

Memory-R1: Enhancing Large Language Model Agents to Manage and Utilize Memories via Reinforcement Learning

Sikuan Yan^{*1}, Xiufeng Yang^{*2}, Zuchao Huang¹, Ercong Nie¹, Zifeng Ding³,
Zonggen Li⁴, Xiaowen Ma¹, Hinrich Schütze¹, Volker Tresp¹, Yunpu Ma^{1†}

¹Ludwig Maximilian University of Munich ²Technical University of Munich

³University of Cambridge ⁴University of Hong Kong

s.yan@campus.lmu.de, cognitive.yunpu@gmail.com

Abstract

Large Language Models (LLMs) have demonstrated impressive capabilities across a wide range of NLP tasks, but they remain fundamentally *stateless*, constrained by limited context windows that hinder long-horizon reasoning. Recent efforts to address this limitation often augment LLMs with an external memory bank, yet most existing pipelines are static and heuristic-driven, lacking any learned mechanism for deciding what to store, update, or retrieve. We present Memory-R1, a reinforcement learning (RL) framework that equips LLMs with the ability to actively manage and utilize external memory through two specialized agents: a *Memory Manager* that learns to perform structured memory operations, including adding, updating, deleting, or taking no operation on memory entries; and an *Answer Agent* that selects the most relevant entries and reasons over them to produce an answer. Both agents are fine-tuned with outcome-driven RL (PPO and GRPO), enabling adaptive memory management and utilization with minimal supervision. With as few as 152 question-answer pairs and a corresponding temporal memory bank for training, Memory-R1 outperforms the strongest existing baseline and demonstrates strong generalization across diverse question types and LLM backbones. Beyond presenting an effective approach, this work provides insights into how RL can unlock more agentic, memory-aware behavior in LLMs, pointing toward richer, more persistent reasoning systems.

1 Introduction

Large Language Models (LLMs) have shown remarkable ability in understanding and generating natural language, making them central to recent advances in AI (OpenAI et al. 2024; Qwen et al. 2025). Yet, they remain fundamentally *stateless* (Yu, Lin, and Li 2025; Fan et al. 2025; Goodyear, Guo, and Johari 2025): each incoming query is processed independently of other interactions, because LLMs are constrained by a finite context window that prevents them from retaining and leveraging information across long conversations or evolving tasks (Wang et al. 2024; Fei et al. 2023).

One early and influential effort in addressing this statelessness is the Tensor Brain framework, which introduced a memory retrieval mechanism similar to retrieval-augmented

generation (RAG) (Tresp et al. 2023). In addition to retrieval, it highlights the cognitive importance of semantic and episodic memory, particularly in perception and reasoning. Building on this idea, subsequent work augments LLMs with external memory modules (Zhang et al. 2024). Most adopt the RAG paradigm (Pan et al. 2025; Salama et al. 2025), appending retrieved memory entries to the model’s input prompt. While this extends access to past information, it also creates a fundamental retrieval challenge: heuristics may return too few entries, omitting crucial context, or too many, flooding the model with irrelevant information and degrading performance (Liu et al. 2023). In this paradigm, retrieved memories are passed to the LLM without meaningful filtering or prioritization, forcing the model to reason over both relevant and irrelevant content, which makes it prone to distraction by noise. Humans, by contrast, retrieve broadly but then filter selectively, integrating only the most useful pieces to maintain coherent, evolving knowledge.

Equally important is the challenge of *memory management*: deciding what to remember, update, or discard. Some systems (Packer et al. 2023; Modarressi et al. 2024; Xiong et al. 2025) adopt CRUD-style operations—create, read, update, and delete—which were originally introduced in database systems (Martin 1983; Sulemani 2021). A more recent work (AIOS Foundation 2024) augments this paradigm with a search operator, while MemO (Chhikara et al. 2025) investigates the operator set {ADD, UPDATE, DELETE, NOOP}. We adopt this setting, as it provides a minimal yet expressive framework for modeling memory dynamics. However, existing approaches mainly rely on vanilla LLMs to choose operations from in-context instructions without any learning signal tied to correctness (Packer et al. 2023; Chhikara et al. 2025). Even simple cases can fail. Figure 1, a simplified example drawn from a LOCOMO conversation (Maharana et al. 2024a), shows how a user first says “*I adopted a dog named Buddy*” and later adds “*I adopted another dog named Scout*”. A vanilla system misinterprets this as a contradiction, issuing DELETE+ADD and overwriting the original memory. A trained agent, however, consolidates with an UPDATE: “*Andrew adopted two dogs, Buddy and Scout.*” Appendix A.1 provides a real dialogue trace illustrating this case in practice.

These challenges of retrieving and managing memory

^{*}Equal contribution

[†]Corresponding author

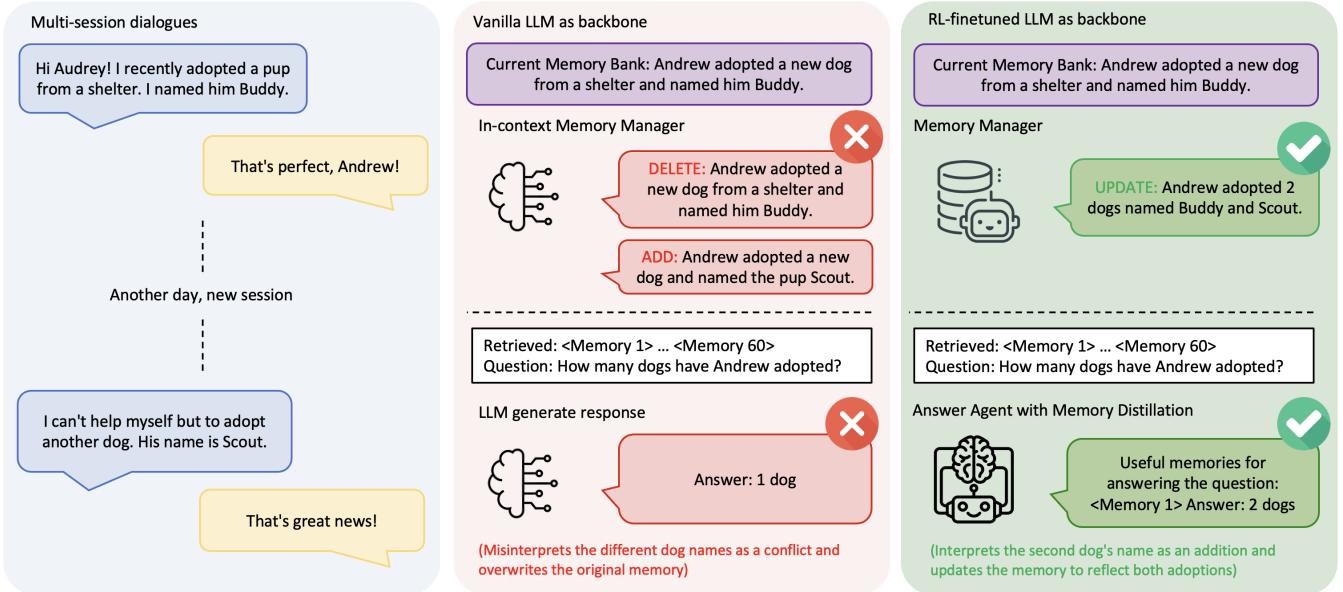


Figure 1: Comparison of Memory-R1 and a vanilla LLM memory system. (Left) In a multi-session dialogue, the user mentions the adoption of two dogs in separate sessions. (Middle) The vanilla Memory Manager misinterprets the second adoption as a contradiction and issues DELETE+ADD, fragmenting memory. (Right) The RL-trained Memory Manager issues a single UPDATE to consolidate the memory, and the Answer Agent applies Memory Distillation: from 60 memories retrieved via RAG (e.g., <Memory 1> “Andrew adopted 2 dogs named Buddy and Scout”; <Memory 2> “Andrew feels a bit jealous of Audrey’s dogs”; etc.), answer agent first filters the memories that are truly useful to answer the question, which is <Memory 1>, then reasons over the selected entry to produce the correct answer (“2 dogs”).

remain largely unsolved. Supervised fine-tuning provides limited help because it is impractical to label every memory operation or retrieval decision. Reinforcement learning (RL), by contrast, has recently shown strong potential for aligning LLM behavior with high-level objectives, including tool use (Qian et al. 2025; Wang et al. 2025), web navigation (Wei et al. 2025), and search optimization (Jin et al. 2025; Song et al. 2025). Building on this success, we argue that RL is the missing ingredient for adaptive memory in LLM agents. By optimizing outcome-based rewards, models can learn when to add, update, delete, or retain information and how to use retrieved memories for reasoning.

