗	✗
A-Mem	✓	✓	✓	✗	✗	✓	✓	✗	✓
Zep	✗	✗	✓	✓	✗	✓	✓	✗	✗
MemoryOS	✗	✗	✗	✓	✗	✓	✓	✗	✗
HippoRAG2	✓	✗	✓	✓	✓	✗	✓	✗	✗
AWM	✓	✓	✗	✗	✗	✗	✗	✓	✗
ReasoningBank	✓	✓	✗	✗	✗	✓	✗	✓	✗
PLUGMEM	✓	✓	✓	✓	✓	✓	✓	✓	✓

Building on these insights, recent systems incorporate different memory types to support long-context understanding (Lee et al., 2024), long-term interactions (Li et al., 2025), structured memory organization (Anokhin et al., 2024; Rasmussen et al., 2025), and experience-driven strategy refinement (Zhao et al., 2024; Wang et al., 2024b; Fang et al., 2025). However, most approaches are task-specific and do not jointly support multiple memory types. In contrast, PLUGMEM standardizes heterogeneous episodic experience and organizes extracted knowledge into a propositional-prescriptive structure, enabling task-agnostic reuse.

Memory Module Designs Many agent memory systems adopt retrieval-based external memory, storing past interactions and retrieving them at inference time. Early task-agnostic methods rely on flat retrieval over unstructured episodic memory, such as vanilla retrieval and RAG (Lewis et al., 2021; Wang et al., 2024a), resulting in redundant and episode-specific memory reuse. Later work introduces structure over episodic memory, including hierarchical and graph-based retrieval (e.g., GraphRAG) to support multi-hop reasoning (Edge et al., 2025; Sarthi et al., 2024; Gutiérrez et al., 2025; Wang & Han, 2025). While improving access efficiency, these methods largely preserve episodic traces as the primary memory unit. In parallel, task-specific systems explicitly transform experience into higher-level representations, such as temporal knowledge graphs or workflow mem-

ories (Gutiérrez et al., 2025; Wang et al., 2024b; Ouyang et al., 2025). Although effective within fixed tasks, their abstractions are tightly coupled to task assumptions and limit transferability.

Overall, as shown in Table 1, prior work highlights a distinction between improving retrieval over episodic memory and transforming experience into reusable knowledge, with only the latter supporting cross-task generalization. PLUGMEM adopts this principle by organizing memory around propositional and prescriptive knowledge units, enabling more effective retrieval of decision-relevant information, while retaining episodic traces as verifiable evidence.

For a more detailed discussion of related work, including the full versions of the above sections and additional discussion on memory benchmarks, see Appendix B.

3 METHODOLOGY

We present PLUGMEM, a task-agnostic plugin memory module to support long-term decision-making for LLM agents. Rather than treating past interactions as flat episodic text, PLUGMEM structures experience into knowledge-level representations that are more compact, generalizable, and directly relevant to downstream retrieval and reasoning.

As shown in Figure 2, PLUGMEM consists of three core components: *a structuring module* that standardizes heterogeneous episodic memories and induces propositional and prescriptive knowledge; *a retrieval module* that selects relevant knowledge from structured memory graphs via abstraction-aware retrieval; and *a reasoning module* that further adapts retrieved knowledge into actionable guidance for the base agent. In the following sections, we describe each component in detail.

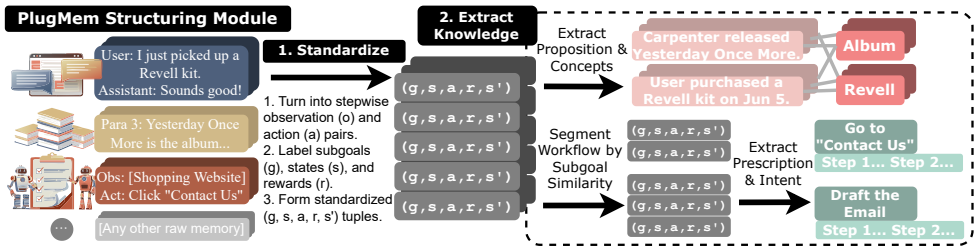


Figure 3: The structuring module in PLUGMEM transforms heterogeneous memory into a formalized knowledge-dense memory graph.

3.1 STRUCTURING MODULE

Table 2: **Mapping Memory Properties to Graph Architecture.** We analyze long-term memory properties to derive our memory graph design. The main rationale is **aligning memory structure with the granularity at which knowledge is acquired, stored, and reasoned over**, reflected here as ensuring core nodes represent complete, self-contained, and verifiable **knowledge blocks** (Propositions/Prescriptions), thus improving the efficiency and fidelity of downstream graph operations.

Memory Type	Nature & Description	Knowledge-Dense Unit	Subgraph Structuring Logic
Semantic	**Declarative & Static** Context-independent concepts, facts, and world knowledge.	**The Proposition (Fact Block)** A complete statement conveying verifiable truth.	**Concept-Centric Semantic Mem Structuring** *Logic:* Concepts acts as lightweight indices pointing to heavy Proposition payloads. *Structure:* `Concept` $\xleftarrow{mentions}$ `Proposition`
Procedural	**Executive & Goal-Oriented** Dynamic "how-to" knowledge for problem solving.	**The Prescription (Workflow Block)** A full action sequence to execute a complex task.	**Intent-Centric Procedural Mem Structuring** *Logic:* Intents (User Goals) serve as keys to find holistic Solution blocks. *Structure:* `Intent` $\xleftarrow{solves}$ `Prescription`
Episodic	**Autobiographical & Linear** Raw record of past interactions and observations. Large volume.	**The Source Trace (Event Window)** A trajectory segment for grounding and verification.	**Episodic Mem as the Anchor** *Logic:* Episodic acts as the "ground truth" layer validating the abstract knowledge graphs. *Structure:* `Knowledge` $\xleftarrow{proves}$ `Source`

As shown in Figure 3, the structuring module serves as the foundation of PLUGMEM by transforming raw episodic experience, such as dialogue turns, document snippets, or episodic trajectories, into knowledge representations that are reusable, compact, and aligned with agent decision-making. Specifically, we structure memory to reflect the role different information plays in reasoning and action selection.

Our design is guided by three principles motivated by cognitive theories of human memory. First, episodic memory captures concrete interaction traces and serves primarily as verifiable evidence rather than directly actionable knowledge. Second, decision-relevant information is most effectively represented at the knowledge level, where semantic memory encodes factual propositions ("knowing that") and procedural memory encodes reusable strategies ("knowing how"). Third, ef-

fective long-term memory requires separating knowledge abstraction from task-specific execution details, enabling memory to generalize across heterogeneous environments. These principles imply that different memory types should be represented using structural units and organization logics aligned with their properties. Table 2 summarizes how episodic, semantic, and procedural memories are mapped to corresponding graph units and structuring mechanisms, reflecting their functional roles in abstraction, retrieval, and verification.

Building on this design, the structuring module operationalizes memory abstraction in two stages: *i)* standardizing heterogeneous interaction traces into a unified episodic representation, and *ii)* inducing propositional and prescriptive knowledge that can be independently indexed and reused across tasks. We describe each stage as follows.

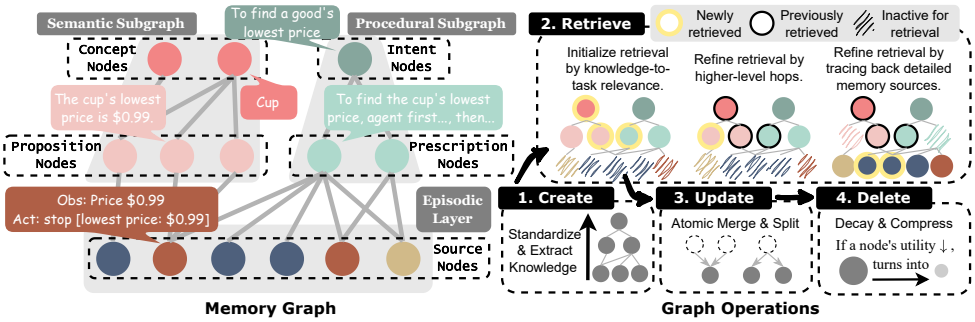


Figure 4: PLUGMEM's knowledge-centric memory graph design and the standard graph operations it supports.

3.1.1 STANDARDIZE

Episodic memory constitutes the fundamental substrate from which semantic and procedural memories are derived (Tulving, 1972). For agents, episodic memories originate from heterogeneous sources, including user–agent interactions (Wu et al., 2024), factual documents (Yang et al., 2018), and action trajectories in complex environments (Zhou et al., 2024). This heterogeneity motivates a unified, task-agnostic representation that can support downstream knowledge induction.

Episodic Formalization. We represent a raw interaction trace as a sequence of observation-action pairs: $\tau = [(o_t, a_t)]_{t=1}^{T}$. While episodic memory is widely used in agent systems, its internal structure is often treated as unstructured text. In contrast, we explicitly formalize episodic memory at the step level by mapping each interaction into a structured tuple. Specifically, each pair (o_t, a_t) is standardized as: $e_t = (o_t, s_t, a_t, r_t, g_t)$, where s_t denotes the agent state at time t, g_t denotes the subgoal associated with executing a_t, and r_t denotes the reward of the action with respect to g_t.

The state s_t is derived from (s_{t-1}, a_{t-1}, o_t) via LLM-based information extraction. Both g_t and r_t are annotated by an LLM conditioned on the task instruction and local interaction context. Aggregating all standardized steps yields an episodic memory sequence $M_{\text{epi}} = [e_t]_{t=1}^{T}$. Implementation details of episodic standardization, including the prompt template, are provided in Appendix C.1.

3.1.2 EXTRACT KNOWLEDGE

We focus this section on the design of the knowledge extraction and organization process. Implementation details, including model choices, parameter settings, and prompt configurations, are deferred to Appendix C.2.

Given standardized episodic memory M_{epi}, we induce two complementary forms of long-term memory: semantic memory and procedural memory. Both are extracted from episodic experience and organized as structured memory graphs with provenance.

Semantic Memory. The semantic memory module extracts and stores factual knowledge from episodic memory to support later retrieval. Given an episodic unit e_t, the module uses an LLM to extract a set of atomic propositions that describe salient facts implied by the interaction. Each proposition is accompanied by a set of associated concepts, which serve as semantic tags for indexing. For example, a proposition may be: *"Tam Sventon, known in Swedish as Ture Sventon, is a fictional private detective based in Stockholm."* The associated concept set is {*Tam Sventon, fictional private detective, Stockholm*}. To ensure extraction quality, we apply several constraints during LLM extraction, including coreference resolution, proposition deduplication, and length control.

The extracted propositions and concepts are stored in a semantic graph G^S. Each proposition and concept is instantiated as a node with a cached dense embedding. Two types of edges are constructed: *i) membership* edges linking propositions to their associated concepts, and *ii) provenance* edges linking propositions to their source episodic units in the episodic graph G^E. This design allows retrieved semantic knowledge to be traced back to its originating experience.

Procedural Memory. The procedural memory module extracts reusable action strategies from episodic trajectories for future decision making. Given an episodic sequence M_{epi}, the module first segments the trajectory into coherent sub-trajectories by detecting boundaries where the similarity between adjacent subgoals g_{t-1} and g_t falls below a predefined threshold. For each trajectory segment, the module uses an LLM to induce a compact *(intent, prescription)* pair. The intent represents the objective pursued in the segment, while the prescription specifies an environment-agnostic action workflow that captures the key steps and cause-effect patterns required for successful execution. An example prescription is: *"To identify the lowest price of an item, search for the item using the search bar, sort the results by price, and verify the minimum across variants."* To enable quality-aware reuse, each induced prescription is assigned a scalar *return* score. The score is from an LLM-based evaluator that assesses whether the intent is achieved and how well the prescription is executed.

The extracted intents and prescriptions are stored in a procedural memory graph G^P. Each intent and prescription is instantiated as a node with a cached dense embedding. Edges in G^P encode two types of relations. First, *hierarchical* edges link each high-level intent node to its associated low-level prescription nodes. Second, *provenance* edges link prescription nodes to their originating episodic units in the episodic graph G^E, enabling procedural knowledge to be traced back to concrete interaction experience.

3.2 Retrieval Module

This section describes the high-level retrieval process over semantic and procedural memory graphs. Detailed prompt templates, the step-by-step retrieval algorithm, and more technical details are deferred to Appendix C.3.

In the structuring stage, PlugMem constructs three interlinked memory graphs: an episodic graph G^E, a semantic graph G^S, and a procedural graph G^P. Both G^S and G^P maintain explicit provenance links to G^E, enabling verifiable grounding of retrieved knowledge and experience. Figure 4 illustrates the overall memory organization.

Given a task description or query Q, an LLM-based retriever first determines which memory types to emphasize: *episodic*, *semantic*, or *procedural*. Retrieval primarily operates over G^S and G^P using an abstraction-specificity interleaving strategy. When episodic memory is prioritized, the same retrieval process (as will be introduced below) is applied, but the system ultimately returns provenance-linked episodic nodes in G^E.

Retrieval begins by encoding Q into an embedding q and scoring it against all low-level nodes (i.e., proposition or prescription nodes) to initialize a candidate set C_0. At hop t, the retriever conditions on (Q, C_t) to generate an abstract query q_t^a. For G^S, q_t^a is represented as a set of concepts, while for G^P it is represented as a set of intents.

The abstract query q_t^a is matched against high-level (i.e., concept or intent nodes) nodes, which act as routing signals to activate adjacent low-level nodes that are added to C_{t+1}. Only low-level nodes are retained as candidates, while high-level nodes serve exclusively as intermediate traversal signals. When $|C_t|$ exceeds a predefined budget (e.g., top-K), candidates are re-ranked and pruned based on relevance and importance. This multi-hop retrieval process iterates until sufficient evidence is accumulated or a maximum hop limit is reached.

3.3 Reasoning Module

The reasoning module is a *test-time running module* that transforms retrieved memory into immediately actionable guidance for the playing agent. In many cases, retrieved memory may contain multiple overlapping or verbose descriptions of past interactions that are individually relevant but collectively redundant for the current decision. The reasoning module leverages the LLM to aggregate and condense such information into a compact, task-aligned representation, distilling the shared signal across messages into a single actionable summary. See Appendix C.4 for more details.

3.4 Summary and Supported Operations

As shown in Figure 3 and 4, starting from raw agent interactions, PlugMem standardizes episodic memory, extracts semantic and procedural knowledge, organizes them into structured memory graphs, and enables retrieval and reasoning over stored experience to support downstream decision making. At the system level, PlugMem supports a set of basic memory graph operations, including: *i) create*, which inserts newly observed episodic experience into structured memory, *ii) retrieve*, which retrieves relevant semantic, procedural, or episodic memory given a task or query, *iii) update*, which revises existing memory entries when new evidence becomes available, and *iv) delete*, which removes obsolete or low-utility memory.

The benchmark evaluations in the main paper primarily evaluate the *create* and *retrieve* operations. Additional experiments for *update* and *delete* operations are in Appendix C.5.

4 EXPERIMENTS

4.1 EVALUATION FRAMEWORK

We evaluate PLUGMEM using standard benchmark-wise metrics (e.g., accuracy, F1-score, success rate, etc.) to measure end-task performance. However, such metrics alone are insufficient for evaluating agentic memory, as they fail to capture the trade-off between decision-relevant utility and agent-side cost. We therefore propose an information-theoretic measure that quantifies the *decision-relevant information gain per memory token* contributed by the memory module.

Specifically, for each decision instance with state s and gold optimal action a^*, let the base agent's prior belief be $P_{\text{base}}(a^* \mid s)$ and the memory-augmented posterior be $P_{\text{mem}}(a^* \mid s, m)$ after consuming memory m. We define the *Decision Information Gain* as point-wise mutual information (PMI):

$$\text{PMI}(a^*; m \mid s) = \log_2 \frac{P_{\text{mem}}(a^* \mid s, m)}{P_{\text{base}}(a^* \mid s)} \quad (1)$$

and normalize by memory length $|m|$ (in tokens) as *Memory Information Density* (bits / token):

$$\rho(a^*, m) = \frac{\text{PMI}(a^*; m \mid s)}{|m|} \quad (2)$$

Over a dataset, we report a global, amortized density via a ratio-of-sums:

$$\rho_{\text{global}} = \frac{\sum_i \text{PMI}(a_i^*; m_i \mid s_i)}{\sum_i |m_i|} \quad (3)$$

Measured in bits per token, our metric is task-agnostic and thus comparable across tasks. Cross-task variation in its magnitude reflects a utility–cost trade-off: higher density arises when memory yields larger decision-relevant gains or does so with fewer tokens, while lower density occurs when the base agent already solves the task well or when useful memory must be expressed verbosely. Appendix D details the complete analysis framework and additional components beyond the main-text description.

Table 3: Results on LongMemEval. $\#\text{Tok}_{\text{Avg.}}$ is the average length of memory tokens. Experiments use NV-Embed-v2 (abbreviated as NVE) as the embedding model for retrieval, and Qwen2.5-32B (Q32) / Qwen2.5-72B (Q72) / gpt-4o (4o) as base LLMs for structuring and reasoning. * denotes results taken from previous work. † denotes methods evaluated on a subset of the full benchmark. Best is **bolded**.

Method	Emb	LLM	Acc.	$\#\text{Tok}_{\text{Avg.}}$	Info. Density
Vanilla Baseline					
No Context	-	Q72	14.8	-	-
All Context	-	Q72	62.4	107K	4.2e-5
Task-Agnostic					
Vanilla Retrieval	NVE	Q72	63.6	3742.52	1.2e-3
A-Mem†	NVE	4o + Q72	61.0	4225.85	1.0e-3
Task-Specific					
Zep*	BGE-m3	4o	71.2	1600	-
LiCoMemory†	NVE	4o + Q72	73.0	5914.85	9.3e-4
Ours					
PLUGMEM	NVE	Q32 + Q72	**75.1**	**362.58**	**1.6e-2**

Table 4: Results on HotpotQA. EM means Exact Match. * denotes results taken from previous work. We underline the upper bound performance and **bold** the best.

