GRAM: Empowering Agent with Actively Managed Graph-Structured Memory via Reinforcement Learning

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Abstract

Large Language Model (LLM) agents face a fundamental bottleneck called *context flooding* in multi-turn information retrieval: as evidence accumulates across interaction turns, their context windows become saturated with redundant, conflicting, and outdated facts. Existing research either compresses interaction history into rolling summaries, sacrificing relational precision, or relies on retrieval-augmented pipelines that lack mechanisms for resolving knowledge conflicts and maintaining a globally consistent belief state. In this work, we introduce GRAM, a reinforcement learning framework designed to train an agent to actively manage and utilize a dynamic graph-structured memory. Rather than passively accumulating retrieved text, the agent learns to incrementally construct and revise a coherent knowledge graph that serves as its persistent belief state, resolving contradictions and preserving logical relationships in memory. Furthermore, we employ Group Relative Policy Optimization to train small language models (under 4B) to master these complex memory-governance behaviors. Experimental results across multiple mainstream question-answering benchmarks demonstrate the superiority of the GRAM framework over existing agentic memory baselines and conventional RAG systems.

1 Introduction

LLMs have demonstrated remarkable capability across a wide range of knowledge-intensive and reasoning tasks, with recent advances in long-context modeling further expanding their applicability to complex scenarios such as multi-document question answering, tool-augmented reasoning, and autonomous agents.

However, these capabilities often break down in *incremental knowledge acquisition* scenarios like multi-turn web search, where information arrives incrementally across multiple turns rather than being provided in its entirety at once. As information accumulates across turns, the context window becomes saturated with redundant, conflicting, and outdated facts, leading to *context flooding* that degrades reasoning accuracy through the "lost-in-the-middle" effect (Liu et al., 2024; Yi et al., 2025) and increases both inference latency and retrieval cost (Xiao et al., 2023).

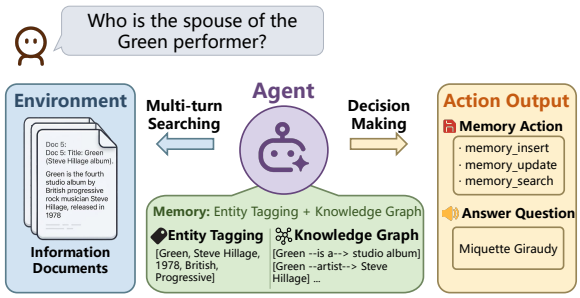

Figure 1: Overview of the multi-document question answering problem.

To address these challenges, previous research (Zhou et al., 2025; Sun et al., 2025; Wu et al., 2025) primarily focuses on context compression, such as summarization or rolling memory. Such emphasis on context length reduction often leads to information loss, especially in tasks requiring precise fact retrieval or multi-hop reasoning. Additionally, some latest studies employ Retrieval-Augmented Generation (RAG) offers an alternative by dynamically selecting relevant context from an external corpus, but it suffers from a critical limitation: retrieval alone does not guarantee that the *right* information is surfaced at the *right time*. Furthermore, current work aims at (Chhikara et al., 2025; Wang et al., 2025) reconstructing the memory structures in agent from passive storage to an actively maintained belief state. They often rely on a rigid two-stage process that processes a static corpus before reasoning begins, which disconnects information gathering from immediate reasoning needs and fails to facilitate real-time belief revision as new evidence emerges. Across all three

paradigms, a shared deficiency persists: none provides a mechanism for *explicit belief revision*, leaving accumulated contradictions and outdated facts unresolved. Therefore, the key capability of an agent in long-horizon tasks is not only *how to read*, but also *how to retain*, *how to revise*, and *how to discard*.

In this work, we propose **GRAM** (**G**raph-**R**etrieval **A**gentic **M**emory), a framework that equips an LLM agent with a dynamic graph-structured memory and a set of explicit cognitive actions: `Insert`, `Update`, and `Search`. As is shown in Figure 1, instead of passive storage, the agent actively constructs and maintains a persistent belief state by integrating new data and resolving contradictions in real time. Crucially, the `Update` operation allows the agent to prune outdated facts or reconcile inconsistencies, ensuring the context remains concise and logically consistent throughout the process of incremental acquisition.

Furthermore, training agent to master such memory-governance behaviors poses a fundamental challenge: the optimal sequence of memory operations is rarely annotated, and supervised learning provides no clear signal for long-horizon memory decisions. Therefore, we formulate GRAM as a reinforcement learning problem and train the agent using Group Relative Policy Optimization (GRPO) (Shao et al., 2024). This allows the agent to learn effective memory management strategies directly from task-level supervision. Experiments show that the trained agent indeed develops a strategy of proactive information consolidation, minimizing the need for expensive searches.