In this paper, we present Memory-R1, an RL fine-tuned, memory-augmented LLM framework with two specialized agents: (1) a *Memory Manager* that learns to perform structured memory operations, including adding, updating, deleting, and taking no operation, to maintain and evolve the memory bank, and (2) an *Answer Agent* that applies a *Memory Distillation* policy to filter memories retrieved via Retrieval-Augmented Generation (RAG) and reason over the selected entries to produce answers. Both agents are fine-tuned using PPO (Schulman et al. 2017) or GRPO (Shao et al. 2024), achieving strong performance with as few as 152 question–answer pairs. On the LOCOMO benchmark (Maharana et al. 2024a), Memory-R1 delivers substantial gains over the most competitive baseline, Mem0 (Chhikara et al. 2025). Using the LLaMA-3.1-8B-Instruct backbone, Memory-R1-GRPO achieves relative

improvements of 48% in F1, 69% in BLEU-1, and 37% in LLM-as-a-Judge. These improvements set a new state of the art on LOCOMO and underscore Memory-R1’s ability to achieve large performance gains with minimal supervision, highlighting its efficiency.

Our contributions are summarized as follows:

- We introduce Memory-R1, the first RL framework for memory-augmented LLMs, consisting of a *Memory Manager* to perform structured memory operations and an *Answer Agent* to filter and reason over memories retrieved via RAG.
- We develop a data-efficient fine-tuning strategy using PPO and GRPO that enables Memory-R1 to achieve strong performance with as few as 152 question–answer pairs, demonstrating that large memory improvements can be achieved with minimal supervision.
- We provide in-depth analysis of RL choices, model size, and memory design, offering actionable insights for building the next generation of memory-aware, reasoning-capable LLM agents.

2 Related Work

2.1 Memory Augmented LLM-based Agents

LLMs have emerged as powerful general-purpose reasoners, capable of engaging in multi-turn dialogues, decomposing tasks into actionable steps, and leveraging prior context to guide decision making (Brown et al. 2020; Chowdhery

et al. 2022; OpenAI et al. 2024). Building on these capabilities, LLM-based agents have been proposed to solve complex tasks in interactive settings, such as conversational assistance (Thoppilan et al. 2022; Ouyang et al. 2022), tool-augmented reasoning (Schick et al. 2023; Yao et al. 2023), and autonomous decision making in structured or partially observable environments (Park et al. 2023; Wang et al. 2023; Shinn et al. 2023).

To address the limitations of fixed-length context windows and short-term memory, recent works have explored augmenting LLM agents with external memory modules. These memory-augmented agents aim to support long-horizon reasoning and persistent knowledge accumulation by selectively storing, retrieving, and updating relevant information. Notable approaches include LOCOMO (Maharana et al. 2024b), a benchmark model that evaluates agents’ ability to retrieve and reason over temporally distant conversational history; ReadAgent (Lee et al. 2024), which incorporates retrieval mechanisms for memory-grounded dialogue; MemoryBank (Zhong et al. 2024), a compositional memory controller for lifelong agent memory; MemGPT (Packer et al. 2023), which introduces working and long-term memory buffers with memory scheduling policies; and A-Mem (Xu et al. 2025), a hybrid architecture that combines dynamic memory access with reinforcement learning(RL). These systems represent key steps toward building LLM agents with scalable, interpretable, and persistent memory capabilities. For a comprehensive taxonomy of memory systems in AI agents, we refer readers to the recent survey (Du et al. 2025).

2.2 LLM and Reinforcement Learning

The intersection of LLM and RL has received increasing attention as researchers seek to move beyond static supervised fine-tuning and enable models to learn from dynamic, interactive feedback. Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al. 2022) is a foundational method used to align LLM outputs with human preferences. Recent works extend RL to more structured decision-making tasks for LLMs. For instance, Toolformer (Schick et al. 2023) and ReAct-style agents (Yao et al. 2023) frame tool use as an RL problem, where the LLM learns when to query external tools or APIs. Search-R1 (Jin et al. 2025) trains LLMs to issue web search queries using RL to maximize final answer correctness. Similarly, the Trial and Error approach (Song et al. 2024) optimizes agents to select better reasoning paths. These approaches demonstrate that RL can improve complex behavior sequences in LLMs. However, memory management and utilization in LLMs remain underexplored in the RL setting. Existing memory-augmented LLM systems (Chhikara et al. 2025; Packer et al. 2023; Lee et al. 2024) typically rely on heuristics to control memory operations, lacking adaptability and long-term optimization. Our work, Memory-R1, is among the first to frame memory operation selection, and the utilization of relevant memories as an RL problem.