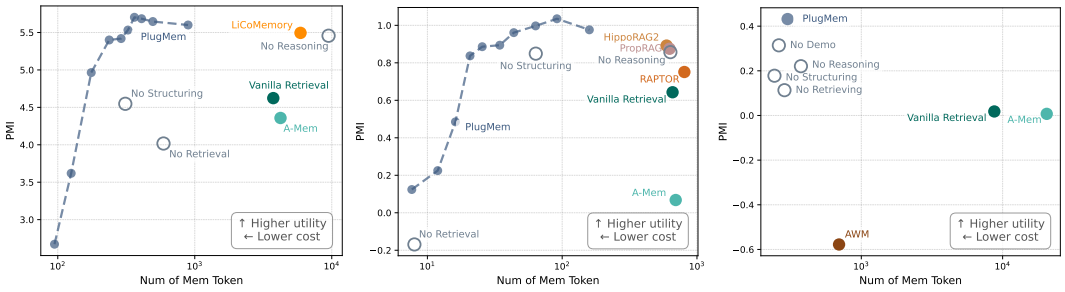
Mem. Method	Emb	LLM	EM	F1	$\#\text{Tok}_{\text{Avg.}}$	Info. Density
Vanilla Baseline						
No Context	-	Q32	22.1	31.0	-	-
Gold Context	-	Q32	69.2	82.1	86.5	1.6e-1
Task-Agnostic						
Vanilla Retrieval	NVE	Q32	51.7	62.7	659.2	1.2e-2
A-Mem	NVE	Q32	43.8	53.6	695.6	1.2e-2
Task-Specific						
GraphRAG*	NVE	L70	55.2	68.6	-	-
RAPTOR	NVE	Q32	56.7	69.7	806.3	1.1e-2
PropRAG	NVE	Q32	57.8	72.1	626.1	1.9e-2
HippoRAG2	NVE	Q32	60.0	73.3	595.1	1.9e-2
Ours						
PLUGMEM	NVE	Q32	**61.4**	**74.1**	**81.6**	**1.4e-1**

Table 5: Results on WebArena. SR means Success Rate. Each site-domain is split into (online/offline) sets. Shopping contains (38/149) tasks, GitLab contains (37/143), and Multi-set contains (10/38). * denotes results taken from previous work. AWM does not natively support Multi-site tasks. Best SR is **bolded**.

			SR % (on/off)				
Method	Emb	Agent	Shopping	GitLab	Multi-site	$\#\text{Tok}_{\text{Avg.}}$	Info. Density
Vanilla Baseline							
AgentOccam*	-	4o	42.1/43.6	37.8/39.2	**20.0**/15.8	-	-
Task-Agnostic							
Van. Retrieval	NVE	Q32+4o	43.0 /42.3	40.5/41.3	10.0/18.4	8733	2.0e-6
A-Mem	NVE	Q32+4o	44.7/44.3	37.8/38.5	**20.0**/15.8	20516	3.4e-7
Task-Specific							
AWM	-	4o	26.3/28.2	27.0/27.3	-	696	-7.9e-4
Ours							
PLUGMEM	NVE	Q32+4o	**52.6/58.4**	**51.4/55.2**	**20.0/21.6**	**301**	**1.4e-3**

4.2 COMMON EXPERIMENTAL SETUP

We evaluate PLUGMEM unchanged across three heterogeneous benchmarks that stress different aspects of agentic memory: *i)* LongMemEval (Wu et al., 2024) for long-horizon conversational memory, *ii)* HotpotQA (Yang et al., 2018) for multi-hop knowledge retrieval and reasoning, and *iii)* WebArena (Zhou et al., 2024) for interactive web-based decision-making. Across all benchmarks, we adopt a unified memory evaluation protocol to ensure fair comparison. Baselines are grouped into three categories: *i)* Vanilla, which do not rely on external memory; *ii)* Task-agnostic, which employ generic retrieval or agentic memory mechanisms not tailored to the benchmark; and *iii)* Task-specific, which incorporate benchmark-specific memory representations or retrieval heuristics. See Appendix E for detailed experiment settings, prompt templates, and benchmark-level analysis.



LongMemEval HotpotQA WebArena

Figure 5: Utility–cost analysis across benchmarks. Each point represents a memory method, with the x-axis indicating agent-side memory cost (in tokens) and the y-axis indicating decision-relevant utility (in bits). The slope of the line connecting a point to the origin corresponds to information density (bit per token). Curves are obtained by sweeping the memory token budget on a randomly sampled subset of benchmark tasks, illustrating how memory utility initially increases with budget, then saturates, and may eventually decline as additional memory becomes counterproductive, for example by introducing noise or interference in decision-making. **PLUGMEM consistently achieves a more favorable utility–cost trade-off, dominating prior approaches by providing higher decision-relevant utility under smaller memory budgets across benchmarks.**

4.3 RQ1: DOES PLUGMEM IMPROVE PERFORMANCE AND MEMORY EFFICIENCY ACROSS TASKS?

Our first research question examines whether a single, task-agnostic memory module can consistently improve agent performance while reducing memory consumption across heterogeneous tasks. Results on LongMemEval, HotpotQA, and WebArena (Tables 3, 4, 5) show a consistent pattern despite large differences in task structure and interaction modality. First, PLUGMEM improves end-task performance over both task-agnostic and task-specific baselines. Second, these gains are achieved with substantially fewer memory tokens injected into the agent context. Thus, PLUGMEM attains the highest *information-gain density* under the unified information-theoretic analysis introduced in Section 4.1. This trade-off is further illustrated by the utility–cost visualization in Figure 5, where PLUGMEM consistently shifts toward higher utility and lower agent-side cost across all three benchmarks.

The results indicate PLUGMEM retrieves *more decision-relevant memory*. By abstracting raw experience into compact knowledge, the memory module provides higher utility per token, enabling the base agent to reason more effectively under tight context budgets.

4.4 RQ2: WHAT IS THE ROLE OF EACH COMPONENT IN PLUGMEM?

We next analyze the contribution of each component in PLUGMEM via ablations on all benchmarks (Tables 6, 7, 8). Removing retrieval leads to the most severe performance degradation across tasks, underscoring that memory is *only* useful when relevant experience can be accessed at decision time. However, this does not imply that retrieval alone drives performance gains. Rather, retrieval determines whether memory is operative at all, while its effectiveness is bounded by how memory is represented. The structuring module improves retrieval by organizing memory at appropriate abstraction levels, allowing the retriever to more effectively identify and access task-relevant knowledge. The reasoning module plays a complementary role, primarily affecting memory efficiency by controlling how retrieved knowledge is compressed and consumed.

Overall, retrieval determines *whether* memory helps, structuring determines *what* can be retrieved, and reasoning determines *how efficiently* retrieved memory can be used.

Table 6: Ablation study on LongMemEval

Method	Emb	LLM	Acc.	$\#Tok_{Avg.}$	Info. Density
PLUGMEM	NVE	Q32 + Q72	**75.1**	362.58	**1.6e-2**
No Structuring	NVE	Q32 + Q72	62.8	**311.12**	1.4e-2
No Retrieval	-	Q32 + Q72	57.2	591.2	6.8e-3
No Reasoning	NVE	Q32	72.4	9478.59	5.8e-4

Table 7: Ablation study on HotpotQA

Method	Emb	LLM	EM	F1	$\#Tok_{Avg.}$	Info. Density
PLUGMEM	NVE	Q32	**61.4**	**74.1**	**81.6**	**1.4e-1**
No Structuring	NVE	Q32	51.4	62.0	116.7	6.8e-2
No Retrieval	-	Q32	20.0	24.3	8.0	-3.8e-1
No Reasoning	NVE	Q32	59.3	71.8	635.1	1.7e-2

In No Retrieval, we randomly sample corpus items to fit the reasoning module's context window. The sampled items are often irrelevant, so the reasoning module outputs little to no distilled context, yielding a much smaller $\#Tok_{Avg.}$ (e.g., 8).

Table 8: Ablation Study on WebArena. No Human Demo means no human demonstrations are inserted into the memory graph between online and offline evaluation. We collect 23/18/5 demos for Shopping/GitLab/Multi-site.

			SR % (on/off)				
Method	Emb	Agent	Shopping	GitLab	Multi-site	$\#Tok_{Avg.}$	Info. Density
PLUGMEM	NVE	Q32+4o	**52.6/58.4**	**51.4/55.2**	**20.0/21.6**	301	**1.4e-3**
No Structuring	NVE	Q32+4o	50.0/51.7	41.7/42.0	**20.0**/18.4	**243**	7.2e-4
No Retrieval	NVE	Q32+4o	42.1/46.3	45.8/44.0	**20.0**/15.8	286	3.8e-4
No Reasoning	NVE	Q32+4o	**52.6**/53.7	41.7/43.4	**20.0**/18.4	374	5.6e-4
No Human Demo	NVE	Q32+4o	**52.6** /52.3	**51.4** /51.0	**20.0** /18.4	261	1.2e-3

Retrieval thus constitutes the defining bottleneck, while structuring and reasoning modulate effectiveness and efficiency once retrieval is in place.

4.5 RQ3: Knowledge Transfer and Memory Reuse

Our third research question examines whether agent memory enables transferable knowledge that generalizes across task instantiations and environments. To study this, we design a specialized evaluation protocol on WebArena.

We focus on the Shopping, GitLab, and Multi-site subsets. Shopping and GitLab involve procedure-heavy tasks with large volumes and relatively low baseline success rates (Yang et al., 2025b), avoiding saturation effects. Multi-site tasks require compositional reasoning across multiple websites, making them particularly suitable for evaluating cross-task knowledge reuse.

To explicitly test memory evolution and reuse, we split tasks based on WebArena intent templates into an *online* and an *offline* set. For each template, one instantiation is assigned to the online set and the remaining instantiations to the offline set. The agent is first evaluated on the online set, where PlugMem can insert and retrieve memory. We then augment the memory graph with a small number of high-quality human demonstrations, representing external procedural knowledge.

Finally, we evaluate on the offline set with memory insertion largely disabled and only retrieval allowed. This setup tests memory as reusable knowledge rather than episodic recall: the offline agent can be viewed as a new agent inheriting a pre-built memory graph. Additional details are provided in Appendix E.3.

As shown in Table 5, PlugMem substantially improves offline success rates across domains, with particularly strong gains on Multi-site tasks. These results demonstrate effective reuse of accumulated procedural and semantic knowledge, mitigating cold-start issues and supporting compositional generalization.

4.6 Discussion: Why Can a Task-Agnostic Memory Outperform Task-Specific Designs?

A natural question is why a task-agnostic memory module can outperform systems tailored to individual benchmarks. Our results suggest that the key difference lies not in rejecting task-specific heuristics, but in prioritizing what fundamentally makes agentic memory effective. Task-specific designs often encode benchmark-specific insights through customized memory units or transformations, implicitly assuming that relevant memory will be available when needed. While effective within their scope, such approaches conflate memory transformation with memory utility. In contrast, our findings highlight that agentic memory is fundamentally retrieval-driven. Without effective retrieval, neither task-specific abstractions nor carefully engineered memory representations translate into performance gains, as consistently shown in our ablations. At the same time, retrieval alone is insufficient. Its effectiveness is bounded by how memory is structured, since structuring determines which aspects of experience can be indexed and recovered. Our knowledge-centric structuring enables retrieval over semantically meaningful and decision-relevant abstractions, allowing useful information to surface at decision time.

Importantly, PlugMem is designed as a task-agnostic memory backbone that targets the shared retrieval and representation challenges underlying agentic memory designs. From this perspective, task-specific memory approaches and heuristics can be naturally layered on top of PlugMem, rather than viewed as alternatives to it. Our framework therefore provides a common foundation on which task-specific adaptations can be applied to further improve performance. We empirically validate this view through additional task-adaptation experiments, where representative task-specific heuristics and memory transformation strategies from prior baselines are integrated into PlugMem. These adaptations consistently lead to further performance improvements beyond using PlugMem alone, indicating that task-specific techniques and our task-agnostic memory design are *complementary*. Detailed experimental setups and results are provided in Appendix F.

5 Conclusions

We presented PlugMem, a task-agnostic plugin memory module that organizes agent experience into knowledge-centric representations to enable effective retrieval of decision-relevant memory across diverse agentic tasks. Through extensive experiments, we demonstrate that PlugMem consistently improves end-task performance while reducing agent-side memory cost under a unified utility–cost evaluation framework. Beyond standalone usage, PlugMem serves as a general memory backbone that can be augmented with task-specific heuristics, with task-adaptation experiments showing further gains. Overall, these results position PlugMem as principled foundation for transferable and efficient memory in LLM agents, pointing toward more general and extensible memory systems for long-horizon decision-making.

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A Real Benchmark Cases Illustrating Why PlugMem Outperforms Task-Agnostic and Task-Specific Baselines

A.1 LongMemEval

Case Study: Hierrachical Retrieval for Episodic Memory. Table 9 show an examples of PlugMem retrieving episodic memory hierrachically on LongMemEval.

Table 9: Example 1 of retrieval trace showing hierarchical retrieval for episodic memory.

LongMemEval Case Study: Hierarchical Retrieval
Query. *"How many weddings have I attended in this year?"*
Semantic Memory Retrieved
▷ **Semantic Memory 669** : *User's sister's wedding was amazing, and User had a great time planning it with her, including choosing the dress and deciding on the menu.* ▷ **Semantic Memory 141** : *User is planning a wedding and dreams of having a small, outdoor ceremony at a beach or in a park. User recently attended their college roommate's wedding in the city which had a rooftop garden ceremony overlooking the skyline.* ▷ **Semantic Memory 146** : *Social media platforms like Instagram and Pinterest can be used to follow wedding planners, venues, and photographers. Reading reviews on Yelp or Google provides insights into the venue's reputation.* ...
Episodic Memory Retrieved
▷ **Episodic Memory Session 24** : *Date: 2023/10/15 (Sun) 04:44 User: I'm planning my own wedding and I was wondering if you could give me some tips on how to choose the perfect venue. By the way, I just got back from a friend's wedding last weekend, and it was amazing - the bride, Jen, looked stunning in her bohemian-inspired dress, and her husband, Tom, was clearly smitten with her. It was at a rustic barn in the countryside, and it was so cozy and relaxed...* ▷ **Episodic Memory Session 6** : *Date: 2023/10/15 (Sun) 10:57 User: I'm planning my own wedding and I need some help with finding a venue. I've always dreamed of having a small, outdoor ceremony, maybe at a beach or in a park. Do you have any recommendations or resources for finding the perfect spot? By the way, I just got back from my college roommate's wedding in the city, and it was beautiful - they had a rooftop garden ceremony overlooking the skyline, and it was so romantic. My friend Emily finally got to tie the knot with her partner Sarah, and it was amazing to see them so happy after waiting for marriage equality...* ...
Reasoning
▷ *To determine how many weddings you have attended this year, let's review the information from the relevant memories provided:* *1.* ***Cousin's Wedding at a Vineyard (August)****: You mentioned attending your cousin Rachel's wedding at a vineyard in August.* *2.* ***College Roommate's Wedding in the City****: You mentioned attending your college roommate's wedding, which had a rooftop garden ceremony.* *3.* ***Friend Jen's Wedding at a Rustic Barn****: You mentioned attending your friend Jen's wedding at a rustic barn in the countryside last weekend...*
Answer. "Therefore, you have attended 3 weddings this year.".

Takeaways The example highlights a key reason why PlugMem outperforms task-agnostic baselines on LongMemEval. Unlike Zep Rasmussen et al. (2025), which contains episode nodes in its graph but only performs retrieval at the semantic level (semantic entities and facts), and LiCoMemory Huang et al. (2026), which performs graph retrieval for original dialogue chunks solely based on entities, PlugMem retrieves episodic memories by leveraging semantic memory extracted from those episodic memories. Specifically, the retrieval module first identifies semantic memories relevant to the query. In the example, semantic memory 669, semantic memroy 141, and semantic memory 146 are all related to wedding, which is the topic of the question. It then locates the source episodic memory corresponding to each retrieved semantic memory and selects those containing a sufficient number of semantic memories retrieved. In the example, semantic memory 669 and some other retrieved memories are extracted from episodic memory session 24, so episodic memory session 24 is selected. So does episodic memory session 6. We can notice that, although question-related, semantic memory 141 and 146 do give sufficient information about which wedding they are describing, making them ambiguous when counting the number. But by tracing back to its source

episodic memory, PLUGMEM successfully distinguishes them, showing the importance of episodic memory which is neglected in Zep. Also, although LiCoMemory retrieves back origin dialogue chunks, the retrieval process is based on semantic entities. Due to the fact that episodic memory related a single entity is definitely more than episodic memory related to a specific piece of semantic memory, it is less efficiency and may bring more noise.

A.2 HOTPOTQA

Case Study: Bridge-Entity Multi-hop Retrieval. Table 10 and Table 11 show two examples of multi-hop retrieval on HotpotQA alternating abstract node like concept and specific node like semantic node.

Table 10: Example 1 of retrieval trace showing bridge-entity discovery and evidence compression.

HotpotQA Case Study 1: Bridge-Entity Multi-hop Retrieval
Query. *" 'One Less Set of Footsteps' is a song written and performed by a singer born in which year? "*
Hop 0 (init). Tags for query: [One Less Set of Footsteps, songwriter, performer, birthdate] ▷ **node 5891** : *"One Less Set of Footsteps" is a song written and performed by Jim Croce. It was released in 1973 as the first single from his album "Life and Times".* (bridge entity identified: **Jim Croce**) ▷ node 5892 : "One Less Set of Footsteps" reached a peak of #37 on the "Billboard" Hot 100, spending ten weeks on the chart. ..... ▷ node 15424: Mariah Carey, born on March 27, 1969 or 1970, is an American singer, songwriter, record producer, and actress.
Query_new = `Integrated` (Query, top-k nodes)
Hop 1 (refine & expand). Tags for query: [Jim Croce, birth year] ▷ **node 5897** : *James Joseph "Jim" Croce was born on January 10, 1943, and died on September 20, 1973.* (golden fact retrieved: **Jan 10, 1943**) node 5895 : James Joseph "Jim" Croce was an American folk and rock singer active between 1966 and 1973. He released five studio albums and singles during this period. ..... node 5883 : "It Doesn't Have to Be That Way" was originally released early in 1973 as the B-side of the "One Less Set of Footsteps" single and was reissued in December of the same year as the third and final single from the album "Life and Times".
Reasoning (compressed). ▷ *"One Less Set of Footsteps" is written and performed by Jim Croce.* ▷ *Jim Croce was born on January 10, 1943.*
Answer. 1943.

Table 11: Example 2 of retrieval trace showing bridge-entity discovery and evidence compression.