Our main contributions are summarized as follows:

- We introduce GRAM, a reinforcement learning framework that enables LLM agents to actively manage a dynamic graph-structured memory in incremental knowledge acquisition environments, treating memory governance as a sequential decision-making problem.

- We design a set of explicit cognitive actions, including `Insert`, `Update`, and `Search` that allow the agent to acquire knowledge incrementally by constructing, revising, and querying a coherent knowledge graph as its persistent belief state, with `Update` providing explicit conflict resolution absent from prior approaches.

- Experimental results demonstrate that our GRAM driven by small language models, training through only task-level reward, can acquire sophisticated memory governance behaviors and substantially outperform existing methods on complex multi-hop reasoning benchmarks.

2 Related Work

2.1 Graph-Augmented LLMs

Integrating Knowledge Graphs (KGs) with LLMs has emerged as a promising direction to mitigate hallucinations and enhance multi-hop reasoning capabilities (Pan et al., 2024). Early approaches, such as RAG (Retrieval-Augmented Generation) (Lewis et al., 2020), primarily rely on vector similarity to retrieve relevant text chunks. However, these methods often struggle with "reasoning across documents" or detecting structural patterns that are not semantically adjacent.

To address this, Graph-Augmented methods have been proposed. Systems like GraphRAG (Edge et al., 2024) and G-Retriever (He et al., 2024) leverage pre-constructed community summaries or subgraph retrieval to provide structured context. Think-on-Graph (ToG) (Sun et al., 2023) and MindMap (Wen et al., 2024) further enable LLMs to perform beam search or random walks over static KGs to reason explicitly. However, a common limitation of these approaches is their reliance on static, pre-defined graphs. The graph is typically assumed to be a read-only external database provided beforehand. In contrast, our work focuses on the incremental knowledge acquisition scenarios, where the agent must dynamically construct and evolve the graph memory from scratch while processing sequential information, handling conflicts and redundancy in real-time.

2.2 LLM Agents with Active Memory

Standard LLMs are constrained by fixed context windows, leading to the development of agents with active memory management. MemGPT (Packer et al., 2023) introduces an OS-like hierarchy, allowing agents to manage context via virtual memory paging, effectively extending the context window indefinitely. Generative Agents (Park et al., 2023) utilize a reflection mechanism to store and retrieve synthesized text logs in a vector database. More recently, Mem1 (Zhou et al., 2025) trains agents to maintain a "working memory" in the form of a

compressed text summary, updating it iteratively via reinforcement learning.

While these methods enable long-horizon interactions, their memory representations are predominantly unstructured or semi-structured. Textual summaries often suffer from information loss or "fuzziness" when handling precise, multi-hop dependency chains. Furthermore, most agents lack explicit mechanisms to correct stored errors once written. Our method, GRAM, differentiates itself by employing a structured graph memory. By training with **PPO** (Schulman et al., 2017) or **GRPO** (Shao et al., 2024), our agent learns discrete actions to strictly manage knowledge triplets. This structure offers superior precision for multi-hop reasoning and enables specific "surgical" updates to resolve conflicts, a capability often absent in summary-based memory systems.

3 Method

Given a user query q and a list of documents $D = \{d_1, d_2, \ldots, d_L\}$, the agent functions as a policy $\pi_\theta(a_t|s_t)$ that interacts with an evolving Knowledge Graph $\mathcal{G}$. At each time step t, the agent observes a state s_t, which encapsulates the query, a textual summary of the current graph topology, and the current document d_k. Our GRAM framework, characterizing the dynamic graph memory, the discrete agentic action space, and the Group Relative Policy Optimization (GRPO) training pipeline, aims at generating an optimal trajectory of actions to construct a coherent answer, as illustrated in Figure 2.

3.1 Dynamic Graph Memory

Unlike traditional RAG systems that rely on static vector databases or linear context buffers, GRAM maintains a dynamic knowledge graph for active memory management. Formally, at any time step t, the memory is denoted as a directed graph $\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t)$, where $\mathcal{V}_t$ represents the set of unique entities and $\mathcal{E}_t \subseteq \mathcal{V}_t \times \mathcal{R} \times \mathcal{V}_t$ denotes the set of semantic relations. This structure supports two primary cognitive functions: topology evolution for belief revision and structure-aware retrieval for multi-hop reasoning.