Algorithm 1: Memory-R1 Pipeline for Memory Manager

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1: Input: Dataset  $D$  of tuples: dialogue turns  $ds$ , temp
   memory bank  $M$ , question-answer pairs  $(q_i, a_i)$ ; Mem-
   ory Manager LLM  $\mathcal{L}_m$ ; Answer LLM  $\mathcal{L}_a$ ; Reward
   Function  $\mathcal{F}$ 
2: Output: Fine-tuned Memory Manager LLM  $\mathcal{L}_m$ 
3: procedure TRAINMEMORYMANAGER( $D, \mathcal{L}_m, \mathcal{L}_a, \mathcal{F}$ )
4:   for each tuple  $(ds, M, q_i, a_i) \in D$  do
5:     for  $d_i \in ds$  do
6:       Facts Extraction:  $f_i \leftarrow \text{LLMExtract}(d_i)$ 
7:       Memory Retrieval:  $M_{ret} \leftarrow \text{RAG}(f_i, M)$ 
8:       Determine operation:  $o_i \sim \mathcal{L}_m(f_i, M_{ret})$ 
9:       if  $o_i = \text{ADD}$  then
10:         $M \leftarrow M \cup \{f_i\}$ 
11:       else if  $o_i = \text{UPDATE}$  then
12:         $m_j \leftarrow \text{Merge}(m_j, f_i)$ 
13:       else if  $o_i = \text{DELETE}$  then
14:         $M \leftarrow M \setminus \{m_j\}$ 
15:       else if  $o_i = \text{NOOP}$  then
16:         $M \leftarrow M$ 
17:       end if
18:     end for
19:     Get Context:  $C_{ret} \leftarrow \text{RetrieveTopK}(q_i, M)$ 
20:     Get Response:  $r_i \sim \mathcal{L}_a(q_i, C_{ret})$ 
21:     Policy Update:  $\mathcal{L}_m \leftarrow \text{RL}_{step}(\mathcal{L}_m, q_i, r_i, \mathcal{F})$ ,
22:     where  $\text{RL} \in \{\text{PPO}, \text{GRPO}\}$ 
23:   end for
24:   return  $\mathcal{L}_m$ 
25: end procedure

```

3 Method

In this section, we describe the Memory-R1 approach for multi-session dialogue tasks, where each dialogue contains multiple *sessions* (separate interactions occurring at different times) and each session consists of several *turns* (a back-and-forth exchange between two users). Answering a question often requires synthesizing information spread across these sessions, posing a strong challenge for long-horizon memory management and reasoning. We first present the overall pipeline (Section 3.1), followed by RL fine-tuning of the Memory Manager (Section 3.2) and the Answer Agent (Section 3.3).

3.1 Memory-R1 Pipeline

This section provides an overview of the Memory-R1 pipeline. Figure 2 outlines the pipeline. At each dialogue turn, an LLM determines information that is worth to remember and summarize it into a piece of information. Then it triggers a retrieval step using Retrieval-Augmented Generation (RAG) to locate related entries in the memory bank. The *Memory Manager* then decides whether to ADD, UPDATE, DELETE, or NOOP, maintaining and evolving the memory state.

For question answering, the user’s query retrieves up to 60 candidate memories, following the setup of (Chhikara et al. 2025). The *Answer Agent* applies a Memory Distillation policy to filter the most relevant entries and generate an answer.

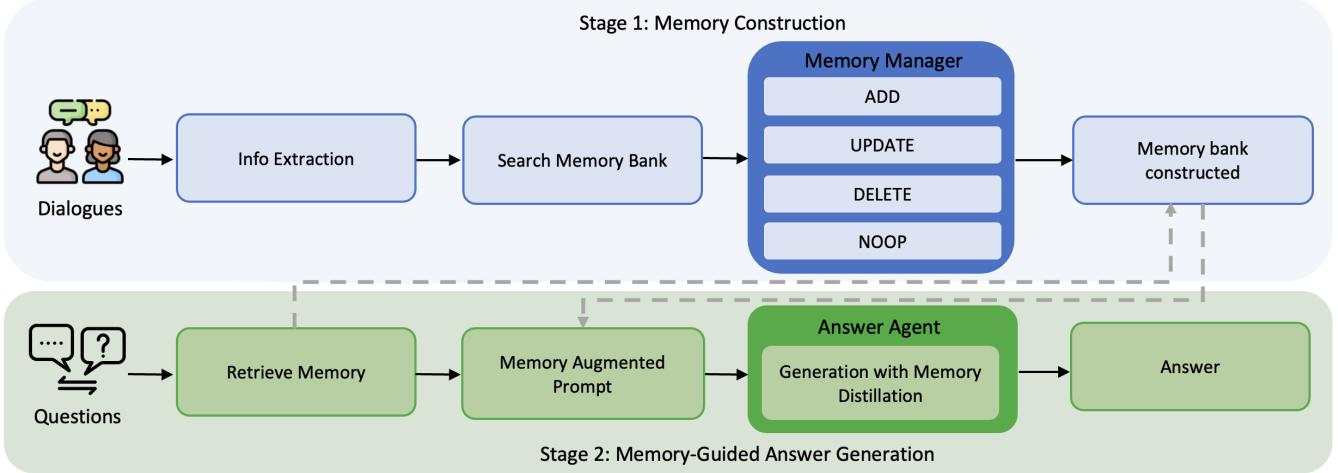


Figure 2: Overview of the Memory-R1 framework. Stage 1 (blue) constructs and updates the memory bank via the RL-fine-tuned Memory Manager, which chooses operations {ADD, UPDATE, DELETE, NOOP} for each new dialogue turn. Stage 2 (green) answers user questions via the Answer Agent, which applies a Memory Distillation policy to reason over retrieved memories.

Both agents are fine-tuned with PPO and GRPO, enabling outcome-driven learning of memory operations and selective utilization.

3.2 RL Fine-tuning for Memory Manager Agent

Task Formulation The *Memory Manager* maintains and updates the memory bank by selecting the appropriate operation from {ADD, UPDATE, DELETE, or NOOP} for each new piece of information extracted from a dialogue. It outputs both the operation and the updated memory content m' .

Training uses (i) a partially constructed memory bank and (ii) a new dialogue turn containing information relevant to downstream question answering. The Memory Manager learns which operation produces a memory state that enables the Answer Agent to answer correctly. Training data is drawn from the LOCOMO dataset to ensure realistic multi-session dialogue settings (details in Appendix B).

As shown in Algorithm 1, the Memory Manager is formalized as a policy π_θ that takes the extracted information x and retrieved memories \mathcal{M}_{old} as input, and outputs an operation $o \in \{\text{ADD}, \text{UPDATE}, \text{DELETE}, \text{NOOP}\}$ with associated content m' :

$$(o, m') \sim \pi_\theta(\cdot | x, \mathcal{M}_{\text{old}}) \quad (1)$$

where x is the extracted information and \mathcal{M}_{old} the current memory bank.

PPO for Memory Manager We fine-tune the Memory Manager using *Proximal Policy Optimization* (PPO, Schulman et al. 2017). Given a candidate memory x and an existing memory bank \mathcal{M}_{old} , the Memory Manager outputs a memory operation o along with content m' . These actions are sampled from the current policy π_θ and applied to update the memory bank, which is then passed to the frozen Answer Agent. The correctness of the answer provides the reward signal. PPO optimizes a clipped surrogate objective to stabilize training:

$$\mathcal{J}(\theta) = \mathbb{E} [\min (\rho_\theta A, \text{clip}(\rho_\theta, 1 - \epsilon, 1 + \epsilon) A)], \quad (2)$$

where $\rho_\theta = \frac{\pi_\theta(o, m' | x, \mathcal{M}_{\text{old}})}{\pi_{\text{old}}(o, m' | x, \mathcal{M}_{\text{old}})}$ is the importance ratio between the new and old policies, and A is the advantage computed from the improvement in the Answer Agent’s final answer accuracy. The clipping range $[1 - \epsilon, 1 + \epsilon]$ constrains policy updates and ensures stable learning.

GRPO for Memory Manager We also apply *Group Relative Policy Optimization* (GRPO, Shao et al. 2024) as an alternative to PPO for training the Memory Manager. GRPO samples a group of G candidate actions and assigns relative advantages within the group, eliminating the need for a learned value function while preserving PPO-style stability.

Given a state $s = (x, \mathcal{M}_{\text{old}})$, the old policy π_{old} generates G candidate actions. The GRPO objective is:

$$\mathcal{J}(\theta) = \mathbb{E} \left[\frac{1}{G} \sum_{i=1}^G \rho_\theta^{(i)} A_i - \beta \mathbb{D}_{\text{KL}} [\pi_\theta \| \pi_{\text{ref}}] \right], \quad (3)$$

where $\rho_\theta^{(i)}$ follows the same importance ratio definition as in PPO, now applied per sampled action. The group-relative advantage is computed by standardizing the QA rewards of all sampled actions:

$$A_i = \frac{r_i - \text{mean}(\mathbf{r})}{\text{std}(\mathbf{r})}, \quad \mathbf{r} = \{r_1, \dots, r_G\}. \quad (4)$$

The KL term $\mathbb{D}_{\text{KL}} [\pi_\theta \| \pi_{\text{ref}}]$ constrains updates, preventing drift from the reference policy.

Reward Design for Memory Manager We adopt an outcome-driven reward design for the Memory Manager. At each step, the Memory Manager selects an operation o and proposes new content m' for the memory bank. Rather than

scoring individual edits, we evaluate the updated memory bank by its impact on downstream question answering: the Answer Agent can only produce the correct answer if the Memory Manager’s operations were effective. The reward is defined as:

$$R_{\text{answer}} = \text{EM}(y_{\text{pred}}, y_{\text{gold}}) \quad (5)$$

where y_{pred} is the Answer Agent’s prediction after the update and y_{gold} is the ground-truth answer. This outcome-based signal eliminates the need for manual memory relevance labels and keeps supervision simple and scalable. Freezing the Answer Agent during training avoids attribution ambiguity, and despite the indirect signal, exact-match rewards alone are sufficient to teach the Memory Manager effective memory operations.