HotpotQA Case Study 2: Bridge-Entity Multi-hop Retrieval
Query. *"Bill Nelson flew as a Payload Specialist on a Space Shuttle launched for the first time in what year?"*
Hop 0 (init). Tags for query: [Bill Nelson, Payload Specialist, Space Shuttle, first launch] ▷ **node 1375** (v=0.501): *In January 1986, Clarence William Nelson II became the first sitting member of the United States House of Representatives to fly in space, serving as a Payload Specialist on the Space Shuttle Columbia.* (bridge entity identified: **Space Shuttle Columbia**) ▷ node 1371: In 1983, Byron Kurt Lichtenberg and Ulf Merbold became the first Payload Specialists to fly on the shuttle. ..... ▷ node 1383: Dirk Dries David Damiaan, Viscount Frimout, flew aboard NASA Space Shuttle mission STS-45 as a payload specialist, making him the first Belgian in space.
Query_new = `Integrated` (Query, top-k nodes)
Hop 1 (refine & expand). Tags for query: [Space Shuttle Columbia, first launch] ▷ **node 1365**: *Space Shuttle "Columbia" (Orbiter Vehicle Designation: OV-102) launched for the first time on mission STS-1 on April 12, 1981, marking the first flight of the Space Shuttle program.* (golden fact retrieved: **1981**) ▷ node 1380: STS-61-C's seven-person crew included . . . and Representative Bill Nelson (D-FL), the second sitting politician to fly in space. ..... ▷ node 1384: A payload specialist (PS) is an individual selected and trained . . . for a NASA Space Shuttle mission.
Reasoning (compressed). ▷ *Bill Nelson (Clarence William Nelson II) served as a Payload Specialist on the Space Shuttle Columbia.* ▷ *Space Shuttle Columbia first launched on April 12, 1981 (STS-1).*
Answer. 1981.

Takeaways. Across both case studies, PLUGMEM succeeds by explicitly separating *what to retrieve next* from *where the evidence resides*. In Hop0, the retriever typically surfaces a small set of low-level propositions that are semantically close to the question but may only partially resolve it. Crucially, rather than repeatedly expanding within a local neighborhood around these propositions (as in many graph-based retrievers that rely on 1–2 hop adjacency), PLUGMEM elevates the intermediate result into an *abstract routing signal*, a bridge concept (e.g., *Jim Croce*) or a bridge entity/context (e.g., *Space Shuttle Columbia*). This abstraction step turns multi-hop QA into a sequence of targeted sub-queries: first identify the missing bridge, then retrieve the specific fact needed to answer.

Technically, this behavior is enabled by the bipartite organization of our memory graphs, where high-level nodes (concepts/intents) connect to many low-level nodes (propositions/prescriptions). Routing through the abstract layer allows the retriever to "jump" beyond the narrow vicinity of an initial seed proposition and activate a much broader set of candidate evidence, which is especially important on HotpotQA where supporting facts often lie in different articles or distant parts of the corpus. In both examples, the first hop retrieves a bridge-bearing statement; the next hop uses the bridge to directly access the answer-bearing statement (birth year or first-launch year), while irrelevant but superficially related candidates (e.g., other payload specialists, other singer-songwriters) are naturally deprioritized once the bridge entity is fixed.

Finally, the reasoning module plays a complementary role by compressing the retrieved pool into a minimal sufficient evidence set (typically two propositions in these examples), which improves robustness and token efficiency. Overall, PLUGMEM's abstraction-to-specificity routing and budgeted candidate control expand the reachable search space and deepen evidence chaining, without being constrained to short range neighbor expansion from an arbitrary starting node.

A.3 WEBARENA

Case Study: PLUGMEM Dynamically Construct Useful Guidance for Agent through Retrieval and Reasoning This WebArena case study demonstrates that the advantage of PLUGMEM lies not in executing a particular workflow correctly, but in how guidance is constructed, adapted, and consumed during decision-making. As shown in Table 12, PLUGMEM enables the agent to solve

the task without relying on static workflows or verbose episodic recall, instead producing compact, step-adaptive guidance that directly reflects the agent's current informational bottleneck.

Compared to **task-agnostic** retrieval-based methods, the core limitation exposed by this task is not retrieval coverage but retrieval granularity. Flat retrieval systems can surface past trajectories or similar task descriptions, but these memories are typically either too specific (tied to particular pages or layouts) or too verbose to be directly actionable. As a result, the agent must internally interpret and reconcile large amounts of loosely relevant information, leading to context explosion and brittle decision making. In contrast, PLUGMEM retrieves procedural knowledge units—such as category navigation, constraint-based filtering, and ranking under partial observability—and further compresses them through its reasoning module into concise, decision-aligned instructions. The benefit is not simply fewer tokens, but a sharper alignment between retrieved memory and the agent's immediate control decision.

On the other end of the spectrum, **task-specific** web agents such as AWM and SteP hard-code or accumulate a single canonical workflow per domain. While effective when tasks closely match the assumed structure, such workflows lack the ability to adapt their internal logic as the task unfolds. This case highlights that web navigation tasks are not monolithic: the agent alternates between qualitatively different reasoning regimes (e.g., locating the correct semantic scope, enforcing numeric constraints, and resolving ties under incomplete information). A static workflow cannot anticipate these shifts. Although AWM updates its workflow after task completion, it does not revise guidance within a task or condition it on intermediate observations. PLUGMEM, by contrast, recomputes guidance at each step, allowing the agent's strategy to evolve as the environment reveals new structure.

More broadly, this example illustrates that PLUGMEM 's advantage comes from treating knowledge as the unit of memory access, rather than raw trajectories or fixed workflows. Task-agnostic methods fail because they retrieve too much unstructured experience; task-specific methods fail because they retrieve too little adaptability. PLUGMEM occupies a middle ground: it abstracts experience into reusable procedural knowledge while retaining the ability to contextualize and re-specialize that knowledge through reasoning. This combination allows PLUGMEM to generalize across WebArena tasks while still producing highly targeted, step-specific guidance, which neither task-agnostic nor task-specific designs can reliably achieve.

Table 12: Example 1 of PLUGMEM assisting WebArena agent.

WebArena Case Study: Adaptive Retrieval and Refined Guidance

Query. *" Buy the highest rated product from the meat substitute category within a budget between 100 and 200. "*

PLUGMEM Reasoning.

▷ **Reasoning:**

The user's goal is to buy the highest-rated product from the "meat substitute" category within a budget of 100 to 200. The current observation does not provide direct access to the "meat substitute" category or relevant products. Additionally, the visible products on the page do not appear to belong to the "meat substitute" category. To efficiently locate the desired product, the agent should use the dropdown menu to navigate to the "meat substitute" category and then apply a price filter to narrow down the options to the specified budget range. If the platform supports advanced search, it can also be used to filter by category and price range.

▷ **Final Information**:

1. Use the dropdown menu to navigate to the "Grocery & Gourmet Food" category, then locate the "meat substitute" subcategory.
2. Once in the "meat substitute" category, apply a price filter to display products within the 100 to 200 range.
3. Sort the results by rating to identify the highest-rated product within the budget.
4. If the platform supports advanced search, use it to filter by category ("meat substitute") and price range (100 to 200) to streamline the process.
5. Once the highest-rated product is identified, proceed to add it to the cart.

AgentOccam Action 1: hover [1490]. (agent operates the dropdown menu)

...

PLUGMEM Reasoning.

▷ **Reasoning**

The user's goal is to buy the highest-rated product from the "Meat Substitutes" category within a budget of 100 to 200. The current page lists various products in this category, but the budget constraint narrows the options to only those priced between 100 and 200. To efficiently identify the highest-rated product within this range, the agent should apply the price filter for 100-199.99 and then sort the results by rating. This ensures that only relevant products are considered, and the highest-rated one is selected.

▷ **Final Information**

1. Apply the price filter for the range 100.00 - 199.99 by clicking the corresponding link under the "Price" section.
2. Once the filtered results are displayed, sort the products by "Rating" to identify the highest-rated product.
3. Select the highest-rated product from the filtered list and click "Add to Cart."
4. Confirm that the product meets the budget and rating criteria before proceeding.

AgentOccam Action 3: click [6093]. (agent selects the price range)

PLUGMEM Reasoning.

▷ **Reasoning**

The user's goal is to buy the highest-rated product from the "Meat Substitutes" category within a budget of 100 to 200. The current page already displays products filtered by the specified price range. The next step is to identify the product with the highest rating among the listed options and add it to the cart. The observation provides details about the products, including their names, prices, and ratings, which are essential for making the selection.

▷ **Final Information**

1. Review the listed products on the current page and identify the one with the highest rating. Based on the observation:
- "Beyond Meat Beef Beefy Crumble, 5 Pound – 2 per case" has a rating of 50 and costs 108.27.
- Other products do not have visible ratings in the observation.
2. Since "Beyond Meat Beef Beefy Crumble" has the highest rating and falls within the budget, proceed to click the "Add to Cart" button for this product.
3. Confirm that the product has been successfully added to the cart before proceeding further.

AgentOccam Action 4: click [10183]. (agent inspects the item information)

...

B Related Work

B.1 Cognitive Science Based Agent Memory

Cognitive science has long studied the mechanisms of human memory, providing valuable insights into how memory can be leveraged in agents. The Atkinson–Shiffrin memory model defines long-term memory as information that can be retained and recalled over extended periods of time (Atkinson & Shiffrin, 1968). Long-term memory is further categorized into three major types (Tulving, 1972; Squire, 2004): semantic memory, which stores concepts and factual knowledge; procedural memory, which is responsible for knowing how to perform actions and skills; and episodic memory, which represents raw records of personal experiences and events. For intelligent agents, most interactions with the environment are episodic memory, such as raw contexts and working trajectories. From these episodic experiences, agents can extract more reusable representations. For example, user preferences can be distilled as semantic memory (Li et al., 2025), while web navigation skills can be abstracted as procedural memory (Wang et al., 2024b). In this sense, semantic and procedural memories are not isolated components, but rather structured abstractions derived from episodic memory. Knowledge can be viewed as a further abstraction over memory. Specifically, propositional knowledge corresponds to highly structured and verifiable abstractions of semantic memory, while prescriptive knowledge represents generalized and reusable forms of procedural memory that describe how to accomplish goal-oriented tasks (Diebolt & Perrin, 2013).

Inspired by these cognitive theories, many studies have explored memory mechanisms for intelligent agents. Episodic and semantic memory have been introduced to handle long-context information, such as long documents in document understanding agents (Lee et al., 2024) and long-term user–agent interactions in conversational agents (Li et al., 2025). Additionally, some approaches construct knowledge graphs containing both episodic and semantic subgraphs to better organize and manage agent memory (Anokhin et al., 2024; Rasmussen et al., 2025). Procedural memory has also been incorporated into decision-making agents, particularly web agents, where accumulated experiences are leveraged to improve future strategies (Zhao et al., 2024). This line of research moves toward self-evolving agents that continuously refine their decision-making policies based on incoming memory (Wang et al., 2024b; Fang et al., 2025; Ouyang et al., 2025).

However, most existing methods are designed for specific tasks and are unable to effectively support all memory types simultaneously. In contrast, PlugMem standardizes heterogeneous episodic memories across diverse tasks and stores extracted knowledge in a propositional–prescriptive dual knowledge graph, thereby overcoming the limitations of task generalizability present in prior approaches.

B.2 Memory Module Designs

Across agentic systems, external memory is most commonly realized through retrieval. Agents store past interactions, observations, or documents outside the model context and retrieve relevant information at inference time to condition decision making. This retrieval first paradigm forms the basic prototype of external memory, and nearly all subsequent memory designs can be viewed as extensions built on top of it.

Early task agnostic memory systems adopt flat retrieval over unstructured episodic memory. Vanilla retrieval and vanilla RAG store raw interaction histories or documents as text and retrieve relevant segments based on similarity to the current query (Lewis et al., 2021; Wang et al., 2024a). These methods provide a simple and broadly applicable memory interface, but the retrieved content remains tightly bound to specific episodes. As a result, retrieved memories often contain redundant details and exhibit low information density when reused across different decision contexts.

To improve retrieval effectiveness, later work introduces structure on top of episodic memory. Graph based and hierarchical retrieval systems organize stored content to support multi hop retrieval, aggregation, or global reasoning (Edge et al., 2025; Sarthi et al., 2024). Related approaches further refine retrieval by altering the internal organization of memory graphs, such as ranking paths or linking propositions (Gutiérrez et al., 2025; Wang & Han, 2025). While these methods differ in structure and traversal strategy, they largely preserve the same retrieval oriented abstraction. Memory remains organized around episodic traces, entities, or text spans, and structural mechanisms primarily serve to improve access to stored experiences rather than to transform their content.

In parallel, task-specific memory systems explore more aggressive forms of memory processing. Temporal knowledge graphs for conversational agents, workflow memories for web navigation, and reasoning oriented memory banks explicitly extract higher level representations from experience (Gutiérrez et al., 2025; Wang et al., 2024b; Ouyang et al., 2025). These systems demonstrate that abstracting experience into reusable representations can substantially improve performance within a fixed task setting. However, the abstraction process is typically guided by task-specific

assumptions, which constrains reuse of the memory module across heterogeneous agents and environments.

Viewed together, prior work reveals a key distinction in how memory is treated. Some systems focus on improving retrieval over episodic experience, while others implicitly or explicitly transform experience into more abstract forms. Only the latter enables memory to generalize across episodes and tasks, since episodic memory is inherently tied to a particular agent and interaction trajectory, whereas semantic and procedural knowledge abstract away task-specific execution details. This observation motivates memory to knowledge transformation as a critical operation for reusable agent memory.

PLUGMEM builds on this evolution by making memory-to-knowledge transformation an explicit and central component of the memory module. Instead of treating episodic traces as the primary unit of retrieval, PLUGMEM organizes memory around propositional and prescriptive knowledge units corresponding to semantic and procedural memory. These knowledge units serve as the basis for memory organization, retrieval, and reasoning, while episodic memory is retained as verifiable source evidence. By elevating knowledge to the unit of memory manipulation, PLUGMEM enables memory to be reused across agents and tasks without task-specific redesign, while remaining compatible with the retrieval based external memory paradigm.

B.3 MEMORY BENCHMARKS AND EVALUATION SCOPE

A broad range of benchmarks have been used to study memory related behaviors in language models and agents, spanning diverse task settings and evaluation objectives. One prominent line of work focuses on long context utilization, evaluating whether models can access and reason over large inputs within a single inference window, such as long document understanding, narrative comprehension, or needle in a haystack style retrieval (Liu et al., 2023; Bai et al., 2024; Zhang et al., 2024). These benchmarks assess context usage and attention behavior, but do not model memory accumulation, update, or reuse across time. A separate line of work focuses on long-horizon conversational agents and user-centric memory, evaluating whether systems can accumulate, maintain, and reuse information such as preferences, personal attributes, and dialogue context over extended interactions (Wu et al., 2024; Maharana et al., 2024). These benchmarks explicitly stress episodic accumulation and robustness to redundancy and noise, and are commonly used to study memory abstraction in interactive settings. Another class of benchmarks evaluates retrieval-augmented question answering over static knowledge sources, including factoid and multi-hop QA tasks, where memory is treated as a fixed external repository and the primary challenge lies in retrieval and evidence composition rather than memory evolution (Petroni et al., 2021; Kwiatkowski et al., 2019; Yang et al., 2018; Trivedi et al., 2022). While effective for studying semantic retrieval and composition, these benchmarks assume a static memory base and do not capture how memory is constructed or refined through interaction. In agentic settings, additional benchmarks evaluate end-to-end task performance in interactive environments, including web navigation, tool use, and embodied reasoning, where memory interacts with planning, perception, and action execution (Zhou et al., 2024; Trivedi et al., 2024; Furuta et al., 2024; Shridhar et al., 2021; Liu et al., 2025). In such benchmarks, memory is often entangled with other agent capabilities, making it difficult to isolate memory-specific contributions.

While these benchmarks differ widely in surface form, they each probe only a limited slice of memory behavior. Collectively, prior work reveals a fragmented evaluation landscape, where no single benchmark provides comprehensive coverage of how memory is accumulated, abstracted, organized, and reused in agent decision-making.

Within this landscape, memory benchmarks can be distinguished by how memory is constructed, organized, and reused. Some benchmarks emphasize long term accumulation of episodic experience, requiring agents to extract stable information from extended interaction histories. Others focus on structured access to semantic knowledge, stressing multi-hop retrieval and organization over memory. A third class emphasizes procedural reuse, where agents must generalize skills or workflows acquired from prior experience to new task instances. No single benchmark captures all of these aspects simultaneously, motivating the need for a complementary evaluation suite.

Based on this perspective, we intentionally select three benchmarks that probe distinct and complementary memory behaviors. LongMemEval targets long-horizon conversational settings where memory is accumulated over time and relevant information must be abstracted from noisy episodic interactions (Wu et al., 2024). HotpotQA evaluates semantic memory organization and multi-hop retrieval over a large static knowledge source, serving as a canonical benchmark for structured memory access and composition (Yang et al., 2018). WebArena evaluates procedural memory in interactive environments, where agents must reuse and adapt previously acquired strategies across multiple task instances derived from shared intent templates (Zhou et al., 2024).

Beyond their complementary coverage of episodic accumulation, semantic organization, and procedural reuse, the selected benchmarks are representative within their respective evaluation settings. LongMemEval, HotpotQA, and WebArena have each been widely adopted in prior work, with a broad range of memory and agent baselines already evaluated on these benchmarks. This established usage allows existing systems to be reliably reproduced and compared under consistent protocols, reducing evaluation bias introduced by task-specific tuning. As a result, evaluating memory modules on these benchmarks enables fairer and more stable comparison across heterogeneous memory designs, while supporting conclusions that generalize beyond any single task or interaction pattern.

C Implementation Details

Table 13: **Layered Memory System Construction via Standardized Formalization.** PLUGMEM adopts a layered memory graph: raw interactions (τ) are first formalized into episodic memory (Phase 1). This formalized history then serves as the input for inducing semantic and procedural knowledge blocks (Phase 2). All memory types are managed through a universal API by standard data operations.