Topology Evolution. The topology of the graph is designed for self-organization through non-monotonic state transitions. Let $\mathcal{T}_{in}$ be the set of new knowledge triplets extracted from the current document. The state transition from $\mathcal{G}_t$ to $\mathcal{G}_{t+1}$ is governed by a policy that first performs Online Entity Alignment to resolve entity aliasing. For a new mention m, a linking function $\phi : \mathcal{V}_{new} \to \mathcal{V}_t$ is employed; if the semantic similarity between m and an existing node $v \in \mathcal{V}_t$ exceeds a threshold δ, the mention is merged. This process ensures that fragmented attributes are aggregated into a unified representation:

$$v_{new} = \text{Aggr.}\left(\{m \mid \text{sim}(m, v) > \delta\} \cup \{v\}\right) \quad (1)$$

Furthermore, to address the contradictions inherent in incremental documents, the policy facilitates explicit conflict resolution. Unlike standard memory architectures that accumulate facts monotonically ($\mathcal{G}_{t+1} \supseteq \mathcal{G}_t$), GRAM allows the agent to identify a set of edges to add (Δ_t^+) and a set of obsolete or conflicting edges to prune (Δ_t^-). This results in a refined state transition:

$$\mathcal{G}_{t+1} = (\mathcal{G}_t \cup \Delta_t^+) \setminus \Delta_t^- \quad (2)$$

This mechanism allows the agent to actively resolve conflicts and maintain a globally consistent state that reflects the latest valid information.

Structure-Aware Retrieval. To mitigate the information loss common in compressed contexts, GRAM utilizes a structure-aware retrieval protocol. When the agent executes a search action, it triggers a query to retrieve a local subgraph $\mathcal{G}' \subset \mathcal{G}_t$ rather than relying on isolated vector similarity. This protocol is specifically designed to uncover latent connections through multi-hop bridging. By defining $\mathcal{P}_{i,k}$ as the set of relational paths connecting entities v_i and v_k up to a maximum length L, the retrieval function traverses the graph to identify logical dependencies:

$$\mathcal{P}_{i,k} = \{(v_i \xrightarrow{r_1} v_j \ldots \xrightarrow{r_L} v_k) \in \mathcal{G}_t\} \quad (3)$$

By recovering these paths, the agent identifies logical dependencies between entities that never co-occurred in the same source document. The retrieved topological information $\mathcal{G}'$ is then linearized into a coherent summary sequence $S = \text{Linearize}(\mathcal{G}')$, augmenting the agent's working memory with precise, logic-oriented evidence independent of the document stream's temporal order.

3.2 Graph Operation Details

We now describe the concrete procedures that implement the graph operations outlined above.