3.3 RL Fine-tuning for Answer Agent

Task Formulation The Answer Agent leverages a memory bank curated by the Memory Manager to handle questions in long-horizon, multi-session dialogues. Following (Chhikara et al. 2025), for each question, 60 candidate memories are retrieved via a similarity-based RAG search using the question as the query. The agent then performs *memory distillation*: it filters this retrieved memory set to surface the most relevant entries and generates the final answer conditioned on these distilled memories.

We model the Answer Agent’s behavior as a policy π_θ that maps the question q and retrieved memories \mathcal{M}_{ret} to an answer y :

$$y \sim \pi_{\text{ans}}(\cdot | q, \mathcal{M}_{\text{ret}}), \quad (6)$$

where q is the current question and \mathcal{M}_{ret} is the subset of the memory bank retrieved by RAG.

PPO for Answer Agent We fine-tune the Answer Agent using the same PPO framework as in Section 3.1. While the optimization is identical, the task differs: the Answer Agent takes the current question q and retrieved memories \mathcal{M}_{ret} and generates an answer y token-by-token.

The PPO objective mirrors Equation (2), applied over the generated answer sequence. The importance ratio is:

$$\rho_\theta(q, \mathcal{M}_{\text{ret}}) = \frac{\pi_\theta(y | q, \mathcal{M}_{\text{ret}})}{\pi_{\text{old}}(y | q, \mathcal{M}_{\text{ret}})}, \quad (7)$$

where y is the full generated answer. Advantages are computed from final answer quality (e.g., exact match with the reference), and clipping keeps updates within a trust region for stability.

GRPO for Answer Agent We also fine-tune the Answer Agent with GRPO, following the formulation in Section 3.1. For each input $(q, \mathcal{M}_{\text{ret}})$, the policy samples G candidate answers $\{y_i\}_{i=1}^G$. Their Exact Match scores against the ground-truth answer y_{gt} are normalized into group-relative advantages. GRPO reuses the same importance ratio definition as PPO, applied per candidate answer. By comparing candidates within each group, GRPO provides stable gradient signals without a learned value function, improving sample efficiency and robustness during RL fine-tuning.

Reward Design for Answer Agent We adopt a simple yet effective reward function for the Answer Agent, using the Exact Match (EM) score between the generated answer and the ground-truth answer as the primary reward signal:

$$R_{\text{answer}} = \text{EM}(y_{\text{pred}}, y_{\text{gold}}) \quad (8)$$

This design directly ties the reward to the correctness of the final answer, encouraging the agent to select and reason over memories in a way that yields accurate outputs rather than optimizing for intermediate steps.

4 Experiments

4.1 Experimental Setup

Dataset and Model We evaluate our approach on the LOCOMO benchmark (Maharana et al. 2024b). LOCOMO consists of two components: (i) multi-turn dialogues (about 600 turns per dialogue, averaging 26,000 tokens) and (ii) question-answer (QA) pairs grounded in those dialogues. Each dialogue has roughly 200 questions spanning single-hop, multi-hop, open-domain, and temporal reasoning. We exclude the adversarial subset because it lacks ground-truth answers. LOCOMO is widely used in memory-augmented LLM research (Chhikara et al. 2025; Xu et al. 2025), as many questions require drawing information from distant or fragmented dialogue turns—making it an ideal testbed for evaluating memory management and utilization. The dataset comprises 10 multi-turn dialogues. We adopt a 1:1:8 train/validation/test split: the first dialogue with 152 questions for training, the second dialogue with 81 questions for validation, and eight dialogues with 1,307 questions for testing, providing broad evaluation coverage while keeping training supervision minimal. A detailed description of the data construction process is provided in Appendix B. All experiments are conducted with LLaMA-3.1-8B-Instruct and Qwen2.5-7B-Instruct, ensuring consistency and comparability across evaluations.

Evaluation Metrics We assess performance using three complementary metrics: Token-level F1 Score (F1), measuring overlap between predicted and ground-truth answers; BLEU-1 (B1), capturing unigram-level lexical similarity; and LLM-as-a-Judge (J), which employs a separate LLM to evaluate factual accuracy, relevance, completeness, and contextual appropriateness. While F1 and B1 provide straightforward string-based scores, J captures deeper semantic correctness and offers a more human-aligned assessment. The implementation details and script for LLM-as-a-Judge are provided in Appendix C.

Baselines To evaluate the effectiveness of MEMORY-R1, we compare it against several established baselines for multi-session dialogue reasoning: (1) LOCOMO (Maharana et al. 2024b), the benchmark framework designed to assess LLMs’ ability to retrieve and reason over information from long-range, multi-session conversations; (3) Zep (Rasmussen et al. 2025), a retrieval-based agent that introduces structured memory access strategies for complex, temporally extended queries; (3) A-Mem (Xu et al. 2025), a dynamic agentic memory system that creates,

links, and updates structured memories to enhance reasoning across sessions; (4) LangMem (LangChain 2024), an open-source memory framework that links memory chains across sessions to support long-context reasoning; (5) Mem0 (Chhikara et al. 2025), a modular memory system with explicit in context memory operations designed for scalable deployment.

For a fair comparison, we re-implemented all baselines using both the LLaMA-3.1-8B-Instruct and Qwen-2.5-7B-Instruct models as backbones, with temperature set to 0 and a maximum token limit of 2048. This consistent setup ensures reproducibility and allows us to assess how each method performs across different model architectures.

Implementation Details We fine-tune **Memory-R1** using both the LLaMA-3.1-8B-Instruct and Qwen-2.5-7B-Instruct models to evaluate the framework’s robustness across different architectures. The prompts for memory operation and memory augmented answer generation are adapted from (Chhikara et al. 2025), with details provided in Appendix C. For PPO experiments, we train both actor and critic networks, while for GRPO runs, only the actor is trained since GRPO uses grouped return normalization in place of a critic. Both PPO and GRPO training are implemented using the VERL framework (Sheng et al. 2025). Experiments are performed on 4 NVIDIA H100 GPUs (80GB each) with a total batch size of 128 and a micro-batch size of 2 per GPU. The maximum prompt and response lengths are set to 4096 and 2048 tokens, respectively. The actor and critic (for PPO) are optimized with learning rates of 1×10^{-6} and 1×10^{-5} , using a constant warmup schedule. During RL training, we use a decoding temperature of $\tau = 1.0$ to encourage exploration and capture a wider range of reward signals, which helps stabilize policy learning. For validation and testing, we switch to greedy decoding ($\tau = 0$) to eliminate randomness and ensure consistent metric tracking. Each configuration and model variant is evaluated three times, and we report the mean score to reduce variance and provide a more reliable estimate of performance.

4.2 Main Results

Table 1 reports the performance of **Memory-R1** across LLaMA-3.1-8B-Instruct and Qwen-2.5-7B-Instruct models on the LOCOMO benchmark, covering diverse question types including Single Hop, Multi-Hop, Open Domain, and Temporal reasoning. We evaluate two variants of Memory-R1: one fine-tuned with PPO and another with GRPO, and benchmark them against leading memory-augmented baselines, including LOCOMO, LangMem, A-Mem, and Mem0.