Memory Type	Construction Logic (Input → Output)	Graph Structure	Universal API & Cognitive Heuristics
	Phase 1: Standardize		**1. Create (Ingestion & Induction)** • `memory.create(trajectory)` • Formalizes raw τ into standardized Episodic, and then triggers induction to abstract Facts/Skills from new Episodic entities. **2. Retrieve (Association)** • `memory.retrieve(goal, state)` • Maps Goal and State to Intent/Concept indices and retrieve Knowledge Blocks, then traces back to Episodic Sources for context. **3. Update (Reflection & Refinement)** • `memory.update(feedback)` • Detect and mitigate contradictions (Semantic) or optimize workflow efficiency (Procedural). **4. Delete (Forgetting & Pruning)** • `memory.delete(criteria)` • Decays low-utility Nodes (Semantic/Procedural) while compressing old Episodic Nodes to save space.
Episodic	**Formalization** *Input:* Raw Agent Trajectory (τ) *Process:* $Formalize(\tau) \rightarrow M_{epi}$ *Role:* Converts unstructured logs into standardized Source Nodes.	**Source Node (Event Window)** *Edge:* `Knowledge` $\xleftarrow{proves}$ `Source`	
	Phase 2: Structure		
Semantic	**Fact Induction** *Input:* Episodic Memory (M_{epi}) *Process:* $Induce_{fact}(M_{epi}) \rightarrow M_{sem}$ *Role:* Distills static truths from specific event traces.	**Proposition Node (Fact Block)** **Concept Node (Entity/Term)** *Edge:* `Concept` $\xleftarrow{mentions}$ `Proposition`	
Procedural	**Skill Induction** *Input:* Episodic Memory (M_{epi}) *Process:* $Induce_{skill}(M_{epi}) \rightarrow M_{proc}$ *Role:* Synthesizes reusable workflows from successful history.	**Prescription Node (Workflow Block)** **Intent Node (User Goal/Task)** *Edge:* `Intent` $\xleftarrow{solves}$ `Prescription`	

Overview. This appendix provides implementation-oriented details that complement the high-level description in Section 3.1. As summarized in Table 13, the memory structuring module includes two main phases: Phase 1 "Standardize" and Phase 2 "Structure." In Phase 1, to handle different types of episodic memory, PLUGMEM standardize the raw agent trajectory τ into uniformed episodic memory M_{epi}. Specifically, for each turns of observation and action $\{o_t, a_t\}$, we prompt LLM to derive the state s_t, the subgoal g_t and the reward r_t. In Phase 2, PLUGMEM employs induction processes to distill this episodic memory M_{epi} into Semantic Memory and Procedural Memory. These memory are the inserted into the memory graph, with a series of universal API that manage them.

C.1 Episodic Standardization

To standardize episodic memory at time t, we represent each turns of the raw agent trajectory as an observation-action pair $\{o_t, a_t\}$ and formalize it through a three-stage process:

We first derive the agent state s_t using the previous state s_{t-1}, the previous action a_{t-1}, the current observation o_t, and the initial goal G. Incorporating G ensures the state remains grounded in the agent's initial objective. The derivation is achieved by querying an LLM with the prompt in Listing 1. The resulting state serves as a concise context summary, effectively reducing overall context length for distilling procedural memory when pursuing long-context agentic tasks Wu et al. (2024); Zhou et al. (2024).

Next, we infer a subgoal g_t from s_t, o_t, a_t and G to analyze how the agent decomposes the global task into incremental steps. Using the prompt in Listing 2, this step serves two purposes: it enriches the information available for knowledge extraction and enables trajectory segmentation. Specifically, we can structure the raw trajectory into workflow by chunking episodic memory based on the cosine similarity of adjacent subgoal embeddings.

Finally, we determine the reward r_t based on s_t, a_t, g_t and o_{t+1} using the prompt in Listing 4. This reward quantifies the effectiveness of the action in achieving its intended goal, facilitating the extraction of quality-aware procedural memory.

Listing 1: Template for deriving the current state s_t given previous state s_{t-1}, previous action a_{t-1}, and current observation o_t.

==========

```
Prompt Get_State
============================================================

You will receive four pieces of information:
Goal: The agent's current objective or task.
Previous State (at time t): A natural language summary describing the
    agent's context, history, and partial progress so far.
Action (at time t): The action the agent decided to take next,
    expressed in natural language.
Observation (at time t+1): The outcome or feedback resulting from that
     action.

Your task is to derive the new updated state---a coherent natural
    language summary that integrates all relevant information from the
     previous state, the action, and the new observation.

Steps to Follow:
Interpret the Inputs:
Examine the goal, the previous state, the action, and the observation
    to understand what has changed in the agent's situation and the
    detailed information about location and time.

Reason about the Update:
Describe the logical process by which the new state should differ from
     the previous one. Identify what progress has been made, what new
    information was gained, and how the context or focus may have
    shifted.

Generate the Updated State:
Write a clear and concise natural-language description summarizing the
     new state of the agent at time t+1. The new state should:
-- Include all the detailed information in the action and observation,
     especially information about location and time.
-- Integrate the outcome of the latest action and observation.

Output Format:
### Reasoning
(Explain step by step how the new state should be updated based on the
     inputs.)

### State
(Provide the final updated state summary here.)

---
Input:
Goal: {goal}
Previous State (at time t): {state}
Action (at time t): {action}
Observation (at time t+1): {observation}
```

Listing 2: Template for deriving the subgoal g_t of turn t given initiate goal G, current state s_t, observation o_t and action a_t.

```
============================================================
Prompt Get_Subgoal
============================================================

At time t, the agent takes an action based on its state, observation,
    and overall goal. Your task is to infer the subgoal-the immediate
    or intermediate objective-that best explains why the agent chose
    this action.

Use the following information as context: Overall Goal: {goal} Current
     State (summary of past context): {state} Current Observation: {
    observation} Action at time t: {action}
```

```
Step 1: Reasoning Analyze how the current state and observation relate
     to the overall goal. Explain how the given action helps the agent
     make progress toward that goal-possibly by achieving a smaller
    intermediate objective. Be explicit and causal: describe why this
    action makes sense given the context.

Step 2: Subgoal Inference After reasoning, infer the agent's likely
    subgoal-a short natural-language statement that describes the
    immediate purpose behind the action.

Output Format:

### Reasoning
[Your reasoning process-a few sentences explaining how the action
    relates to the goal and context]

### Subgoal
[A short sentence describing the inferred subgoal]
```

Listing 3: Prompt template for deriving return from procedural memories.

```
============================================================
Prompt Get_Return
============================================================

You will receive:\newline
Goal Description: A text explaining what the agent was trying to
    achieve.\newline
Process Description: A text describing the agent's actions, decisions,
     and progress toward that goal.\newline
\newline
Your task:\newline
Analyze the agent's process and determine how much of the goal was
    completed, considering the following aspects:\newline
\newline
Grading Criteria (Score 1--10):\newline
10: The agent fully accomplishes the goal with no significant
    omissions; actions are fully aligned with the goal.\newline
8--9: The agent completes most of the goal with only minor gaps;
    strong alignment but not perfect.\newline
6--7: Partial completion; the agent covers many key elements but
    leaves notable parts unfinished or poorly executed.\newline
4--5: Limited progress; the agent attempts the goal but completes less
     than half or does so in an ineffective way.\newline
2--3: Very little completion; actions barely connect to the goal or
    achieve only minimal results.\newline
1: No meaningful progress; actions do not contribute to achieving the
    goal at all.\newline
\newline
Important Instructions:\newline
Base the score only on completion level and alignment with the stated
    goal.\newline
Do not provide explanations or commentary unless requested.\newline
Output must follow the format below exactly.\newline
\newline
Output Format:\newline
\texttt{\#\#\# Score}\newline
[number from 1 to 10]\newline
\newline
Input:\newline
---\newline
Goal:\newline
\{subgoal\}\newline
Process:\newline
\{procedural\_memory\}
```

Listing 4: Template for deriving the reward r_t of action a_t given current state s_t, goal g_t and action a_t, as well as next observation o_{t+1}.

```
============================================================
Prompt Get_Reward
============================================================

You will be given:
Goal: the agent's overall objective.
State (at time t): what the agent knew and had done before taking the
    action.
Action (at time t): the single action the agent chose.
Observation (at time t + 1): the immediate outcome produced by that
    action.
Your task is to infer the reward - that is, a evaluation in natural
    language on how the agent's action contributes (positively or
    negatively) to achieving the overall goal, based on the resulting
    observation.
Follow these steps carefully:
1. Reasoning Process:
Explain how the action relates to the Goal given the State, and
    whether the Observation matches the expected helpful or unhelpful
    outcome.
Consider whether the action advances progress, causes setbacks,
    reveals new useful information, or wastes effort.
Summarize your reasoning about the causal contribution of the action
    to the goal.
2. Final Reward:
Use descriptive language to write a concise natural-language
    evaluation of the agent's action.
The reward should express how much and in what way the action helped
    or hindered achieving the goal.
Input:
Goal: {goal}
State (at time t): {state}
Action (at time t): {action}
Observation (at time t + 1): {observation}
Output format:
### Reasoning
[Your reasoning process here]
### Reward
[Natural-language reward statement that evaluate the agent's action]
some prompt
```

C.2 Extract Knowledge

Semantic Given a standardized episodic unit e_t, we extract semantic memories as proposition–tag pairs. We query an LLM using the prompt in Listing 5, which returns up to $N_{\max} = 10$ items in a fixed schema. Each item contains a `Statement` field (a proposition in the main paper) and a `Tags` field (a list of associated concepts). We deterministically parse the LLM output into $(p, \mathcal{T})$ pairs, where p is the proposition text and $\mathcal{T}$ is the corresponding concept set.

We materialize these outputs into the semantic graph G^S by creating a low-level proposition node for each p and high-level concept nodes for each $c \in \mathcal{T}$, caching dense embeddings and metadata for all nodes. We add two edge types: *i) membership* edges linking propositions to their concept tags ($p \to c$), and *ii) provenance* edges linking each proposition back to its source episodic unit in the episodic graph G^E ($p \to e_t$). When multiple propositions originate from the same episodic unit, we additionally connect them with *sibling* edges to preserve local co-occurrence structure.

Listing 5: Prompt template for extracting semantic knowledge from episodic trajectories.

```
============================================================
Prompt Get_Semantic
```

```
============================================================

You are an expert at extracting precise, factual information from
    documents.
Your output must prioritize specificity, avoid ambiguity, eliminate
    redundancy, and strictly follow all formatting rules.

**CORE INSTRUCTIONS:**

1. Fact/Statement Extraction & Deduplication:
* Identify distinct, factual statements from the document.
* Resolving Vague References: If the subject of a statement is a
    pronoun or a vague description (e.g., 'the film', 'the band', 'the
     company', 'he', 'she', 'they'), you MUST rewrite the statement
    based on understanding of whole document so that the subject is a
    fully specified and concrete entity name taken from the document.
    You are NOT allowed to keep vague subjects in the final fact/
    statement.
* Example of Resolving Vague References:
BAD: 'The film was directed by xxx.', 'This movie is produced by xxx'
GOOD: 'Vaada Poda Nanbargal was directed by Manikai.', 'Vaada Poda
    Nanbargal is produced by xxx'
* Concrete Phrasing: Every statement MUST be phrased using explicit,
    identifiable names or titles. You are FORBIDDEN from using ANY
    vague references including but not limited to: 'the tour', 'the
    film', 'the movie', 'the band', 'it', 'he', 'she', or 'they'.
* Example of Concrete Phrasing:
BAD: 'The tour earned over $50 million.'
GOOD: 'NSYNC's Second II None Tour earned over $50 million.'
* Statement Length Policy (IMPORTANT): Each fact/statement does NOT
    have to be a single short sentence. A statement MAY be a compact
    multi-sentence block that groups tightly related information, but
    it must contain AT MOST 4 sentences total. These sentences should
    come from the original document material, potentially lightly
    edited ONLY to resolve vague references.
* Avoid Redundancy: You MUST merge similar or overlapping facts into
    single, comprehensive statements. Do NOT create multiple
    statements that repeat the same core information with minor
    variations.


2. Tag Generation:
* For each fact/statement, generate a list of tags.
* The number of tags per fact is flexible and should reflect the
    information density of the statement.
* Tags should cover key spans such as: entity names, years, numbers,
    nationalities, languages, genres, roles, object types, descriptive
     words, etc.
* The MAJORITY of tags SHOULD be SHORT TEXT SPANS copied VERBATIM from
     the statement (exact substrings). These tags are directly
    grounded in the surface form of the text.
* You MAY occasionally create additional tags that are not literal
    substrings of the current statement, in the following cases:
* You combine adjacent words into a single phrase (e.g., 'romantic
    comedy film').
* You import a surface span (exact phrase) from ANOTHER part of the
    document to make the meaning of the current statement explicit (
    for example, when resolving pronouns or phrases like 'the film', '
    the band', etc.).


* When the subject of a statement is a pronoun or a vague description
    (e.g., 'the movie', 'the band', 'the hotel'), you MUST add at
    least one tag that names the underlying entity explicitly, using
    the exact surface form that appeared elsewhere in the document.
    This cross-statement tag may come from a previous or later
    sentence as long as it is clearly the same entity.
```

```
* If a tag is a verb, you MUST use its base (lemma) form (e.g., 'play
    ', not 'played', 'playing', or 'to play').
* No Schema/Type Labels: You are FORBIDDEN from using meta-labels or
    ontology-like category names such as: 'Name', 'Person', 'Year', '
    Date', 'City', 'Country', 'Location', 'Genre', 'Language', '
    FilmTitle', etc. Tags are NOT type labels; they are content-
    bearing phrases.
* Tags should be relatively short and as fine-grained as needed. For
    example, adjectives and modifiers like 'Indian', 'Tamil-language',
     'romantic', 'comedy' SHOULD usually be separate tags if they
    appear in the statement.


OUTPUT CONSTRAINTS:
* Extract up to 10 facts, but prioritize QUALITY over quantity. If
    there are fewer than 10 truly distinct facts, output fewer.
* Each fact must provide unique information not covered by other facts
    .
* ABSOLUTELY NO generic references -- every statement must explicitly
    name the specific entity.

**DOCUMENT:**
{observation}

OUTPUT FORMAT:

### Facts

1. **Statement:** [statement]
**Tags:** [tag0, tag1, tag2, tag3, ...]
2. **Statement:** [statement]
**Tags:** [tag0, tag1, tag2, tag3, ...]
...
```

Procedural Given a standardized episodic sequence $M_{\text{epi}} = [e_t]_{t=1}^{T}$ with subgoal annotations g_t, we first segment the full trajectory into coherent workflow chunks by detecting shifts in adjacent subgoals. We compute embeddings of each subgoal and start a new segment if the two adjacent subgoals have similarity below a set threshold. Each segment $M_{\text{epi}}^{(i)}$ is then linearized into a compact process trace (e.g., a stepwise state–action–reward description) and fed to an LLM using the prompt in Table 6 to produce a structured *(intent, prescription)* pair $(u^{(i)}, \pi^{(i)})$, where $u^{(i)}$ abstracts the segment objective and $\pi^{(i)}$ describes an environment-agnostic procedure that can be reused in future tasks.

To support quality-aware reuse, we assign each prescription a scalar return score $\rho^{(i)} \in [1, 10]$ via a separate LLM evaluator (Table 3), conditioned on the intent and the segment trace. We then materialize $(u^{(i)}, \pi^{(i)}, \rho^{(i)})$ into the procedural graph G_P by creating an intent node and a prescription node, caching embeddings and metadata for both. To reduce intent proliferation, an incoming intent embedding $\phi(u)$ is matched against existing intent nodes; if the best cosine similarity exceeds threshold θ_{equal}, we merge the two intent strings via an LLM rewrite (Table 7) and refresh the node embedding, otherwise we create a new intent node. The hierarchical relation is represented as a directed adjacency from intent to its prescriptions, i.e., $u \xrightarrow{\text{SOLVES}} \pi$ (implemented as intent-node child lists, hence unidirectional). Finally, each prescription node is linked back to its originating episodic evidence through provenance edges $\pi \to e_t$ for all $e_t \in M_{\text{epi}}^{(i)}$, enabling downstream verification and optional recovery of concrete interaction context when a retrieved procedure requires elaboration.

Listing 6: Prompt template for extracting procedural experience from episodic trajectories.

```
============================================================
Prompt Get_Procedural
============================================================
```

```
You will be given an utterance of an agent. Your task is to analyze
    the utterance and derive
-- a main goal that the agent is pursuing.
-- an experiential insight --- a concise reflection that summarizes
    the agent's behaviour.

Follow this process when generating your response:

Reasoning: Analyze the utterance and write down the generalizable
    information and patterns that would be useful as memory for future
     tasks.

Output goal and experiential insight: Produce one sentence describing
    the general goal of the utterance, using abstract language.
    Produce one paragraph in natural language that clearly expresses
    the experiential insight and the reflection that summarizes the
    agent's behaviour.

Output format:

### Reasoning
[Your reasoning process]

### Goal
[A sentence that concludes the goal]

### Experiential Insight
[The paragraph that expresses the experiential insight]

Input: Trajectory: {trajectory}


============================================================
Prompt Get_Return
============================================================

You will receive:
Goal Description: A text explaining what the agent was trying to
    achieve.
Process Description: A text describing the agent's actions, decisions,
     and progress toward that goal.

Your task:
Analyze the agent's process and determine how much of the goal was
    completed, considering the following aspects:

Grading Criteria (Score 1--10):
10: The agent fully accomplishes the goal with no significant
    omissions; actions are fully aligned with the goal.
8--9: The agent completes most of the goal with only minor gaps;
    strong alignment but not perfect.
6--7: Partial completion; the agent covers many key elements but
    leaves notable parts unfinished or poorly executed.
4--5: Limited progress; the agent attempts the goal but completes less
     than half or does so in an ineffective way.
2--3: Very little completion; actions barely connect to the goal or
    achieve only minimal results.
1: No meaningful progress; actions do not contribute to achieving the
    goal at all.

Important Instructions:
Base the score only on completion level and alignment with the stated
    goal.
Do not provide explanations or commentary unless requested.
Output must follow the format below exactly.

Output Format:
```

```
### Score
[number from 1 to 10]

Input:
---
Goal:
{subgoal}
Process:
{procedural_memory}
```

Listing 7: Prompt template for merging two similar intents.

```
============================================================
Prompt Get_New_Subgoal
============================================================

Each goal may contain overlapping or complementary information.
Your task is to carefully combine them into a single, coherent, and
    well-structured goal that preserves all important details from
    both.
Avoid redundancy and ensure the merged goal sounds natural and
    consistent in tone.

Input:
Earlier goal: {goal_1}
Later goal: {goal_2}

Output:
Merged goal: [Write the unified goal here]
```

C.3 Retrieval with Interleaved Abstraction and Specificity

This appendix provides implementation-oriented details that complement the high-level description in Section 3.2. PlugMem performs interleaved multi-hop retrieval over the semantic graph G^S and procedural graph G^P by alternating between *i)* abstraction-level routing through concept/intent nodes and *ii)* specificity-level expansion over proposition/prescription nodes. Given a query Q, the retriever is orchestrated by three LLM prompts: GetMode (Listing 8) selects the memory type(s) to emphasize; GetPlan (Table 9) proposes the next-hop abstract signals (concept tags for G^S or subgoals/intents for G^P); and MultiHopCtrl (Listing 10) serves as a retrieval controller that decides whether the current evidence is sufficient to stop, or which low-level nodes to prioritize in the next hop.

At hop t, retrieval starts from a low-level candidate pool C_t. We first expand candidates through two complementary channels. *(Embedding channel)* We embed the current query text Q_t and retrieve a set of high-scoring low-level nodes by dense similarity. *(Linking channel)* In parallel, we run GetPlan to produce an abstract plan (concept tags for G^S or intents/subgoals for G^P), match it to the corresponding high-level nodes, and activate their adjacent low-level neighbors via membership edges. The two candidate sets are merged (union), then reranked and pruned back to a fixed budget (top-K) using a value function (primarily relevance, optionally combined with metadata such as importance/recency). Throughout the process, high-level nodes are used only as intermediate routing signals and are not retained in C_t.

After obtaining the budgeted candidate set, we invoke MultiHopCtrl to assess sufficiency. Concretely, MultiHopCtrl returns a strict JSON object with an `enough` flag and an optional list of selected low-level node IDs (`top_node_ids`), constrained to be a subset of the available candidates; if `enough=true`, it returns an empty list. If `enough=true`, retrieval terminates early and the current candidates are returned (or mapped to provenance-linked episodic nodes when episodic memory is requested). Otherwise, we keep only the selected nodes (capped in our experiments) as the "focus set" and integrate them with the previous query to form the next-hop query Q_{t+1}. This integration can be performed by an LLM-based rewriter, but we find that simple concatenation of Q_t and the selected facts performs comparably well and is used as the default for efficiency.

The retrieval loop repeats until MultiHopCtrl signals sufficiency or a hop limit is reached. The overall control flow is summarized in Listing 14.

Listing 8: Prompt template for inferring potential memory type to be used from query.

```
============================================================
Prompt Get_Mode
============================================================

You are given a task description that the agent is pursuing and the
    observation from the task
Please analyze the task description and observation to determine the
    type of memory required to complete it effectively. There are
    three possible memory types:
Episodic Memory: This is needed if the task requires you to answer
    questions based on events. For example, answering user's question
    depending on historical conversation.
Semantic Memory: This is needed if the task requires you to recall
    objective information. For example, answer the question based on
    objective knowledge or information.
Procedural Memory: This is needed if the task is completing a subgoal
    under an interactive environment that agent need to perform a
    workflow. For example, completing an instruction in web navigation
     tasks.
First analyze that task and observation and decide which only one
    memory type needed. When there is a conflict, prioritize the
    information in the Task Description when making decisions.

Output Format:

### Reasoning

[Your analyze of which memory is needed depending on task and
    observation]

### Memory Type

## [Your final decision, episodic_memory or semantic_memory or
    procedural_memory]

Input:
Task Description: {task_type}
Observation: {observation}
```

Listing 9: Prompt template for inferring abstraction concepts for next step of retrieval.

```
============================================================
Prompt Get_Plan
============================================================

You are an expert at analyzing an agent's goal and current observation
     and generating retrieval tags for a goal-directed question-
    answering system.
Your setting:

* Goal: The agent's overall objective to accomplish.
* Current Subgoal: The subgoal the agent is currently pursuing. (can
    be None)
* Current State: A description of the agent's current internal state.
    (can be None)
* Input (Current Observation): The agent's most recent observation (
    typically a question or task instruction).
* Task: Extract a prioritized set of high-quality tags that are most
    likely to retrieve information that directly helps accomplish the
    Goal.

Instructions:

1. Goal-directed Tag Selection (CRITICAL):
```

```
* Read the Goal and the Current Observation carefully.
* Only generate tags that are HIGHLY LIKELY to retrieve evidence
    needed to solve/complete the Goal.
* Prefer tags that identify:
* The target entity/entities the Goal is asking about (people,
    organizations, places, works, events).
* Bridge entities implied by the observation that are likely required
    for multi-hop retrieval.
* Explicit constraints: dates, years, roles, titles, unique
    descriptors, numbers.


* Avoid low-signal or generic tags that are unlikely to retrieve
    helpful evidence (e.g., "known for", "famous", "character" unless
    the Goal specifically depends on them).

2. Concrete, Grounded Tags:

* The MAJORITY of tags MUST be short text spans copied VERBATIM from
    the Goal or the Current Observation (exact substrings).
* You MAY add a SMALL number of non-literal tags only if they are
    short, strongly implied, and clearly necessary for retrieval (e.g
    ., a canonical name expansion or a standard alias).
* If a tag is a verb, you MUST use its base (lemma) form (e.g., "
    direct", not "directed" or "directing").

3. Prioritization & Quantity:

* the number of tags in total should be proper. (not "as many as
    possible").
* Sort tags by expected retrieval usefulness (most useful first).
* Ensure tags are content-bearing and relatively short.

4. CRITICAL -- Forbidden tags:

* Do NOT generate the tag "user".
* Do NOT use meta-labels or type names such as "Name", "Person", "Year
    ", "Date", "City", "Country", "Location", "Genre", "FilmTitle",
    etc.

Output Format:

### Reasoning

[You process of analyzing the information and completing the task]

### Tags

**Tags:** ["tag0", "tag1", "tag2", "tag3", ...]
(for example: "Central Area", "focal point", "famous for", etc)

### Next Subgoal

## [A single best next subgoal that the agent should pursue now.]

Input:
Goal: {goal}
Current Subgoal: {subgoal}
Current State: {state}
Current Observation: {observation}
```

Listing 10: Prompt template for controlling mutli-hop retrieval process.

```
============================================================
Prompt Multi-hop_Retrieval
```

Table 14: Multi-hop retrieval control flow (pseudo-code style).

Input: query Q; graphs (G^E, G^S, G^P) with provenance links to G^E; budget K; hop limit $T_{\max}$
Output: retrieved context $\mathcal{R}$

$\mathcal{F} \leftarrow \text{TaskAdapter}(Q)$ { $\mathcal{F} \subseteq \{E, S, P\}$ }
$C \leftarrow \text{InitLowLevel}(Q, \{G^S, G^P\})$ { score all low-level nodes }
$C \leftarrow \text{TopK}(C, K)$

for $t = 1$ **to** $T_{\max}$ **do**
  if $\text{Stop}(Q, C)$ **then break**
  $q^a \leftarrow \text{Abstract}(Q, C)$ { concepts for G^S; intents for G^P }
  $C \leftarrow C \cup \text{ExpandLowLevel}(q^a, \{G^S, G^P\})$
  $C \leftarrow \text{RerankPrune}(C, K)$ { e.g., relevance, etc. }
end for

if $E \in \mathcal{F}$ **then**
  $\mathcal{R} \leftarrow \text{ToEpisodic}(C, G^E)$ { map via provenance }
else
  $\mathcal{R} \leftarrow C$
end if
return $\mathcal{R}$

```
============================================================

You are a retrieval controller for multi-hop question answering.
Return **STRICT JSON only**:
{
"enough": true/false,
"top_node_ids": [int, int, ...]
}

**Constraints:**
-- top_node_ids length <= {n_facts_new_query}
-- top_node_ids must be a subset of available ids
-- if enough=true => top_node_ids=[]

**Question:**
{question}

**Available node ids:**
{available_ids}

**Retrieved facts:**
{semantic_memory_str}
```

C.4 REASONING

We design tailored reasoning prompts for each memory type based on their unique structural characteristics.
In alignment with the objective of the reasoning module is to aggregate and condense retrieved memory mentioned in Section 3.3, we query the LLM to extract information relevant to the question, utilizing the prompt structure detailed in Listing 12.
Given that episodic memory is often long and unstructured, we observed that information extraction is inefficient as most of the LLM is not deliberately trained on the task. Instead, we find that, like prompt in Listing 11, directly asks the LLM to reason over every memory and answer the question successfully leveraging the reasoning ability of LLM while containing most of the useful informa-

tion in the reasoning process. The entire output including the reasoning process is then preserved as the extracted information.
Procedural memory is primarily utilized during multi-turn decision-making tasks. To support that, we prompt the LLM to integrate diverse experiences consisting of both successful and failed memory from similar tasks. As shown in Listing 13, this process generates coherent and actionable guidance to fuel the agent's next action.

Listing 11: Prompt template for reasoning and compressing for retrieved episodic memories.

```
============================================================
Prompt Reason_Episodic
============================================================

I will give you information of history chats between you and a user.
    Please answer the question based on the information. Answer the
    question step by step: first extract all the relevant information,
     and then reason over the memory to get the answer.

Information:

{information}

Current Date: {time}
Question: {question}
Answer (step by step):
```

Listing 12: Prompt template for reasoning and compressing for retrieved semantic memories.

```
============================================================
Prompt Reason_Semantic
============================================================

I will give you several retrieved facts. Extract all the useful
    information relevant to the question.
In the output reasoning information, use the original wording from the
     retrieved facts as much as possible, and do not replace it with
    synonyms or near-synonyms.
If no useful information found, just return "null".

## Output format:

### Reasoning

(process of extract information)

### Information

## (The useful information you extract)

Input:
Facts: {semantic_memory}
Current Date: {time}
Question: {observation}
```

Listing 13: Prompt template for reasoning and compressing for retrieved procedural memories.

```
============================================================
Prompt Reason_Procedural
============================================================

Following information will be provided:
Question: The question the user is asking.
Information: Several pieces of information that may be relevant to the
     question.
```

```
Your task:

1. Carefully read the user's question.
2. Analyze each piece of retrieved information and determine how
    relevant and useful it is for answering the question.
3. Based on your analysis, integrate all the useful information into a
     single coherent piece of content that helps the agent to answer
    the question. When you think information is insufficient or
    contradictory, generate the most possible information. The
    integrated content should be concise, accurate, and relevant to
    the user's question.

## Output format:

### Reasoning

(Your reasoning for analysis of given question and information.)

### Final Information

## (The synthesized information that should be provided to the agent.)

Input:
Question: {observation}
Information: {procedural_memory}
```

C.5 Full Operations on Memory Graph

Setup. We conduct multiple rounds of controlled experiments on the HotpotQA-induced semantic subgraph. We choose HotpotQA for two practical reasons: *i)* its evidence is largely factual and extractive, which makes semantic memories comparatively stable and less sensitive to stylistic variance; and *ii)* the resulting subgraph is lightweight enough to support fast iteration over different merge thresholds and update policies.

Given a semantic node, our update routine first performs *candidate discovery* by collecting all semantic nodes that share at least one concept/tag with it (i.e., neighbors under the tag-induced projection). We then compute embedding similarity between the current node and each candidate, rank candidates by similarity, and select the top-m candidates whose similarity exceeds a pre-defined threshold τ (we use m=1 by default, i.e., only the most similar candidate above threshold is considered). If a pair (s_i, s_j) is selected, we trigger a merge operation by calling an LLM to *i)* synthesize a new semantic memory that better summarizes the combined information, and *ii)* decide whether to deactivate the original nodes (delete neither, delete both, etc.) according to explicit rules encoded in the prompt; the full prompt is shown in Listing 14.

Listing 14: Prompt template for checking and merging semantic nodes in memory update.

```
============================================================
Prompt Merge_Semantic
============================================================

You are given two memory items about a related topic. One came earlier
     (Information 1) and the other came later (Information 2).

Your tasks:
(1) Merge them into ONE improved, clear, concise statement. Do not
    invent new facts.
(2) Decide whether to deactivate (soft delete) the original two nodes
    after merging.

Inputs:
Information 1 (Earlier Information): {memory_earlier}
Information 2 (Later Information): {memory_later}

Deactivation decision rules (choose exactly ONE case):
```

```
Case A: "UPDATE_SAME_FACT"

* Condition: Information 1 and 2 are essentially describing the same
    fact/event, and Information 2 mainly updates/corrects/refines
    details of Information 1.
* Action: deactivate BOTH originals (earlier and later) because the
    merged node fully supersedes them.

Case B: "SAME_TOPIC_MERGE_WELL"

* Condition: Information 1 and 2 are strongly related under the same
    topic, and the merged statement reads naturally as a unified
    summary (not an awkward splice).
* Action: deactivate BOTH originals (earlier and later).

Case C: "WEAK_RELATED_STITCH_RISK"

* Condition: Information 1 and 2 are only weakly related; merging
    feels like stitching two segments; and deactivating either
    original would likely harm future retrieval.
* Action: deactivate NEITHER original.

Hard constraints:

* Output MUST be valid JSON (no Markdown, no extra text).
* relationship MUST be one of the three labels above.
* If relationship is Case A or B => deactivate_earlier=true AND
    deactivate_later=true.
* If relationship is Case C => deactivate_earlier=false AND
    deactivate_later=false.
* If the two memories conflict, prefer Information 2 as the more up-to
    -date.
* Output the simple reasoning of why you made the decision.

Output MUST be valid JSON with exactly these keys:

* merged_statement (string)
* relationship ("UPDATE_SAME_FACT" | "SAME_TOPIC_MERGE_WELL" | "
    WEAK_RELATED_STITCH_RISK")
* deactivate_earlier (boolean)
* deactivate_later (boolean)
* simple_reasoning (string)

Return ONLY the JSON object.
```

Thresholds and evaluation. We evaluate two merge thresholds, $\tau \in \{0.6, 0.7\}$, on the same HotpotQA subset. We report downstream QA performance (EM/F1) as well as graph statistics before and after update. The results show that performance remains within normal fluctuation, while the graph becomes more compact with more controllable candidate fan-out. Concretely, with τ=0.6, $477/3413$ semantic nodes trigger a merge; with τ=0.7, $171/3413$ nodes trigger a merge, reflecting the expected trade-off between aggressiveness and conservativeness.

We compare the downstream QA performance on the same HotpotQA subset before and after semantic graph update under two merge thresholds. Without update, the system achieves an EM/F1 of $61.00/74.39$. With update at τ=0.6, the EM/F1 becomes $63.00/73.97$, and with update at τ=0.7, the EM/F1 becomes $62.00/74.65$. Overall, these differences are within normal run-to-run fluctuation, suggesting that semantic graph update/merge does not materially degrade end-to-end performance on this subset.

Graph quality: compactness and candidate controllability. We characterize the structural effect of update/merge along two axes.

- **Compactness.** We measure compactness using the number of active semantic nodes N_s, the number of used tags N_t, and the number of semantic–tag bipartite edges E_{bip} (attachments). With the stricter threshold τ=0.7, the updated graph reduces active semantic nodes from 3413 to 3242 (-5.0%), used tags from 12501 to 11812 (-5.5%), and bipartite edges

from 23230 to 20604 (-11.3%), indicating lower redundancy in semantic memories and their tag attachments. We also report the (non-deduplicated) upper bound of tag-induced semantic co-occurrence pairs, $\sum_t \binom{\deg(t)}{2}$, which decreases from 78279 to 57581 (-26.5%). This suggests that update/merge effectively prunes redundant co-attachments that would otherwise create dense but uninformative connectivity.

- **Candidate controllability.** Our retrieval/update pipeline uses tag-induced candidate generation: for a semantic node, we take the union of semantic IDs attached to its tags as the candidate set. To quantify how controllable the candidate fan-out is, we sample active semantic nodes and compute the size of their candidate sets (unique neighbors reachable via tags, excluding itself). With τ=0.7, the candidate set size becomes substantially smaller and thus more controllable: the sampled mean decreases from 38.36 to 31.28 (-18.5%), and the sampled median decreases from 18.0 to 14.0 (-22.2%). Intuitively, by merging near-duplicate semantic items and deactivating redundant originals, the graph reduces unnecessary expansions through shared tags, improving computational stability without degrading downstream EM/F1.

Overall, these results indicate that semantic update/merge can improve graph compactness and reduce redundancy while preserving retrieval support, as evidenced by stable HotpotQA accuracy under both thresholds.

D Information-Theoretic Evaluation of Memory Efficiency

We present a framework to quantify the utility of generated memory. We decompose memory efficiency into two dimensions: accuracy (Pointwise) and certainty (Distributional), and provide a unified interpretation of their connections.

D.0.1 Preliminaries and Notation

We define the operational environment and the agent's decision-making process.

- **State Space** ($\mathcal{S}$): The set of all possible environmental states or contexts. Let $s \in \mathcal{S}$ denote the current state.
- **Action Space** ($\mathcal{A}$): The set of all possible actions. Let $a \in \mathcal{A}$ denote an action taken by the agent.
- **Optimal Action** (a^*): Let $a^* \in \mathcal{A}$ denote the ground-truth optimal action (or the actual action chosen by a demonstrator/oracle) given the current state s.
- **Memory Space** ($\mathcal{M}$): The output space of the memory generation module. Let $m \in \mathcal{M}$ denote a generated memory sequence. Here, m is not necessarily a subsequence of the raw corpus, but can be a constructed representation (e.g., abstraction, inference, or summary) optimized to augment the agent's decision-making in the current state s.
- **Memory Generator** ($\mathcal{G}_\phi$): A parameterized function (e.g., a search engine, or an LLM) that maps the current state s and a raw memory base $\mathcal{K}$ to a memory artifact. We define the process as $m = \mathcal{G}_\phi(s, \mathcal{K})$. This function encapsulates operations like retrieval and reasoning to explicate implicit logic.
- **Memory Length** ($|m|$): Let $|m|$ denote the length of the memory sequence m in number of tokens.

D.1 Pointwise Metric: Accuracy and Density

D.1.1 Quantifying Information Gain via Pointwise Mutual Information (PMI)

We model the agent's decision-making as a conditional probability distribution over actions and distinguish between the agent's policy with and without access to the memory module.

- **Baseline Policy (Prior):** The probability of selecting the optimal action a^* given only the current state s, without memory augmentation:
$$P_{\text{base}}(a^* \mid s)$$
- **Memory-Augmented Policy (Posterior):** The probability of selecting the optimal action a^* given the current state s and the generated memory m:
$$P_{\text{mem}}(a^* \mid s, m)$$

To quantify the specific contribution of the generated memory m toward selecting the correct action a^*, we employ **Pointwise Mutual Information (PMI)**.

We define the **Decision Information Gain** as:

$$\mathrm{PMI}(a^*; m \mid s) = \log_2 \frac{P_{\text{mem}}(a^* \mid s, m)}{P_{\text{base}}(a^* \mid s)}.$$

INTERPRETATION.

- If $\mathrm{PMI} > 0$: The memory m provided positive information, increasing the probability of selecting the correct action a^*.
- If $\mathrm{PMI} = 0$: The memory m was irrelevant to the decision.
- If $\mathrm{PMI} < 0$: The memory m was misleading, decreasing the probability of selecting a^*.