Across both model families, Memory-R1 consistently sets a new state of the art. On LLaMA-3.1-8B, Memory-R1-GRPO delivers the strongest overall performance, improving F1 by 68.9%, B1 by 48.3%, and J by 37.1% over the strongest baseline Mem0. Similarly, Memory-R1-PPO also yields substantial improvements, raising overall F1, B1, and J scores by 47.9%, 35.3%, and 26.5%, respectively.

Notably, the benefits of Memory-R1 transfer robustly to a different backbone. When applied to Qwen-2.5-7B-Instruct,

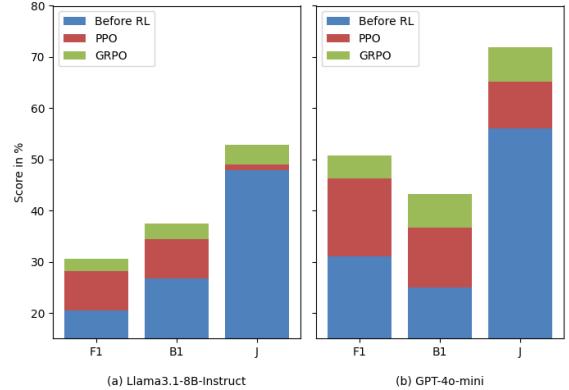


Figure 3: Performance gains of Answer Agent variants (Base/PPO fine-tuned/GRPO fine-tuned) when paired with different Memory Managers: (a) LLaMA 3.1-8B-Instruct and (b) the stronger GPT-4o-mini.

Memory-R1-GRPO again emerges as the top performer, surpassing Mem0 by margins of 57.3% (F1), 41.5% (B1), and 33.8% (J). PPO remains competitive, delivering strong gains over all non-RL baselines.

These consistent improvements across two distinct LLM backbones demonstrate that reinforcement learning(RL) is highly effective for teaching LLMs to manage and leverage long-term memory, independent of model architecture. Moreover, the gains are broad-based—spanning single-hop, multi-hop, open-domain, and temporal questions—highlighting Memory-R1 as a generalizable framework for building adaptive, memory-augmented LLMs capable of long-horizon reasoning.

4.3 Ablation Studies

We conduct ablation studies to examine the contribution of each component in Memory-R1, isolating the effects of the Memory Manager, the Answer Agent, and the Memory Distillation mechanism. We also compare the training dynamics of PPO and GRPO.

Effect of Memory Manager To assess the benefit of our RL-fine-tuned Memory Manager, we compare it against the in-context memory manager, with both variants built on the LLaMA-3.1-8B-Instruct base model. As shown in Table 2, RL training delivers consistent gains: PPO improves overall F1 to 24.60, B1 to 32.55, and J to 59.37; GRPO further improves F1 to 24.91, B1 to 33.05, and J to 59.91. These results confirm that outcome-based RL enables the Memory Manager to execute more accurate and effective operations—reinforcing our central claim that memory control should be learned rather than scripted.

Effect of Answer Agent As shown in Table 3, RL significantly improves the performance of the vanilla LLM when used as the answer agent (baseline: F1 20.54, B1 26.73, J 47.82). PPO fine-tuning raises scores to F1 32.91, B1 41.05, and J 57.54, while GRPO delivers even greater gains, reaching F1 37.51, B1 45.02, and J 62.74. These results demon-

Model	Method	Single Hop			Multi-Hop			Open Domain			Temporal			Overall		
		F1↑	B1↑	J↑												
LLaMA-3.1-8B Instruct	LOCOMO	12.25	9.77	13.81	13.69	10.96	20.48	11.59	8.30	15.96	9.38	8.15	4.65	11.41	8.71	13.62
	Zep	30.15	17.15	52.38	15.04	11.56	33.33	26.67	18.44	45.36	3.49	2.68	27.58	22.60	15.05	42.80
	A-Mem	21.62	16.93	44.76	13.82	11.45	34.93	34.67	29.13	49.38	25.77	22.14	36.43	29.20	24.40	44.76
	LangMem	22.40	15.21	47.26	18.65	16.03	39.81	31.62	23.85	48.38	27.75	21.53	30.94	28.34	21.31	44.18
	Mem0	27.29	18.63	43.93	18.59	13.86	37.35	34.03	24.77	52.27	26.90	21.06	31.40	30.41	22.22	45.68
	Memory-R1-PPO	32.52	24.47	53.56	26.86	23.47	42.17	45.30	39.18	64.10	41.57	26.11	47.67	41.05	32.91	57.54
	Memory-R1-GRPO	35.73	27.70	59.83	35.65	30.77	53.01	47.42	41.24	68.78	49.86	38.27	51.55	45.02	37.51	62.74
Qwen-2.5-7B Instruct	LOCOMO	9.57	7.00	15.06	11.84	10.02	19.28	8.67	6.52	12.79	8.35	8.74	5.43	8.97	7.27	12.17
	Zep	31.02	21.39	42.85	20.42	15.76	23.81	25.25	21.34	42.26	8.94	8.42	29.31	23.22	18.78	38.99
	A-Mem	18.96	12.86	40.78	14.73	12.66	31.32	30.58	26.14	46.90	23.67	20.67	28.68	26.08	21.78	40.78
	LangMem	22.84	16.98	43.64	18.98	16.89	44.38	32.47	25.98	50.45	26.62	20.93	23.08	28.69	22.76	43.42
	Mem0	24.96	18.05	61.92	20.31	15.82	48.19	32.74	25.27	65.20	33.16	26.28	38.76	30.61	23.55	53.30
	Memory-R1-PPO	34.22	23.61	57.74	32.87	29.48	53.01	44.78	38.72	66.99	42.88	30.30	42.25	41.72	33.70	59.53
	Memory-R1-GRPO	33.64	26.06	62.34	23.55	20.71	40.96	46.86	40.92	67.81	47.75	38.49	49.61	43.14	36.44	61.51

Table 1: Evaluation results of **Memory-R1** and baselines across LLaMA-3.1-8B-Instruct and Qwen-2.5-7B-Instruct on the LO-COMO benchmark dataset. Models are evaluated on F1, BLEU-1 (B1), and LLM-as-a-Judge (J) across *Single Hop*, *Multi-Hop*, *Open Domain*, and *Temporal* questions. Higher is better. The best results are marked in Bold.

Method	F1↑	B1↑	J↑
LLaMA3.1-8B	26.73	20.54	47.82
LLaMA3.1-8B + PPO	32.55	24.60	59.37
LLaMA3.1-8B + GRPO	33.05	24.91	59.91

Table 2: Performance of the LLaMA-3.1-8B-Instruct model and its PPO- and GRPO-fine-tuned variants as the Memory Manager, with the answer agent fixed to LLaMA-3.1-8B-Instruct.

Method	F1↑	B1↑	J↑
LLaMA3.1-8B	26.73	20.54	47.82
LLaMA3.1-8B + PPO	34.48	28.13	49.04
LLaMA3.1-8B + GRPO	37.54	30.64	52.87

Table 3: Performance of the base LLaMA-3.1-8B-Instruct model and its PPO- and GRPO-fine-tuned variants as the Answer Agent, with the Memory Manager fixed to LLaMA-3.1-8B-Instruct.

strate that reward-driven fine-tuning substantially elevates answer quality beyond what static retrieval can achieve. A detailed case study comparing the RL-fine-tuned Answer Agent to the vanilla LLM is provided in Appendix A.2.

Effect of Memory Distillation We evaluate the impact of the proposed memory distillation mechanism by comparing the GRPO-fine-tuned Answer Agent with and without distillation (Table 4). Without distillation, the agent consumes all retrieved memories; with distillation, it filters for the most relevant ones before answering. Memory distillation consistently improves performance: F1 rises from 34.37 to 37.51, BLEU-1 from 40.95 to 45.02, and LLM-as-a-Judge from 60.14 to 62.74. These gains show that filtering out irrelevant entries reduces noise and enables the agent to reason more

Method	F1↑	B1↑	J↑
GRPO w/o Memory Distillation	40.95	34.37	60.14
GRPO w. Memory Distillation	45.02	37.51	62.74

Table 4: Performance comparison of GRPO fine-tuned Answer Agent with and without Memory Distillation policy using the LLaMA-3.1-8B-Instruct model.

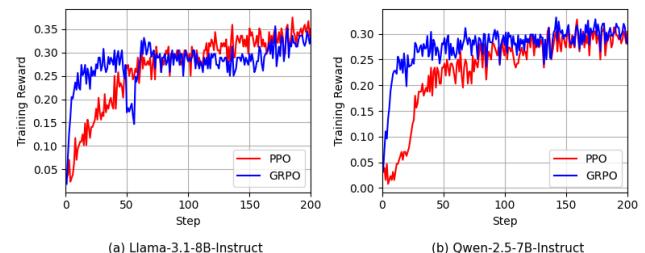


Figure 4: Training reward curves for PPO and GRPO on the Answer Agent using exact match as the reward. GRPO converges faster initially, and both reach similar final rewards.

effectively over high-quality, distilled context.

RL-fine-tuned Answer Agent Gains More with Stronger Memory Manager We examine whether the Answer Agent’s improvements from RL fine-tuning and Memory Distillation depend on the quality of the Memory Manager. Figure 3 compares base, PPO-fine-tuned, and GRPO-fine-tuned Answer Agents paired with either a LLaMA 3.1–8B-Instruct Memory Manager (Figure 3a) or a stronger GPT-4o-mini Memory Manager (Figure 3b). Our RL fine-tuned Answer Agent yields larger gains with the stronger manager: F1 improves by 10.10 points with the LLaMA memory manager vs. 19.72 with GPT-4o-mini memory manager; BLEU-1 by 10.81 vs. 18.19; and

LLM-as-a-Judge by 5.05 vs. 15.76. This demonstrates that Memory-R1’s benefits compound with stronger upstream memory manager, showing the Answer Agent scales effectively with memory quality.

Comparison of RL Policies We compare PPO and GRPO for training the Answer Agent, using exact match against ground-truth answers as the reward signal. As shown in Figure 4, GRPO exhibits faster initial convergence, likely due to its grouped return normalization providing stronger early guidance. However, as training progresses, both methods steadily improve and ultimately reach comparable final reward levels.

5 Conclusion

We introduced Memory-R1, a reinforcement learning (RL) framework that enables large language model agents to manage and utilize external memory effectively. By training two specialized agents, one for memory operations and another for selective reasoning over retrieved memories, our approach overcomes the limitations of static, heuristic-driven memory pipelines. On the LO-COMO benchmark, Memory-R1 outperforms strong baselines across F1, BLEU, and LLM-as-a-Judge scores, achieving these gains with as few as 152 training examples. Ablation studies further confirm that RL enhances every component of the system. Memory-R1 opens new directions for research on compositional memory architectures, long-term knowledge retention, and more agentic LLM behavior, underscoring RL as a path to adaptive memory capabilities.

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A Case Study of Behavior of Agents before and after Fine-tuning

A.1 From In-context Memory Manager to RL fine-tuned Memory Manager

To demonstrate how RL fine-tuning improves memory operations, we present two real representative example. In the first case, the user initially mentions adopting a dog named Buddy, and later states that they have adopted another dog named Scout.

Dialogue Excerpts:

- Audrey: That's great news! What's the pup's name?
- Andrew: It took us a while to decide, but we ended up going with 'Scout' for our pup - it seemed perfect for their adventurous spirit.

Vanilla Memory Manager Actions (failed):

Operations Issued:

- DELETE: "Andrew adopted a new dog from a shelter and named him Buddy because he is his buddy."
- DELETE: "Andrew enjoys taking walks with his newly adopted dog, Buddy, as a way to spend quality time together and get fresh air."
- ADD: "Andrew adopted a new dog and named the pup 'Scout' because the name seemed perfect for their adventurous spirit."

Memory-R1 Memory Manager Actions (successful):

Operations Issued:

- UPDATE: "Andrew adopted a new dog from a shelter and named him Buddy because he is his buddy."
-> "Andrew adopted a dog from a shelter and named him Buddy because he is his buddy, and later adopted another dog named Scout."

Discussion: The vanilla LLM-based memory manager misinterpreted the second adoption as a contradiction because it saw two separate statements: "adopted a dog named Buddy" and "adopted another dog named Scout", and assumed that the differing dog names implied the new statement replaced the old one. As a result, it deleted the first dog ("Buddy") and added the second ("Scout"), leaving the memory fragmented and inaccurate. In contrast, the RL fine-tuned Memory Manager recognized the events as complementary and consolidated them with a single UPDATE, maintaining a coherent memory bank and enabling the system to answer correctly. This case illustrates how reinforcement learning enhances the Agent to understand the nuance between ADD, UPDATE, and DELETE, allowing the model to handle overlapping or related information more intelligently.

To further demonstrate how RL fine-tuning improves memory operations, we present another real-world example from a user-agent dialogue involving Joanna's feelings about pets and her allergies, particularly toward turtles.

Dialogue Excerpts:

- Joanna: I wish I wasn't allergic! I would get two turtles today if I could! I found out recently I'm allergic to cockroaches as well, so who knows if I'll ever get a pet. •
- Nate: Sorry! Maybe there are other animals you could consider! In the meantime though, I'll be sure to send you pics of my turtles so you can still watch them grow without getting too close.

Vanilla Memory Manager Actions (failed):

Operations Issued:

- DELETE: "Joanna is allergic to most reptiles and animals with fur, which causes her face to get puffy and itchy. Despite this, she finds other ways to be happy."
- DELETE: "Joanna finds turtles peaceful and believes they bring calm and joy."
- DELETE: "Joanna thinks having pets must be a wonderful experience."
- ADD: "Joanna is allergic to turtles and cockroaches, which affects her ability to have pets."

Memory-R1 Memory Manager Actions (successful):

Operations Issued:

- UPDATE: "Joanna is allergic to most reptiles and animals with fur, which causes her face to get puffy and itchy. Despite this, she finds other ways to be happy." -> "Joanna is allergic to most reptiles, including turtles and cockroaches, and animals with fur, which causes her face to get puffy and itchy. Additionally, she is also allergic to turtles and cockroaches, which affects her ability to have pets."
- UPDATE: "Joanna finds turtles peaceful and believes they bring calm and joy." -> "Joanna finds turtles peaceful and believes they bring calm and joy, but she is allergic to them."

Discussion: The vanilla Memory Manager misinterpreted the new allergy information in two aspects. First, it viewed the difference between "allergic to most reptiles and animals with fur" and "allergic to turtles and cockroaches" as a contradiction in allergy type—failing to recognize the latter as a more specific elaboration rather than a conflicting

statement. Second, it interpreted Joanna’s expressed fondness for turtles as incompatible with her allergy to them, incorrectly assuming that emotional attachment and physical limitations cannot coexist. As a result, it issued a series of DELETE operations followed by a single ADD, discarding valuable emotional context such as Joanna’s admiration for turtles and her general enthusiasm toward pets. In contrast, the RL fine-tuned Memory Manager recognized that these pieces of information were complementary: Joanna likes turtles but cannot keep them due to her allergies. It updated the relevant memories accordingly using targeted UPDATE operations, preserving both factual accuracy and emotional nuance. This case demonstrates how reinforcement learning equips the model to reason about overlapping and evolving information more intelligently, favoring memory consolidation over fragmentation.

A.2 From Vanilla LLM to Memory-Distilled RL Answer Agent

To illustrate how RL fine-tuned Answer Agent with *Memory Distillation* improves answer accuracy, we compare the original model’s output with the RL fine-tuned model on a representative example from LOCOMO. The prompt provided to the model is shown in Figure 7.

Question: Does John live close to a beach or the mountains?

Original Model Output (Before Fine-Tuning):

Answer: He lives near mountains.

Memory-R1 Output (After RL Fine-Tuning with Memory Distillation):

Memories selected as relevant:
• 8:30 pm on 1 January, 2023: John has a nostalgic memory of having a film camera as a kid and taking many pictures at the beach.
• 1:24 pm on 25 May, 2023: John shared a picture of his family at the beach, expressing a sense of making a difference and commitment to continue their efforts.

Answer: beach

Discussion: The original model consumed all retrieved memories indiscriminately and defaulted to “mountains,” likely influenced by irrelevant mentions of mountaineering. In contrast, Memory-R1 filtered out distractors, surfaced only beach-related memories, and generated the correct answer. This case highlights how *Memory Distillation* helps the model discard noise, focus on true signals, and improve factual accuracy.

B Data Construction

To train MEMORY-R1, we construct separate training data for the *Memory Manager* and the *Answer Agent* from the LOCOMO multi-turn dialogues.

Memory Manager Training Data. For every dialogue turn t , GPT-4o-mini builds a temporal memory bank from the

Algorithm 2: Data Construction for Memory-R1 Training