D.1.2 MEMORY INFORMATION DENSITY (POINTWISE GAIN PER TOKEN)

We normalize the total information gain by the cost of processing the memory (its token length). The **Memory Information Density** is defined as:

$$\rho(a^*, m) = \frac{\mathrm{PMI}(a^*; m \mid s)}{|m|}.$$

Substituting the PMI definition:

$$\rho(a^*, m) = \frac{1}{|m|} \cdot \log_2 \left(\frac{P_{\text{mem}}(a^* \mid s, m)}{P_{\text{base}}(a^* \mid s)} \right).$$

UNIT. Bits per Token (bits/token).

D.1.3 SUMMARY OF THE METRIC

This framework evaluates the memory module not only on *effectiveness* (did it help?) but also on *conciseness* (did it help efficiently?).

- **Objective:** Maximize $\rho(a^*, m)$.
- **Optimization Goal:** Generate memory content that maximizes the likelihood of a^* while minimizing the token count $|m|$.

D.1.4 AGGREGATE EVALUATION: GLOBAL MEMORY EFFICIENCY

To evaluate the memory module's performance over a dataset

$$\mathcal{D} = \{(s_i, a_i^*, m_i)\}_{i=1}^N,$$

consisting of N decision instances, we compute the **Global Memory Information Density**, denoted as ρ_{global}.

Unlike the arithmetic mean of individual instance efficiencies (which can be numerically unstable for short memory sequences), ρ_{global} represents the *amortized information gain* per token consumed across the entire evaluation set. It answers the question: *"For every token of memory generated by the system, how many bits of decision-relevant information are gained on average?"*

We define ρ_{global} as the ratio of the total cumulative Pointwise Mutual Information to the total cumulative memory length:

$$\rho_{\text{global}} = \frac{\sum_{i=1}^N \mathrm{PMI}(a_i^*; m_i \mid s_i)}{\sum_{i=1}^N |m_i|}.$$

Expanding the PMI term, the calculable form is:

$$\rho_{\text{global}} = \frac{\sum_{i=1}^N \log_2 \left(\frac{P_{\text{mem}}(a_i^* \mid s_i, m_i)}{P_{\text{base}}(a_i^* \mid s_i)} \right)}{\sum_{i=1}^N |m_i|}.$$

PROPERTIES OF THIS METRIC

1. **Token-Level Weighting:** By summing the lengths in the denominator, this metric implicitly weighs the contribution of longer memory sequences more heavily, ensuring that expensive generations must justify their cost with proportionally higher information gain.

2. **Robustness:** It is robust to the "small denominator problem," where an instance with a very short memory context (e.g., $|m_i| = 1$) might otherwise produce an artificially high efficiency score that skews the dataset average.

3. **System-Wide Interpretation:** A value of $\rho_{\text{global}} = 0.5$ indicates that, on aggregate, the system requires two tokens of memory context to gain one bit of information about the optimal action.

D.1.5 Control and Filtering: Defining the Evaluation Scope

To ensure the metric captures the *marginal utility* of the memory module rather than the underlying difficulty of the tasks, we introduce a filtering mechanism. This isolates instances where the agent stands to benefit from external information.

The Redundancy Filter (High Prior Confidence) We exclude instances where the baseline policy is already confident in the optimal action, as memory generation in these cases is functionally redundant.

We define the **Active Evaluation Subset**, denoted as $\mathcal{D}_{\text{active}} \subseteq \mathcal{D}$, as:

$$\mathcal{D}_{\text{active}} = \left\{(s_i, a_i^*, m_i) \in \mathcal{D} \mid P_{\text{base}}(a_i^* \mid s_i) < \tau_{\text{conf}}\right\},$$

where τ_{conf} is a pre-defined confidence threshold (e.g., $\tau_{\text{conf}} = 0.8$ or 0.9).

Rationale. If $P_{\text{base}} \geq \tau_{\text{conf}}$, the agent "knows" the answer. Any generated memory m, even if relevant, yields negligible Information Gain ($\text{PMI} \to 0$). Including these lowers ρ_{global} unfairly.

The Empty Memory Generation Case We must account for cases where the memory module decides not to generate any information or returns an empty sequence ($|m| = 0$).

- **Handling:** If $|m_i| = 0$, the instance is excluded from the density calculation because the denominator is zero.

- **Note:** While excluded from the *density* metric (efficiency), these samples should still be tracked separately for *recall rate* (effectiveness).

Refined Global Metric Combining the "Ratio of Sums" approach with the "Redundancy Filter," the final operational metric is calculated only over the active subset:

$$\rho_{\text{final}} = \frac{\sum_{i \in \mathcal{D}_{\text{active}}} \text{PMI}(a_i^*; m_i \mid s_i)}{\sum_{i \in \mathcal{D}_{\text{active}}} |m_i|}.$$

This refined formulation ensures we measure the *efficiency of necessary memories*, providing a cleaner signal of the module's contribution to complex reasoning.

D.2 Geometric Analysis: The Utility–Cost Landscape

To understand the mechanism behind efficiency gains, we analyze the memory module through a geometric lens. We construct a Utility–Cost coordinate system where:

- **X-Axis (Cost):** Memory length, $L = |m|$.

- **Y-Axis (Utility):** Information gain, $I(L) = \text{PMI}(a^*; m \mid s)$.

Standard intuition might suggest monotonic logarithmic growth of utility with respect to context length. However, in real-world agentic scenarios involving noise, we propose that the curve follows a **unimodal (peaking) distribution**.

D.2.1 The Peaking Phenomenon and Noise Toxicity

We model the effective information gain $I(L)$ not merely as signal accumulation, but as a superposition of signal extraction and attention dilution:

$$I(L) = S(L) - \eta(L),$$

where $S(L)$ is the logarithmic signal-accumulation function (monotonically increasing), and $\eta(L)$ represents the **noise toxicity** or cognitive-load penalty.

We identify three qualitative regions on this curve:

1. **Under-fitting Region** ($dI/dL > 0$, $d^2I/dL^2 > 0$): High marginal utility; critical semantic information is being generated.

2. **The Sweet Spot** ($dI/dL \approx 0$): The peak $I_{\max}$ where signal is maximized relative to noise.
3. **Toxicity Region** ($dI/dL < 0$): The *negative marginal utility* zone. Extending memory length L introduces more irrelevant tokens (HTML tags, tangents) than valid signal, diluting the agent's attention mechanism. As a result, the probability of the correct action $P(a^*)$ *decreases* despite having "more context."

D.2.2 Geometric Interpretation of Efficiency (ρ)

In this coordinate system, the core metric—**Global Memory Density** ρ—has a precise geometric meaning:

$$\rho(L) = \frac{I(L)}{L},$$

which is the slope of the *secant line* from the origin $(0, 0)$ to the operating point $(L, I(L))$.

This reveals a trade-off between two optimality criteria:

- **Point A: Maximum Performance Point.** The peak of the curve where $\frac{dI}{dL} = 0$. This is the performance ceiling independent of cost.
- **Point B: Maximum Efficiency Point.** The point where the secant line from the origin becomes a tangent to the curve. Geometrically, this maximizes the slope $\rho = I(L)/L$.

Insight: Efficiency–Performance Gap. Typically, Point B lies to the left of Point A. Pursuing maximum performance (moving from B toward A) requires disproportionately more tokens and yields diminishing—or even negative—returns.

The "Epiphany" Threshold (Point C). It is also theoretically instructive to identify the *Inflection Point* (where $I''(L) = 0$), located to the left of Point B. Economically, this represents the point of **Maximum Marginal Utility** ($\max dI/dL$). In the context of memory generation, Point C corresponds to the acquisition of the "Critical Semantic Mass"—the specific token or phrase that provides the initial breakthrough in context (e.g., retrieving the correct entity name). However, stopping at Point C is generally suboptimal (under-fitting), as the agent has acquired the key signal but lacks the necessary context (accumulated between C and B) to robustly execute the decision.

D.2.3 Vector Decomposition of Gains

To quantify the improvement of our proposed memory module relative to other baselines, we perform a vector decomposition in the L–I plane.

Let the baseline vector be

$$\mathbf{v}_{\text{baseline}} = (L_{\text{baseline}}, I_{\text{baseline}})$$

and our improved method be

$$\mathbf{v}_{\text{ours}} = (L_{\text{opt}}, I_{\text{opt}}).$$

The transformation vector is:

$$\Delta\mathbf{v} = \mathbf{v}_{\text{ours}} - \mathbf{v}_{\text{baseline}} = (\Delta L, \Delta I).$$

We classify the improvement direction as:

- **Horizontal Shift** ($\Delta L < 0$, $\Delta I \approx 0$): *Pure Compression*—gains arise solely from cost reduction.
- **Vertical Shift** ($\Delta L \approx 0$, $\Delta I > 0$): *Pure Enhancement*—better reasoning with the same budget.
- **North-West Shift** ($\Delta L < 0$, $\Delta I > 0$): **Hybrid Gain**. This indicates the baseline operates in the Toxicity Region. By refining the memory, we simultaneously reduce cost *and* increase accuracy by removing noise that harmed decision-making.

D.2.4 Pareto Dominance

We posit that the proposed module does not merely traverse the same trade-off curve as the naive baseline. Instead, it induces a **Pareto frontier shift**.

Let the naive baseline curve be $\mathcal{C}_{\text{base}}$ and our method's curve be $\mathcal{C}_{\text{ours}}$. We claim that over the relevant domain:

$$\forall L, \quad I_{\text{ours}}(L) \geq I_{\text{base}}(L).$$

This implies our method raises the theoretical ceiling of the memory system, enabling the agent to handle more complex tasks (higher required I) that were previously infeasible due to the noise constraints of $\mathcal{C}_{\text{base}}$.

REMARK: BASELINE INVARIANCE AND COORDINATE SHIFT. It is worth noting that since the naive baseline confidence $\sum \log P_{\text{base}}(a^* \mid s)$ is constant for a fixed agent, the Utility axis $I(L)$ is functionally a vertical translation of the raw posterior log-likelihood $\sum \log P_{\text{mem}}$. While this constant offset shifts the absolute position of the origin $(0, 0)$—thereby scaling the absolute value of the density slope ρ—it preserves the *topological features* of the landscape. Consequently, the relative comparisons between methods (e.g., the existence of a "toxicity drop" or the location of the "sweet spot") remain invariant to the baseline performance.

D.3 DISTRIBUTIONAL METRIC: CERTAINTY AND CALIBRATION

While PMI quantifies the accuracy of the memory with respect to the ground truth a^*, it fails to capture the global impact of memory on the agent's uncertainty. A memory sequence might slightly increase $P(a^*)$ (positive PMI) while leaving the agent confused among many other suboptimal actions.

To measure the memory's ability to *prune the search space* and *sharpen the decision boundary*, we extend the framework to evaluate the **Distributional Information Density**.

D.3.1 QUANTIFYING ACTION SPACE COMPRESSION VIA UNCERTAINTY REDUCTION

We employ Shannon Entropy to quantify the uncertainty (or "cognitive load") inherent in the agent's policy.

- **Prior Uncertainty** ($\mathcal{H}_{\text{base}}$): The uncertainty of the agent given only the state s.
$$\mathcal{H}_{\text{base}}(s) = -\sum_{a \in \mathcal{A}} P_{\text{base}}(a \mid s) \log_2 P_{\text{base}}(a \mid s)$$
- **Posterior Uncertainty** ($\mathcal{H}_{\text{mem}}$): The uncertainty after processing the memory m.
$$\mathcal{H}_{\text{mem}}(s, m) = -\sum_{a \in \mathcal{A}} P_{\text{mem}}(a \mid s, m) \log_2 P_{\text{mem}}(a \mid s, m)$$

The **Action Space Compression** (or Uncertainty Reduction), denoted as $\Delta\mathcal{H}$, represents the amount of information (in bits) the memory contributes toward resolving ambiguity:

$$\Delta\mathcal{H}(m \mid s) = \mathcal{H}_{\text{base}}(s) - \mathcal{H}_{\text{mem}}(s, m).$$

INTERPRETATION.

- $\Delta\mathcal{H} > 0$: **Sharpening.** The memory reduced the effective size of the search space (pruning invalid options).
- $\Delta\mathcal{H} < 0$: **Confusion.** The memory introduced conflicting information, flattening the distribution and increasing uncertainty.

D.3.2 DISTRIBUTIONAL INFORMATION DENSITY (DISTRIBUTIONAL GAIN PER TOKEN)

Analogous to the pointwise metric, we define the **Distributional Information Density**, ρ_{dist}, as the rate of uncertainty reduction per unit of processing cost:

$$\rho_{\text{dist}}(m) = \frac{\Delta\mathcal{H}(m \mid s)}{|m|} = \frac{\mathcal{H}_{\text{base}}(s) - \mathcal{H}_{\text{mem}}(s, m)}{|m|}.$$

UNIT. Bits of Uncertainty Removed per Token (bits/token).

Safety Analysis: The Confidence-Validity Quadrants To rigorously evaluate memory, we project each instance into a 2D plane defined by:

- **X-Axis (Certainty):** Action Space Compression, $\Delta\mathcal{H}(m \mid s)$.
- **Y-Axis (Accuracy):** Decision Information Gain, $\text{PMI}(a^*; m \mid s)$.

This projection categorizes memory interaction into one of four regimes:

1. **Quadrant I: Efficient Reasoning** ($\Delta\mathcal{H} > 0, \text{PMI} > 0$)
"Sharper and Correct."
The memory confirmed the correct action and ruled out distractors. The agent moved from uncertainty to correct certainty. This is the ideal operational state.

2. **Quadrant II: Corrective Calibration** ($\Delta\mathcal{H} < 0, \mathrm{PMI} > 0$)
   "Breaking False Confidence."
   Here, the agent likely started with high confidence in a *wrong* action (Low Prior Entropy). The memory introduced necessary doubt, flattening the distribution but raising the probability of the true optimal action a^*.
   Significance: This represents a "Rescue" mechanism where the memory fixes the agent's internal misconceptions.

3. **Quadrant IV: The Hallucination Trap** ($\Delta\mathcal{H} > 0, \mathrm{PMI} < 0$)
   "Confident but Wrong."
   The memory reduced uncertainty but pointed away from the ground truth. The agent became "dogmatically wrong."
   Risk: This is "Toxic Certainty," the most dangerous failure mode in retrieval-augmented generation (RAG).

4. **Quadrant III: Destructive Noise** ($\Delta\mathcal{H} < 0, \mathrm{PMI} < 0$)
   "Confused and Misled."
   The memory not only failed to point to the correct answer but also increased overall confusion (entropy), effectively acting as distraction.

D.3.3 Validity-Adjusted Distributional Information Density

To synthesize the quadrant analysis into a single scalar metric that rewards efficient reasoning while penalizing hallucinations, we propose the **Validity-Adjusted Distributional Information Density (ρ_Φ)**. This metric integrates the *magnitude* of the distributional shift with the *directionality* of the accuracy gain.

Metric Definition We define ρ_Φ as the product of the validity sign and the normalized distributional work:

$$\rho_\Phi(m) = \underbrace{\mathrm{sgn}(\mathrm{PMI}(a^*; m \mid s))}_{\text{Direction Validity}} \cdot \frac{|\Delta\mathcal{H}(m \mid s)|}{|m|}$$

where:

- $\mathrm{sgn}(\cdot)$ is the sign function ($+1$ for improvement, -1 for detriment).
- $|\Delta\mathcal{H}(m \mid s)|$ is the absolute magnitude of the uncertainty change (bits).
- $|m|$ is the memory length (tokens).

Properties and Interpretation This formulation provides a unified evaluation across all four cognitive regimes:

1. **Reward for Efficiency (Quadrant I):**
   When the agent becomes more certain about the correct answer ($\Delta\mathcal{H} > 0, \mathrm{PMI} > 0$), the metric is **positive**. Higher density indicates faster convergence to the truth.

2. **Reward for Rectification (Quadrant II):**
   When the memory corrects a confident error ($\Delta\mathcal{H} < 0, \mathrm{PMI} > 0$), the metric remains **positive**. Although entropy increases (the agent becomes less dogmatic), the term $|\Delta\mathcal{H}|$ captures the significant "cognitive work" performed to break the false confidence, and $\mathrm{sgn}(\mathrm{PMI})$ validates this shift as beneficial.

3. **Penalty for Hallucination (Quadrant IV):**
   When the agent becomes confident in a wrong answer ($\Delta\mathcal{H} > 0, \mathrm{PMI} < 0$), the metric becomes **negative**. The more "convincing" the hallucination (higher $\Delta\mathcal{H}$), the severe the penalty. This acts as a soft safety constraint.

4. **Penalty for Destructive Noise (Quadrant III):**
   When the memory confuses the agent and lowers accuracy ($\Delta\mathcal{H} < 0, \mathrm{PMI} < 0$), the metric is **negative**. Here, $|\Delta\mathcal{H}|$ represents the magnitude of the *confusion* introduced. Since the memory failed to support the correct action, this "negative work" is penalized, reflecting the cost of processing distracting information.

SUMMARY. The metric ρ_Φ answers: *"How many bits of valid distributional reshaping (entropy shift) does the memory module provide per token of cost?"*

D.4 THEORETICAL UNIFICATION: THE ORACLE-DIVERGENCE PRINCIPLE

Thus far, we have analyzed memory efficiency through specific metrics: *Accuracy* (PMI) and *Certainty* (Entropy). In this section, we situate these metrics within a broader information-theoretic framework. We propose that the fundamental objective of the memory module is to minimize the information-geometric distance between the agent's policy and the ideal policy.

We term this the **Oracle-Divergence Principle**.

D.4.1 THE GENERAL OBJECTIVE: DIVERGENCE REDUCTION

Let $\mathcal{Q}$ denote the **Oracle Distribution** (or the "God View"), representing the ideal policy for the current state s. The goal of memory generation is to transform the agent's prior belief P_{base} into a posterior P_{mem} that is statistically closer to $\mathcal{Q}$.

We quantify this improvement using the reduction in **Kullback-Leibler (KL) Divergence**. The generalized **Oracle Information Gain**, Δ_{div}, is defined as:

$$\Delta_{\text{div}}(m) = D_{\text{KL}}(\mathcal{Q} \parallel P_{\text{base}}) - D_{\text{KL}}(\mathcal{Q} \parallel P_{\text{mem}}).$$

Since the Oracle distribution $\mathcal{Q}$ and the baseline prior P_{base} are fixed for a given instance, maximizing this gain is equivalent to minimizing the divergence of the posterior:

$$\arg\max_m \Delta_{\text{div}}(m) \equiv \arg\min_m D_{\text{KL}}(\mathcal{Q} \parallel P_{\text{mem}}).$$

Ideally, if the memory is perfect, P_{mem} converges to $\mathcal{Q}$, and the divergence becomes zero.