```

1: Input: LOCOMO multi-turn dialogues  $\mathcal{D}$ 
2: Output: Training tuples for the Memory Manager
   (dialogue turn, temporal memory bank, QA)
3: for each dialogue  $d \in \mathcal{D}$  do
4:   for each turn  $t$  in  $d$  do
5:     Build a temporal memory bank using the pre-
       vious 50 turns with GPT-4o-mini
6:     Combine (i) the temporal memory bank, (ii) the
       current turn  $t$ , and (iii) any QA pairs linked to  $t$ 
7:     Store the combined package as a single training
       tuple
8:   end for
9: end for

```

Algorithm 3: Data Construction for Answer Agent Training

```

1: Input: LOCOMO multi-turn dialogues  $\mathcal{D}$ , trained
   Memory Manager
2: Output: Training tuples for the Answer Agent
   (question, retrieved memories, gold answer)
3: for each dialogue  $d \in \mathcal{D}$  do
4:   Use the Memory Manager to maintain an up-to-date
   memory bank across turns
5: end for
6: for each question  $q$  in  $d$  do
7:   Use the question  $q$  as a query to retrieve the top 30
   most relevant candidate memories for each participant
   from the memory bank
8:   Pair (i) the question  $q$ , (ii) the 60 retrieved memo-
      ries, and (iii) the gold answer  $a_{gold}$ 
9:   Store the triplet as a single training tuple for Answer
   Agent fine-tuning
10: end for

```

preceding 50 turns. The current turn t is then fused with this snapshot, and we annotate the correct memory operation (ADD, UPDATE, DELETE, or NOOP). Each annotated tuple (turn, temporal memory bank, QA) serves as a supervised signal for the Memory Manager to learn how to incrementally update the memory state. The details can be found in Algorithm 2.

Answer Agent Training Data. For each question q in LOCOMO, we retrieve 60 candidate memories using retrieval-augmented search (RAG) over the temporal memory bank. The retrieved set, paired with the question and its gold answer, becomes the training input for the Answer Agent, which learns to distill the relevant entries and generate a concise, correct response.

C Prompts

In developing our Memory Manager Prompt, answer generation agent prompt, and LLM-as-a-Judge prompt, we adapt elements from the prompt released by prior work (Packer et al. 2023; Chhikara et al. 2025)

C.1 Memory Manager Prompt

For training the Memory Manager, we use a detailed prompt that instructs the model how to perform four memory operations: ADD, UPDATE, DELETE, and NOOP. The full prompt spans multiple figures for readability.

C.2 Answer Agent Prompt

We provide the full prompt used to instruct the Answer Agent in our case study. This prompt defines the reasoning process, memory selection criteria, and formatting requirements for the model’s responses. Figure 7 shows the complete instructions, context, and representative retrieved memories.

C.3 LLM-as-a-Judge (J) Prompt

For evaluating the correctness of generated answers, we employ an LLM-as-a-Judge prompt. The judge model is asked to label each answer as CORRECT or WRONG based on comparison with the gold answer. The complete prompt template is shown in Figure 8.

D Alogirthm

The overall Memory-R1 pipeline contains two complementary procedures, outlined in Algorithm 4 and Algorithm 5. Algorithm 4 (Memory Bank Construction) governs how the system incrementally builds and refines the external memory bank as new dialogue turns arrive. For each dialogue input, an LLM extracts key information, retrieves semantically related entries from the memory bank via retrieval-augmented generation (RAG), and invokes the RL fine-tuned Memory Manager to classify the update action as one of {ADD, UPDATE, DELETE, NOOP}. Depending on the chosen action, the memory store is updated accordingly—either inserting a new entry, merging information into an existing one, pruning contradictory content, or leaving the memory unchanged.

Algorithm 5 (Memory-augmented Answer Generation) describes how the system leverages the constructed memory bank to generate answers. Given an incoming question, the model retrieves the top-k relevant memory candidates, concatenates them with the question to form a memory-augmented prompt, and applies the Answer Agent’s Memory Distillation policy to filter for the most relevant facts. The distilled memory context, along with the query, is then passed to the Answer Agent to produce the final response, which is added to the answer set. Together, these algorithms enable Memory-R1 to jointly manage memory and generate memory augmented answers.

Algorithm 4: Memory Bank Construction via Memory Manager

```

1: Input: Multi-turn Dialogue  $\mathcal{D} = \{t_1, t_2, \dots, t_n\}$ , Initial empty memory bank  $M$ 
2: Output: Updated memory bank  $M$ 
3: procedure CONSTRUCTMEMORYBANK( $\mathcal{D}, M$ )
4:   for each dialogue turn  $t_i \in \mathcal{D}$  do
5:     Extract key info:  $f_i \leftarrow \text{LLMExtract}(t_i)$ 
6:     Retrieve memories:  $\mathcal{M}_{ret} \leftarrow \text{RAG}(f_i, M)$ 
7:     Determine operation:
8:      $o_i \leftarrow \text{MemoryManager}(f_i, \mathcal{M}_{ret})$  where  $o_i \in \{\text{ADD}, \text{UPDATE}, \text{DELETE}, \text{NOOP}\}$ 
9:     if  $o_i = \text{ADD}$  then
10:       $M \leftarrow M \cup \{f_i\}$ 
11:    else if  $o_i = \text{UPDATE}$  then
12:       $m_j \leftarrow \text{merge}(m_j, f_i)$ 
13:    else if  $o_i = \text{DELETE}$  then
14:       $M \leftarrow M \setminus \{m_j\}$ 
15:    else if  $o_i = \text{NOOP}$  then
16:       $M \leftarrow M$ 
17:    end if
18:   end for
19:   return  $M$ 
20: end procedure

```

Algorithm 5: Memory-augmented Generation via Answer Agent