D.4.2 PRACTICAL INSTANTIATION: PMI AS A SPECIAL CASE

While the Oracle $\mathcal{Q}$ can theoretically model soft labels or multimodal distributions, in the vast majority of discrete agentic tasks (e.g., tool selection, multi-step reasoning), the objective is canonically defined by a single unique ground truth. Under this standard deterministic setting, the Oracle distribution **collapses** from a general probability vector into a Dirac delta (One-hot) distribution:

$$\mathcal{Q}(a) = \begin{cases} 1 & \text{if } a = a^* \\ 0 & \text{otherwise} \end{cases}$$

Under this specific **One-hot Assumption**, the KL-Divergence term simplifies significantly:

$$D_{\text{KL}}(\mathcal{Q} \parallel P) = \sum_{a \in \mathcal{A}} \mathcal{Q}(a) \log_2 \frac{\mathcal{Q}(a)}{P(a)} = 1 \cdot \log_2 \frac{1}{P(a^*)} = -\log_2 P(a^*).$$

Substituting this back into the generalized gain equation yields:

$$\begin{aligned} \Delta_{\text{div}}(m) &= [-\log_2 P_{\text{base}}(a^*)] - [-\log_2 P_{\text{mem}}(a^* \mid m)] \\ &= \log_2 P_{\text{mem}}(a^* \mid m) - \log_2 P_{\text{base}}(a^*) \\ &= \text{PMI}(a^*; m). \end{aligned}$$

IMPLICATION: TRACTABILITY AND SUFFICIENCY. This derivation reveals that **Pointwise Mutual Information (PMI)** is not merely a heuristic, but the **algebraic collapse** of the generalized Divergence Reduction under the deterministic assumption. This establishes PMI as the optimal engineering metric because it is:

- **Computationally Tractable:** It requires tracking only the probability of the ground truth $P(a^*)$, avoiding the computational cost of modeling the full distributional distance.
- **Theoretically Sufficient:** In the one-hot regime, maximizing PMI is mathematically isomorphic to minimizing the KL-divergence.

Thus, PMI serves as a proxy that effectively bridges abstract information geometry with practical, low-cost evaluation.

D.4.3 THE ENTROPIC COROLLARY

This generalized perspective also explains the role of Entropy Reduction ($\Delta\mathcal{H}$).

Since the Oracle distribution $\mathcal{Q}$ (One-hot) has an entropy of zero ($H(\mathcal{Q}) = 0$), any policy P_{mem} that successfully minimizes the divergence $D_{\text{KL}}(\mathcal{Q} \parallel P_{\text{mem}})$ must necessarily lower its own entropy.

$$P_{\text{mem}} \to \mathcal{Q} \implies H(P_{\text{mem}}) \to 0.$$

Therefore, *Accuracy* (PMI) and *Certainty* (Entropy) are not independent objectives. They are coupled features of the same optimization process:

- **PMI** measures the *alignment* of the probability mass with the peak of $\mathcal{Q}$.
- **Entropy** measures the *compactness* of the distribution, which is a prerequisite for resembling $\mathcal{Q}$.

D.4.4 SUMMARY.

In this unified view, our framework offers a dual-layered approximation of the theoretical trajectory Δ_{div}:

1. **The Accuracy Gain Efficiency Proxy (ρ):** By assuming the standard One-hot Oracle, the Pointwise Mutual Information ρ serves as the **primary computational metric**. It provides an exact, low-cost measurement of the agent's transport toward the optimal action a^*, making it sufficient for large-scale performance benchmarking.
2. **The Validated Certainty Gain Proxy (ρ_Φ):** The Distributional Density ρ_Φ acts as a **diagnostic complement**. It approximates the entropy-minimization requirement of the Oracle-Divergence, explicitly safeguarding against "off-target" confidence (where the agent minimizes entropy toward a wrong distribution $\mathcal{Q}' \neq \mathcal{Q}$).

Thus, future memory research and prompting work can employ ρ to measure *how much* the additional tokens (e.g., the memory tokens) help decision-making, and ρ_Φ to diagnose *how certainly* they do so.

E ADDITIONAL EXPERIMENT DETAILS

E.1 LONGMEMEVAL

Setup. To evaluate the agent's ability to answer questions based on historical user-agent conversations, we utilize LongMemEval Wu et al. (2024). Specifically, we employ the $LongMemEval_S$ subset, which features a conversation context of 115K tokens per test case, aligning with established standards in agent memory research Li et al. (2025); Rasmussen et al. (2025). For the PLUGMEM framework, we adopt Qwen2.5-32B-Instruct for the inference of structuring and retrieval modules, and Qwen2.5-72B-Instruct for the reasoning module. All baseline methods is driven by GPT-4o. NV-Embed-v2 is used for generating embeddings and Qwen2.5-72B-Instruct is used for all methods as the base agent that answer the question depending on memory generated. During the retrieval phase, we set k=10, extracting the top 10 most relevant memory nodes for downstream reasoning.

Baselines. We consider three categories of baselines: *i) Vanilla*, including no historical conversation in its prompt that answer depending on the backbone model's parametric knowledge, or simply answering "I don't know".*ii) Task-agnostic*, which are not specifically designed for agent-user conversation QA benchmarks. Examples include a standard dense RAG pipeline that performs turn-level embedding-based retrieval; and agentic memory approaches such as A-Mem (Xu et al., 2025), which take notes from episodic memory and maintain/update them via a graph-based organization mechanism. *iii) Task-specific*, tailored for historical conversation based QA, including knowledge graph based method Zep Rasmussen et al. (2025), and cognitive science oriented structural retrieval method LiCoMemory Huang et al. (2026). Specifically, for Zep, we adopt the result reported in their paper. For A-Mem and LiCoMemory, we randomly shuffle the test cases in the original `longmemeval_s_cleaned.json` file from LongMemEval and evaluate them on the same 100 prefix cases.

Metrics. We report Accuracy (Acc. in Table 3), which is evaluated based on LLM-as-a-Judge method of LongMemEvalWu et al. (2024), using GPT-4o as evaluator. Additionally, we also report global density relying on information-theoretic measures introduced in Section 4.1. Specifically, we instantiate the likelihood terms in Eq. (1) using per-instance answer overlap: P_{mem} and P_{base} are set to 1.0 if the evaluator judges the answer as correct, and 0.0 otherwise. To avoid mathematical errors when computing $\log(P_{\text{mem}}/P_{\text{base}})$ in cases where either P_{mem} or P_{base} equals 0.0, we apply additive smoothing and use $\log\left(\frac{P_{\text{mem}}+\epsilon}{P_{\text{base}}+\epsilon}\right)$ when computing PMI, where ϵ is **1%** of the success rate of agent without memory on LongMemEval.

Main Results. The experiment results are summarized in Table 3. PLUGMEM outperforms all baselines on LongMemEval. Moreover, PLUGMEM attains the highest *global information-gain density* among all baselines. As shown in Table 15, PLUGMEM achieves competitive performance compared to several task-specific methods. Notably, PLUGMEM delivers the top performance on the multi-session subset. This subset is particularly challenging as it requires both accurate retrieval and precise memory extraction; the agent must retrieve multiple "gold" memories and distinguish between them to maintain an accurate count. This reveals that the architecture of PLUGMEM successfully bridges the gap between massive data retrieval and precise cognitive extraction, proving that integrating external memory modules can significantly enhance an agent's long-term consistency in dynamic, multi-turn environments.

Table 15: Subset Performance on LongMemEval. (S-S-U: single-session-user, S-S-A: single-session-assistant, S-S-P: single-session-preference, K-U: knowledge-update, T-R: temporal reasoning, M-S: multi-session)

Method	S-S-U	S-S-A	S-S-P	K-U	T-R	M-S	**Avg.**
Zep	92.9	80.4	56.7	83.3	62.4	57.9	71.2
LiCoMemory	92.9	90.9	50.0	81.2	65.4	63.0	73.0
PLUGMEM	**94.3**	**98.2**	**60.0**	79.5	**66.2**	**64.7**	**75.1**

Ablations. We further conduct ablation studies on the three components of PLUGMEM. For `no-structuring`, we replace structured indexing with a simple chunking of the original user–agent conversations at the turn level. For `no-retrieving`, we directly concatenate all semantic memories extracted by the structuring module and feed them into the reasoning module without retrieval.As shown in Table 6, removing all the module leads to consistent degradation in both task performance and global information-gain density, highlighting their importance for effective memory utilization. Specifically, removing the retrieval module results in the worst performance, indicating that effective memory utilization must be grounded in retrieval. Removing the structuring module degrades performance to a level comparable to vanilla retrieval. While removing the reasoning module only causes a slight drop in accuracy, it leads to a substantial increase in input memory tokens.

Token Cost Analisys. Table 16 reports the token consumption per sample for different methods on LongMemEval. Since Zep is only partially open-sourced, we randomly evaluate several samples using Graphit, the open-source graph module on which Zep is built, to estimate its token usage.

It is expected that PLUGMEM incurs a relatively higher token count, as it goes beyond semantic memory extraction and additionally standardizes episodic memory and extracts procedural memory. These steps are crucial for task-agnostic memory organization and enable better generalization across diverse tasks, which task-specific methods that only extract semantic memory (e.g., LiCoMemory) cannot easily achieve.

Importantly, while the token consumption of PLUGMEM is within similar order of magnitude as competing approaches, the actual deployment cost differs substantially. PLUGMEM relies exclusively on open-source models for inference, which can be executed offline or at significantly lower per-token cost. In contrast, several competing methods depend on closed-source models such as GPT-4o for inference, whose per-token pricing is considerably higher. As a result, when accounting for model pricing rather than token count alone, PLUGMEM is expected to be substantially more cost-efficient in practice, despite comparable token usage.

E.2 HOTPOTQA

Setup HotpotQA (Yang et al., 2018) is a multi-hop question answering benchmark that is widely used to evaluate multi-step retrieval and reasoning in RAG systems and agentic memory frameworks. Following the evaluation protocol of HippoRAG2 (Gutiérrez et al., 2025), we use their preprocessed subset containing 1,000 examples. For all methods, we adopt Qwen2.5-32B-Instruct (Qwen et al., 2025) as the backbone LLM and NV-Embed-v2 (Lee et al., 2025) as the embedding model, with

Table 16: Token Cost Statistics on LongMemEval. ($\tilde{k}$ tokens per sample)

Method	NVE	$Q32_{in/out}$	$Q72_{in/out}$	$4o_{in/out}$
Task-Agnostic				
Vanilla RAG	107	-	-	-
A-Mem	332	-	-	786/177
Task-Specific				
Zep (Graphit)	194	-	-	2545/1189
LiCoMemory	75	-	-	585/217
Ours				
PLUGMEM	197	1604/418	9/0.4	-

decoding parameters max-tokens = 2048, temperature = 0.0, top-p = 1.0 During retrieval, we set top-k = 10, returning the 10 most relevant memory nodes for downstream reasoning.

Episodic memory standardization. PLUGMEM standardizes agent trajectories into RL-inspired episodic tuples $\langle o_t, a_t, s_t, r_t, i_t \rangle$ (observation, action, state, reward, intent/subgoal). For HotpotQA, the corpus is indexed **passively** rather than generated by an acting agent. We therefore treat each unit of corpus text as a single-step "trajectory" (i.e., $T = 1$): each episodic item contains one observation o_1 (the text unit being indexed), while action-related fields are not instantiated by execution. Concretely, we keep the unified tuple interface by setting a_1, s_1, r_1, and $i_1$to an empty (or `N/A`) placeholder. The semantic extraction and retrieval primarily operate on the observation content.

HotpotQA multi-hop retrieval control. At each hop t, the retriever gathers a pool of candidates via the two-channel update: *i)* link-based expansion via abstract nodes, where the retriever infers a small set of abstract concepts from current query Q_t, matches them to high-level concept nodes in the memory graph, and expands to adjacent low-level proposition nodes via membership edges; *ii)* embedding-based retrieval from query Q_t directly.

We then invoke an LLM controller to assess whether the currently retrieved candidates are sufficient to answer the question. If the controller returns `enough=true`, we terminate early and pass the current fact set to the downstream QA model. Otherwise, the controller selects a small subset of the most promising candidates to drive the next hop; in our experiments we cap this subset at top-2 candidates. To form the next-hop query, we integrate the selected candidates with the previous query. This integration can be performed by an LLM-based re-writer; however, we find that a simple concatenation of the query and selected candidates performs comparably well in practice, and we therefore adopt concatenation as the default for efficiency.

Baselines We consider three categories of baselines: *i) Vanilla*, including no-context inference that relies solely on the backbone model's parametric knowledge, and an oracle (gold-context) setting where the model is provided with the gold supporting context, serving as an approximate upper bound. *ii) Task-agnostic*, which are not specifically designed for knowledge-intensive QA benchmarks. Examples include a standard dense RAG pipeline that treats the input as a one-dimensional text stream, segments it into chunks using a fixed chunk size and overlap window, and performs embedding-based retrieval; and agentic memory approaches such as A-Mem (Xu et al., 2025), which structure the text stream into notes and maintain/update them via a graph-based organization mechanism. *iii) Task-specific*, tailored for knowledge-intensive QA and multi-hop retrieval, including hierarchical/tree-structured retrieval frameworks RAPTOR (Sarthi et al., 2024) and graph-oriented designs GraphRAG (Edge et al., 2025), HippoRAG2 (Gutiérrez et al., 2025), and PropRAG (Wang & Han, 2025).

Metrics. We report token-level Exact Match and F1 score (EM and F1 in Table 4) between the model-generated answer and the reference. Beyond standard end-task metrics such as EM and F1, we also adopt the information-theoretic measures introduced in Section 4.1 and Appendix D to quantify the *information gain* by the memory module. For one sample from benchmark, Pointwise Mutual Information (PMI) is computed as follows:

$$\mathrm{PMI}(a^*; m \mid s) = \log_2 \frac{P_{\text{mem}}(a^* \mid s, m)}{P_{\text{base}}(a^* \mid s)} \tag{4}$$

Over a dataset, we report a global, amortized density via a ratio-of-sums:

$$\rho_{\text{global}} = \frac{\sum_i \mathrm{PMI}(a_i^*; m_i \mid s_i)}{\sum_i |m_i|} \tag{5}$$

Concretely, we instantiate the likelihood terms in Eq. (4) using per-instance answer overlap: P_{mem} is computed from the F1 score between the prediction and the reference answer; Similarly, for P_{base}, the prediction is answer from base agent without memory module. Following the ratio-of-sums aggregation, we report global density by normalizing the summed PMI across instances by the summed number of memory tokens.

It's worth noting that, P_{base} or P_{mem} can be zero for some instances, which would make Eq. (1) ill-defined (division by zero and/or $\log 0$). To stabilize the computation, we apply additive smoothing and use $\log\left(\frac{P_{\text{mem}}+\epsilon}{P_{\text{base}}+\epsilon}\right)$ when computing PMI. We find that choosing ϵ too small can lead to excessively large PMI values when $P_{\text{base}} = 0$ but $P_{\text{mem}} > 0$, which disproportionately affects the aggregate density. Therefore, in our implementation we set ϵ to **1%** of the base agent's F1 score (no memory), and use the same ϵ for both the numerator and denominator.

Table 17: Token Cost Statistics on HotpotQA. ($\tilde{k}$ tokens)

Method	Input	Output	Total
Task-Specific			
RAPTOR	331	40	371
HippoRAG2	1350	490	1840
PropRAG	1651	643	2294
Task-Agnostic			
Vanilla RAG	110	20	130
A-Mem	1778	261	2039
Ours			
PLUGMEM	1919	272	2191

Ablations. We further conduct ablation studies over the three components of PLUGMEM. For `no-structuring`, we replace structured indexing with a chunk-based pipeline (fixed chunk size and overlap) for corpus preprocessing and evaluation; for `no-retrieving`, we populate the retrieval candidate set using randomly sampled structured memory items. As shown in Table 7, removing any single component consistently degrades both task performance and the global information-gain density. In particular, removing retrieval causes the most substantial performance drop, while removing the reasoning module markedly increases the number of memory tokens injected into context, leading to lower information gain per token.

Token Cost Analysis. In addition, we analyze the token cost of PLUGMEM on a HotpotQA subset, logging token usage during both memory construction (indexing) and evaluation-time retrieval and reasoning, and compare it against competing baselines.

As shown in Table 17, the token usage of PLUGMEM is comparable to that of other strong baselines and remains within the same order of magnitude. Notably, PLUGMEM is not the most token-intensive method among the compared approaches, despite providing a richer memory representation. It it noteworthy that PLUGMEM performs a more fine-grained and structured memory construction process, enabling unified memory editing, retrieval, and reasoning in downstream stages. In particular, PLUGMEM jointly constructs three complementary memory types, i.e., episodic, semantic, and procedural, within a single pipeline, whereas most baselines extract only one or two types in isolation.

While HotpotQA predominantly evaluates semantic knowledge, the one-time cost of joint $(E/S/P)$ memory construction enables reuse across tasks and time, allowing the agent to support heterogeneous memory operations without rerunning separate extraction pipelines. Consequently, this upfront investment naturally amortizes in multi-task, continual, or long-horizon settings, potentially leading to lower total token cost in realistic deployments.

E.3 WEBARENA

Setup. WebArena Zhou et al. (2024) is a realistic and reproducible web navigation benchmark consisting of 812 tasks spanning five site domains(e.g. shopping, GitLab, etc.), each task instantiated from a curated collection of 241 intent templates. In this paper, we focus on the Shopping, GitLab, and Multi-site subsets, which collectively cover (i) domain-specific, procedure-heavy interactions (Shopping, GitLab) and (ii) compositional, cross-site workflows (Multi-site). To directly test memory evolution and reuse, we adopt an online/offline split aligned with WebArena's task construction: WebArena intents are written as templates with multiple instantiations, where tasks from the same template share high-level semantics but may require different concrete execution traces. Specifically, for each template (e.g., 5 instantiations), we place one instantiation into the online set and the remaining instantiations into the offline set. To further examine cross-template knowledge adaptation, we leave template with only one task id in the offline set. The exact data split is stored in our code repository.

We first evaluate the agent on the online set, then augment the memory module with a small number of high quality human demonstrations, and finally evaluate on the offline set using the resulting augmented memory module to measure generalization from newly acquired procedural and semantic knowledge. The agent is allowed to insert and retrieve memories as it is being evaluated on the online set, but only retrieval is allowed on the offline set. For PLUGMEM, the base agent is set to be AgentOccam Yang et al. (2025a) with GPT-4o, a strong baseline that operates within the action space defined by WebArena and without relying on specialized memory mechanisms. For all methods, we adopt GPT-4o and Qwen2.5-32B-Instruct (Qwen et al., 2025) as the backbone LLMs and NV-Embed-v2 (Lee et al., 2025) as the embedding model, with decoding parameters max-tokens = 2048, temperature = 0.0, top-p = 1.0. For all LLM calls within PLUGMEM, we use Qwen2.5-32B-Instruct first and only delegate quries to GPT-4o if the output perplexity from Qwen2.5 is higher than

a set threshold. For PLUGMEM, we record the entire action trajectory up to the maximum number of steps allowed for the web agent (20 steps in all experiments). During retrieval, we set top-k = 2, returning the 2 most relevant memory nodes for downstream reasoning.

PLUGMEM integration with AgentOccam. PLUGMEM is integrated with base web navigation agent for our experiments. For a given objective, PLUGMEM first retrieve memory and feed the response from the reasoning module to AgentOccam. After AgentOccam has taken the action (e.g. click [1234]), PLUGMEM generates a short description of the action into natural language form (e.g. click at My account), this creates a new episodic memory along with the new observation after the action is taken. At the end of each task, the episodic memory sequence gets inserted into PLUGMEM using the process described in Methodology and Appendix C. We slightly modified the prompt for AgentOccam by adding an instruction to follow retrieved memory entries from PLUGMEM. Please see Listing 15 for the added instructions.

PLUGMEM incorporates human demonstration. PLUGMEM is able to incorporate human demonstration trajectories into memory graph for warm start. In our experiment, we record human demonstration for failed tasks on the online set, then we inject these recordings for offline evaluation. This is done through 'replaying' the demo trajectory and rebuilding episodic memory sequence for insertion. For the offline set evaluation, we disable memory graph inserts to test the quality of the memory graph. Normally, for a particular task domain, we record and insert human demos in the same task domain. For the Multi-site task domain, in addition to demo on Multi-site tasks, we additionally include trajectories from other task domains to further strengthen the memory graph. In this way, we test the cross-domain retrieval and reasoning capability of PLUGMEM. Over the course of development, we collected 23 Shopping demos, 18 GitLab demos, 10 Reddit demos, 10 Map demos, and 5 Multi-site demos. These human demonstrations are available in our code repository.

Baselines. We consider three categories of baselines: *i) Vanilla*, base agents that does not rely on retrieval augmentation, serving as a measure of performance of the backbone LLM. We use AgentOccam Yang et al. (2025a) as the base agent. *ii) Task-agnostic*, which are baselines that adopts retrieval augmentations not specifically designed for web navigation agents. We include a vanilla dense retrieval pipeline that stores and retrieve past interaction trajectories. We also evaluate A-Mem Xu et al. (2025), an agentic memory system that summarizes past interactions into notes and organizes them in a graph-like structure to allow retrieval of related trajectories. For vanilla retrieval, we set top-k=1. When evaluating A-Mem, we set top-k=3 to best utilize A-Mem's ability to retrieve relevant notes. For both methods, we store the first 10 steps per task at max. *iii) Task-specific*, open-sourced agentic systems that utilizes specialized memory insertion and retrieval mechanisms. We include AWM Wang et al. (2024b), which summarizes past interactions into workflows. To examine and compare how high quality human demonstrations could be utilized cross all methods, we add human demonstration trajectories between online and offline evaluations for all task-agnostic and task-specific baselines.

Metrics. WebArena evaluates task completion using functional correctness validator, i.e., programmatic checks that determine whether the execution achieves the intended goal. We use WebArena's evaluators and report the success rates on both the online and offline set. We compute PMI per task sample. We apply additive smoothing and use $\log\left(\frac{P_{\text{mem}}+\epsilon}{P_{\text{base}}+\epsilon}\right)$ when computing PMI. We set ϵ to be 1% of AgentOccam's average success rate over WebArena.

Ablations. We further conduct ablation studies over the three components of PLUGMEM. For `no-structuring`, replace the memory graph construction pipeline with vanilla retrieval process, while keeping the reasoning module; for `no-retrieving`, we populate the retrieval candidate set using randomly sampled structured memory items. Additionally, for `no-human demo`, we omit the intermediate step where we insert high quality human demonstrations between online and offline evaluations. According to Table 8, the removal of any components would degrade agent success rates or global information density. We find that removing the retrieval component has the biggest negative impact on all metrics measured.

Token Cost Analysis. As shown in Table 18, PLUGMEM exhibits a higher average token usage than task-agnostic and task-specific baselines on WebArena. This difference reflects the additional computation required for memory-to-knowledge abstraction, rather than redundant processing.

In WebArena, reusable knowledge is predominantly procedural, and each task involves multiple interaction steps that must be recorded, segmented, and abstracted. Accordingly, PLUGMEM allocates additional tokens to standardizing long episodic trajectories and organizing them into subgoal-aligned procedural memory units. Compared to methods that store only raw trajectories or single static workflows, this process naturally involves more computation.

Table 18: Token Cost Statistics on WebArena. (k̃ tokens per sample)

Method	$Q32_{in/out}$	$4o_{in/out}$
Task-Agnostic		
Vanilla RAG	-	-
A-Mem	-	7431/1758
Task-Specific		
AWM	-	4918/1202
Ours		
PLUGMEM	10587/1377	3128/371

Notably, the additional tokens consumed by PLUGMEM are mostly generated using open-source models, whereas several baselines rely on a small number of calls to closed-source models. While such approaches may appear token-efficient, their per-token cost is substantially higher in practice. In contrast, PLUGMEM 's token usage remains within a practical range while enabling richer and reusable procedural representations.

Moreover, these costs are primarily incurred during the online phase and can be amortized across multiple task instances that share similar user intents. Once constructed, the procedural memory graph can be reused without re-running the full abstraction pipeline, leading to decreasing effective cost as task horizon and diversity increase.

Listing 15: Additional instruction for AgentOccam to incorporate retrieved memory.

```
============================================================
Prompt AgentOccam Retrieved Memory Instruction
============================================================

The retrieved memory contains relevant information from past
    experiences that may help you complete the current task. Use this
    memory to:
- Learn from similar past tasks and their successful strategies
- Avoid repeating previous mistakes
- Apply proven approaches that worked in similar situations
- Understand patterns and relationships that can guide your actions
When retrieved memory is provided, carefully consider how it relates
    to your current task and incorporate relevant insights into your
    decision-making process.

Some task may require access to Wikipedia, the only way you may access
     Wikipedia is through the url "http://<BASE_URL>:8888/
    wikipedia_en_all_maxi_2022-05/A/User:The_other_Kiwix_guy/Landing"
BASE_URL: localhost
```

F TASK ADAPTATION VIA INTEGRATING TASK-SPECIFIC HEURISTICS ON TOP OF PLUGMEM

F.1 LONGMEMEVAL

Reflective Memory Management. RMM Tan et al. (2025) introduces a novel reflective mechanism for long-term memory management. In general, RMM employs Prospective Reflection for knowledge extraction and memory updating, and Retrospective Reflection to refine memory retrieval in an online reinforcement learning manner.

Inspired by these ideas, we perform task adaptation of PLUGMEM to LongMemEval by incorporating the Prospective Reflection mechanism from RMM for semantic memory extraction and semantic node updating. Specifically, for memory extraction, we adopt the memory extraction prompt proposed in RMM to distill semantic memory for PLUGMEM. Compared to the original semantic memory extraction prompt used in PLUGMEM (Listing 5), the task-adapted version places greater emphasis on extracting user-specific personal information and includes in-context examples to better align with the LongMemEval setting. For memory updating, we follow the reflective updating strategy introduced in RMM to update semantic memory within the memory graph. Specifically, unlike the original PLUGMEM, which directly inserts newly extracted memory, the task-adapted version first retrieves the Top-K most similar existing semantic memories from the memory graph by computing cosine similarity between semantic memory embeddings and ranking them accordingly. The LLM is then queried to decide whether the new memory should be added as a new node

or merged with an existing similar node. The prompt to extract memory and update memory is shown in Listing 16 and Listing 17.

Experiment. We conduct experiments on the multi-session subset of LongMemEval, with results shown in Table 19. The multi-session subset is among the most challenging portions of LongMemEval, as it requires the agent to answer questions that primarily involve counting the occurrences of a series of similar events across multiple sessions. This setting not only places significant demands on the retrieval module of the memory module to retrieve multiple gold memories simultaneously, but also challenges the structuring and reasoning module to generate precise semantic memories and perform accurate counting over them. The task-adapted version outperforms the original method for two main reasons: first, the task-adapted memory extraction prompt produces more precise semantic memories; second, the reflective updating strategy prevents redundant and repetitive semantic memories from being inserted into the memory graph, thereby enabling more efficient retrieval.

Table 19: Task Adaptation on the multi-session subset of LongMemEval.

Method	Acc. (Multi-session)	PMI	$\#\text{Tok}_{\text{Avg.}}$	Info. Density
PLUGMEM	64.7	5.06	311.9	1.62e-2
PLUGMEM $_{\text{adapt}}$	70.7	5.62	327.5	1.71e-2

Listing 16: Prompt template to extract semantic memory for task adaptation.

```
============================================================
Prompt Extract_Memory
============================================================

Task Description: Given a session of dialogue between User and Agent,
    extract the personal summaries of User. Ensure the output adheres
    to the following rules:
Output results in OUTPUT format. The top-level tittle is "### Memory".
     The value should be a list of dictionaries, where each dictionary
     has the key "Summary":
- summary: A concise personal summary, which captures relevant
    information about User experiences, preferences, and background,
    across multiple turns.
If no personal summary can be extracted, return NO_TRAIT.
Example:
INPUT:
Turn 0:
- User: Did you check out that new gym in town?
- Agent: Yeah, I did. I am not sure I like the vibe there, though.
Turn 1:
- User: What was wrong with it?
- Agent: The folks there seemed to care more about how they looked
    than working out. It was a little too trendy for me. I am pretty
    plain.
Turn 2:
- User: Ah, got it. Well, maybe one of the older gyms will work out
    better for you-or I guess you could get that treadmill you were
    talking about before. Are you leaning one way or the other yet?
- Agent: I am leaning towards the treadmill. I think it will work
    better for my lifestyle. I just do not know which type to get.
    There are so many choices out there. Do you use a treadmill at
    your gym? Do you have a suggestion for a home one?
Turn 3:
- User: I usually just lift weights there, to be honest. But I think I
     have heard good things about the NordicTrack?
- Agent: Yeah, I have heard good things about that, too. I like the
    idea of a multi-exercise piece of equipment. As long as the
    weather is not too bad, then I prefer to go for a run. But since
    it rains quite a bit here, I like the idea of an inside option.
    How is the weather in New England?
OUTPUT:
### Memory:
```

```
1. **Summary:** User asked about a new gym in town and suggested older
     gyms or a treadmill as alternatives.
2. **Summary:** User usually lifts weights at the gym rather than
    using a treadmill.
3. **Summary:** User has heard good things about the NordicTrack
    treadmill.
Task: Follow the OUTPUT format demonstrated in the example above and
    extract the personal summaries for User from the following
    dialogue session.
Input: {episodic_memory}
Output:
```

Listing 17: Prompt template to update semantic memory for task adaptation.

```
============================================================
Prompt Update_Memory
============================================================

Task Description: Given a list of history personal summaries for a
    specific user and a new and similar personal summary from the same
     user, update the personal history summaries following the
    instructions below:
Input format: Both the history personal summaries and the new personal
     summary are provided in JSON format, with the top-level keys of "
    history_summaries" and "new_summary".
Possible update actions:
- Add: If the new personal summary is not relevant to any history
    personal summary, add it.
Format: Add()
- Merge: If the new personal summary is relevant to a history personal
     summary, merge them as an updated summary.
Format: Merge(index, merged_summary)
Note: index is the position of the relevant history summary in the
    list. merged_summary is the merged summary of the new summary and
    the relevant history summary. Two summaries are considered
    relevant if they discuss the same aspect of the user personal
    information or experiences.
Do not include additional explanations or examples in the output-only
    return the required action functions.
Example:
INPUT:
History Personal Summaries:
- {{"history_summaries": ["SPEAKER_1 works out although he does not
    particularlyenjoy it."]}}
New Personal Summary:
- {{"new_summary": "SPEAKER_1 exercises every Monday and Thursday."}}
OUTPUT ACTION:
Merge(0, SPEAKER_1 exercises every Monday and Thursday, although he
    does not particularly enjoy it.)
Task: Follow the example format above to update the personal history
    for the given case.
INPUT:
History Personal Summaries: {history_summaries}
New Personal Summary: {new_summary}
OUTPUT ACTION:
```

F.2 HotpotQA

Inspiration from HippoRAG2. Our retrieval design is partly inspired by HippoRAG2, which demonstrates that introducing an explicit graph structure and a controlled multi-hop traversal can outperform purely similarity-based retrieval on multi-hop QA. In particular, HippoRAG2 separates *recognition* (filtering/selecting relevant structured units) from *expansion* (graph-based propagation to retrieve supporting evidence), reducing spurious hops and improving evidence quality. PLUG-

MEM adopts this high-level principle but generalizes it to typed agent memory. We construct semantic and procedural memory graphs and use abstract nodes (concepts/intents) as routing signals to activate specific proposition/prescription nodes, enabling abstraction-to-specificity traversal. Moreover, analogous to HippoRAG2's recognition step, PlugMem employs an LLM-based controller to *i)* select memory types (GETMODE), *ii)* propose next-hop abstract signals (GETPLAN), and *iii)* decide early stopping or focus candidates under a fixed budget (MULTIHOPCTRL). Finally, we integrate a two-channel candidate update—link-based expansion through abstract nodes and embedding-based retrieval from a refined query—followed by reranking/pruning and optional reasoning-based compression.

Test-time Scaling. Beyond the default configuration, PLUGMEM admits two practical test-time "knobs" that consistently improve performance. First, we can increase the hop limit $T_{\max}$, effectively scaling the amount of retrieval computation at inference time. This allows the retriever to chain additional abstraction–specificity steps and is analogous to test-time scaling in reasoning-centric methods. We experiment with a subset on HotpotQA, when increasing the multi-hop limit $T_{\max}$ from 2 to 4, we observe a performance gain from 66.00/74.73 to 69.00/78.11 (measured in Exact Match/F1-Score).

Secondly, when forming the next-hop query Q_{t+1}, we optionally replace naive concatenation of $(Q_t, \text{selected facts})$ with an LLM-based query synthesizer that rewrites a focused and self-contained query. Empirically, synthesis-based refinement reduces lexical drift and redundancy, and helps the embedding channel retrieve more targeted evidence in later hops. We treat both mechanisms as controllable components within the retrieval controller, enabling a smooth accuracy–cost trade-off depending on the task budget.

F.3 WEBARENA

Prior work designed specifically for WebArena often incorporates manually engineered *domain-level instructions* (or "tips") into the agent's input context. A common pattern in task-specific adaptations—such as AWM Wang et al. (2024b), SteP Sodhi et al. (2024), and more recently ColorBrowserAgent Zhou et al. (2026)— is the inclusion of explicit guidance that biases the agent toward particular interaction patterns within a site domain (e.g., navigation conventions or preferred UI elements). In contrast, in our main experiments we deliberately avoid injecting such handcrafted instructions or explicitly defined action policies. Instead, we rely solely on PLUGMEM 's ability to automatically store, retrieve, and re-apply both agent-generated and human demonstration trajectories as structured memory, allowing behavior to emerge from experience rather than prompt engineering.

Further task adaptation We additionally conduct a targeted case study to examine whether PLUGMEM can benefit from manual task adaptation when such domain-specific constraints are known. We identify a subset of WebArena tasks that remain challenging for PLUGMEM and introduce a small set of manually designed instructions into the reasoning module. Specifically, we observe that PLUGMEM occasionally instructs the agent to navigate via category dropdown menus when the correct strategy in WebArena is to use the search bar. By incorporating the additional guidance shown in Prompt 18, we resolve several previously failing cases (see Example 20) by explicitly conditioning the agent's action selection. WebArena uses strict, programmatic success criteria but concise queries, where otherwise reasonable strategies may be scored as incorrect. Although PLUGMEM successfully retrieves relevant procedural knowledge for tasks such as "searching for teeth grinding mouth guards," it does not, by default, infer that certain plausible actions are disallowed by the benchmark's implicit rules. This case study demonstrates that PLUGMEM natively supports fine-grained manual conditioning when necessary, while remaining effective without task-specific prompting in the general case.

Listing 18: Additional instructions for the agent and reasonig module for further task-adaptation

```
============================================================
Prompt WebArena Task-specific Instructions
============================================================

1. When asked about a kind of product (not a category), search for the
     product using the search bar instead of using the category
    dropdown menu.
2. When asked about a category of product, access the dropdown menu
    through hover actions.
```

Table 20: Example of PLUGMEM with manual instructions.

WebArena Manual Instruction Effect

Query. *" What is the price range of teeth grinding mouth guard in the One Stop Market? "*

PLUGMEM with Manual Instruction.

▷ **Reasoning**

The user's question is about determining the price range of wireless earphones in the One Stop Market. According to the guidelines, when asked about a specific kind of product (e.g., "wireless earphone"), the agent must use the search bar to locate the product instead of navigating through dropdown menus. The current observation shows that the search bar is present but appears disabled. However, based on the relevant experience provided, attempting to use the search bar is still recommended, as its functionality may not be accurately represented by its appearance.

▷ **Final Information**

1. Use the search bar to type "wireless earphone" and press Enter to locate relevant products.
2. Once the search results are displayed, review the prices of the listed wireless earphones to determine the price range.
3. If the search bar does not function, report the issue and consider alternative methods to locate the product, such as contacting support or exploring other navigation options.

AgentOccam Action 1: type [1913] [wireless earphone] [1]. (agent uses the search bar)

...

PLUGMEM without Manual Instruction.

▷ **Reasoning**

The user's question is about finding the price range of teeth grinding mouth guards in the One Stop Market. The observation does not provide any direct information about teeth grinding mouth guards or their prices. However, the relevant experience suggests that the agent should use the hierarchical menu structure to navigate to the appropriate category (likely under "Beauty & Personal Care" or "Health & Household") and then refine the search to locate the specific product type. If a price filter is available, it can be applied to determine the price range.

▷ **Final Information**

To answer the question, the agent should:

1. Hover over the hierarchical menu structure, starting with categories like "Beauty & Personal Care" or "Health & Household."
2. Look for subcategories related to oral care or dental care.
3. Navigate to the relevant subcategory (e.g., "Oral Care" or "Mouth Guards").
4. Review the products listed in the subcategory to identify teeth grinding mouth guards and note their prices.
5. If a price filter is available, apply it to determine the price range more efficiently.
6. Summarize the price range of the identified products.

AgentOccam Action 1:
hover [1534]. (agent operates the dropdown menu (WRONG!))

...