```

1: Input: Question set  $Q = \{q_1, q_2, \dots, q_m\}$ , Memory bank  $M$ 
2: Output: Answer set  $\hat{A}$ 
3: procedure GENERATEANSWERS( $Q, M$ )
4:   for each question  $q_i \in Q$  do
5:      $\mathcal{M}_{ret} \leftarrow \text{RetrieveTopK}(q_i, M)$ 
6:      $p_i \leftarrow \text{Concat}(q_i, \mathcal{R}_i)$   $\triangleright p_i$  is the memory augmented prompt
7:      $\mathcal{M}_{distill}, \hat{a}_i \leftarrow \text{AnswerAgent}(q_i, \mathcal{M}_{ret})$ 
8:   end for
9:   return  $\hat{A}$ 
10: end procedure

```

Memory Manager Prompt (Part 1): Overview and ADD/UPDATE Instruction

You are a smart memory manager which controls the memory of a system. You can perform four operations: (1) add into the memory, (2) update the memory, (3) delete from the memory, and (4) no change.

Based on the above four operations, the memory will change.

Compare newly retrieved facts with the existing memory. For each new fact, decide whether to:

- ADD: Add it to the memory as a new element
- UPDATE: Update an existing memory element
- DELETE: Delete an existing memory element
- NONE: Make no change (if the fact is already present or irrelevant)

1. ****Add****: If the retrieved facts contain new information not present in the memory, then you have to add it by generating a new ID in the id field.

- Example:

Old Memory:
[
 {"id" : "0", "text" : "User is a software engineer"}]
Retrieved facts: ["Name is John"]

New Memory:
{
 "memory" : [
 {"id" : "0", "text" : "User is a software engineer", "event" : "NONE"},
 {"id" : "1", "text" : "Name is John", "event" : "ADD"}
]
}

2. ****Update****: If the retrieved facts contain information that is already present in the memory but the information is totally different, then you have to update it.

If the retrieved fact contains information that conveys the same thing as the memory, keep the version with more detail.

Example (a) { if the memory contains "User likes to play cricket" and the retrieved fact is "Loves to play cricket with friends", then update the memory with the retrieved fact.

Example (b) { if the memory contains "Likes cheese pizza" and the retrieved fact is "Loves cheese pizza", then do NOT update it because they convey the same information.

Important: When updating, keep the same ID and preserve old_memory.

- Example:

Old Memory:
[
 {"id" : "0", "text" : "I really like cheese pizza"},
 {"id" : "2", "text" : "User likes to play cricket"}]
Retrieved facts: ["Loves chicken pizza", "Loves to play cricket with friends"]

New Memory:
{
 "memory" : [
 {"id" : "0", "text" : "Loves cheese and chicken pizza", "event" : "UPDATE",
 "old_memory" : "I really like cheese pizza"},
 {"id" : "2", "text" : "Loves to play cricket with friends", "event" : "UPDATE",
 "old_memory" : "User likes to play cricket"}
]
}

Figure 5: Memory Manager Prompt (Part 1): Overview and ADD/UPDATE operation instruction.

Memory Manager Prompt (Part 2): DELETE/NO_OPERATION Instructions

3. ****Delete**:** If the retrieved facts contain information that contradicts the memory, delete it. When deleting, return the same IDs | do not generate new IDs.

- Example:

Old Memory:
[
 {"id" : "1", "text" : "Loves cheese pizza"}
]
Retrieved facts: ["Dislikes cheese pizza"]

New Memory:
{
 "memory" : [
 {"id" : "1", "text" : "Loves cheese pizza", "event" : "DELETE"}
]
}

4. ****No Change**:** If the retrieved facts are already present, make no change.

- Example:

Old Memory:
[
 {"id" : "0", "text" : "Name is John"}
]
Retrieved facts: ["Name is John"]

New Memory:
{
 "memory" : [
 {"id" : "0", "text" : "Name is John", "event" : "NONE"}
]
}

Figure 6: Memory Manager Prompt (Part 2): DELETE/NO_OPERATION instructions.

Full Prompt and Retrieved Memories

You are an intelligent memory assistant tasked with retrieving accurate information from conversation memories.

CONTEXT:
You have access to memories from two speakers in a conversation. These memories contain timestamped information that may be relevant to answering the question.

INSTRUCTIONS:

1. Carefully analyze all provided memories from both speakers
2. Pay special attention to the timestamps to determine the answer
3. If the question asks about a specific event or fact, look for direct evidence
4. If the memories contain contradictory information, prioritize the most recent memory
5. If there is a question about time references (like "last year", "two months ago"), calculate the actual date based on the memory timestamp.
6. Always convert relative time references to specific dates, months, or years.
7. Focus only on the content of the memories. Do not confuse character names
8. The answer should be less than 5-6 words.
9. IMPORTANT: Select memories you found that are useful for answering the questions, and output it before you answer questions.
10. IMPORTANT: Output the final answer after **Answer:**

APPROACH (Think step by step):

1. Examine all relevant memories
2. Examine the timestamps carefully
3. Look for explicit mentions that answer the question
4. Convert relative references if needed
5. Formulate a concise answer
6. Double-check the answer correctness
7. Ensure the final answer is specific
8. First output the memories that you found are important before you answer questions

Memories for user John:

- 7:20 pm on 16 June, 2023: John has a special memory of a vacation to California where he experienced a gorgeous sunset and an enjoyable night strolling the shore, creating meaningful memories with loved ones.
- 6:13 pm on 10 April, 2023: John explored the coast in the Pacific Northwest and visited some national parks, finding the beauty of nature absolutely breathtaking.
- 3:14 pm on 13 August, 2023: John enjoys spending time outdoors with his family, including activities such as hiking, hanging out at the park, and having picnics. He also values indoor family activities like playing board games and having movie nights at home.

... (In total 30 most relevant memories from John's Memory Bank are provided) ...

Memories for user Maria:

- 6:29 pm on 7 July, 2023: John experienced a severe flood in his old area last week, which caused significant damage to homes due to poor infrastructure.
- 1:24 pm on 25 May, 2023: Maria appreciates the beauty of small, meaningful moments in life, as reflected in her reaction to a family beach photo shared by John.
- 3:14 pm on 13 August, 2023: Maria appreciates family bonding and is interested in the activities that John and his family enjoy doing together.

... (In total 30 most relevant memories from Maria's Memory Bank are provided) ...

Question: Does John live close to a beach or the mountains?

Figure 7: Prompt and retrieved memories used in the case study, showing all instructions, context, and memory entries provided to the model.

LLM-as-a-Judge Prompt Template

Your task is to label an answer to a question as 'CORRECT' or 'WRONG'.

You will be given the following data:

- (1) a question (posed by one user to another user),
- (2) a 'gold' (ground truth) answer,
- (3) a generated answer,

which you will score as CORRECT or WRONG.

The point of the question is to ask about something one user should know about the other user based on their prior conversations.

The gold answer will usually be a concise and short answer that includes the referenced topic, for example:

Question: Do you remember what I got the last time I went to Hawaii?

Gold answer: A shell necklace

The generated answer might be longer, but you should be generous with your grading | as long as it touches on the same topic as the gold answer, it should be counted as CORRECT.

For time-related questions, the gold answer will be a specific date, month, or year. The generated answer might include relative references (e.g., "last Tuesday"), but you should be generous | if it refers to the same time period as the gold answer, mark it CORRECT, even if the format differs (e.g., "May 7th" vs. "7 May").

Now it's time for the real question:

Question: {question}

Gold answer: {gold_answer}

Generated answer: {generated_answer}

First, provide a short (one sentence) explanation of your reasoning, then finish with CORRECT or WRONG.

Do NOT include both CORRECT and WRONG in your response, or it will break the evaluation script.

Return the label in JSON format with the key as "label".

Figure 8: LLM-as-a-Judge prompt used to evaluate model answers. The judge model labels each generated answer as CORRECT or WRONG based on comparison with the gold answer, with explicit instructions for handling time references and topic matching.