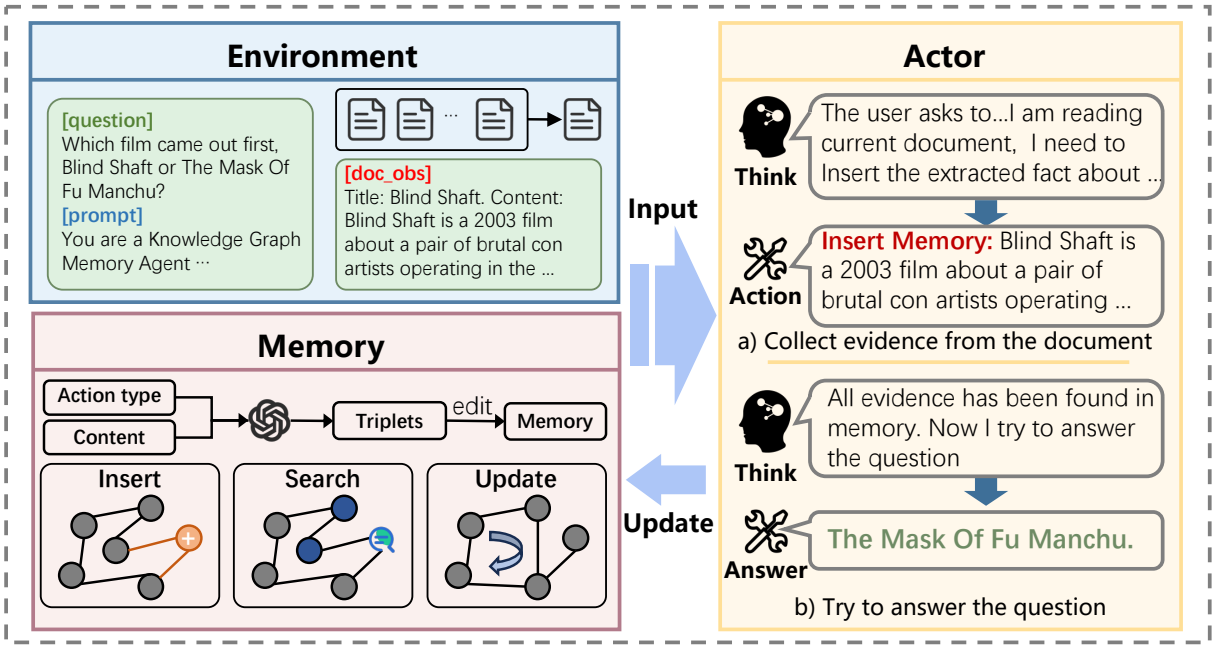

Figure 2: **Overview of the GRAM Framework.** The agent processes a sequential document stream to construct a dynamic Knowledge Graph (KG) for complex reasoning. At each step, the agent observes the query, the current document, and a textual summary of the graph state. Following the ReAct mode, the agent first generates a think trace to analyze information gaps, and then executes a symbolic action.

Online Entity Alignment. When the agent issues a `Memory_Insert` action, we first extract entity mentions from the incoming text via an LLM-based extraction module. Each extracted mention m is compared against the existing node set $\mathcal{V}_t$ by computing cosine similarity over their embeddings. If $\text{sim}(m, v) > \delta$ for some $v \in \mathcal{V}_t$, the mention is merged into v by aggregating their attribute sets; otherwise, a new node is created. The formal pseudocode is provided in Appendix A.3 (Algorithm 1).

Graph Search Procedure. When the agent issues a `Memory_Search` action with a natural-language query q, retrieval proceeds in two stages. In the first stage (*Entity Matching*), entity mentions are extracted from q using the same extraction module and matched against $\mathcal{V}_t$ via embedding similarity to identify a set of anchor nodes $\{v_1, \ldots, v_m\}$. In the second stage (*Subgraph Retrieval*), a bounded breadth-first traversal up to depth L is performed from each anchor node to collect local subgraph $\mathcal{G}' \subseteq \mathcal{G}_t$. The resulting subgraph is linearized into a triplet sequence $S = \text{Linearize}(\mathcal{G}')$ and appended to agent's context.

Conflict Detection and Update Rules. A conflict is detected whenever a newly extracted triplet (s, r, o_{new}) shares both its subject s and relation r with an existing edge (s, r, o_{old}) yet differs in the object. Upon detecting such a conflict, the `Update` action enables the agent to issue a natural-language revision instruction, which is subsequently parsed into a pair of graph edit sets (Δ^+ and Δ^-) through the structured prompt described in Appendix D.

3.3 Agentic Action Space

The information flow within GRAM is governed by a discrete action space:

$$\mathcal{A} = \{\texttt{Insert}, \texttt{Update}, \texttt{Search}, \texttt{Answer}\} \quad (4)$$

At each step, the agent follows the ReAct mode (Yao et al., 2022): generating a reasoning trace z_t to evaluate the current state before sampling a single atomic action $a_t \in \mathcal{A}$. These actions are categorized into knowledge maintenance and information navigation.

Knowledge Maintenance Action. The actions facilitate the integration of new evidence from the current document d_k into the graph $\mathcal{G}$. The `Memory_Insert` action extracts atomic triplets from d_k to expand the topology of the graph. Alternatively, the `Memory_Update` action allows the agent to issue natural language instructions to revise or prune outdated nodes and edges in $\mathcal{G}_{t-1}$. This ensures the consistency of the belief state

when conflicting information is encountered. Once either maintenance action is completed, the system assumes the current document has been processed and advances the pointer to d_{k+1}.

Information Navigation Action. The actions allow the agent to pause the traversal of the document to gather context or terminate the task. The `Memory_Search` action performs a retrieval operation on $\mathcal{G}_{t-1}$. Critically, this action does not advance the document pointer but enriches the context of the agent with retrieved relational paths to support the understanding of d_k in subsequent steps. Finally, the `Answer` action terminates the interaction trajectory and generates a response based on the accumulated evidence.

3.4 Reinforcement Learning Pipeline

While the optimal sequence of memory operations is not explicitly annotated, we model the interaction as a Markov Decision Process (MDP) and optimize it through Reinforcement Learning (RL). Specifically, we employ Group Relative Policy Optimization (GRPO) as the RL algorithm. For each query Q, we sample a group of trajectories $\{\tau_1, \ldots, \tau_K\}$ from the current policy π_θ. The objective function maximizes the advantage of the generated outputs relative to the group average:

$$\mathcal{J}(\theta) = \mathbb{E}_{Q\sim\mathcal{D},\epsilon\sim\pi_\theta} \left[\frac{1}{K}\sum_{i=1}^{K} \min\left(\frac{\pi_\theta(\tau_i)}{\pi_{old}(\tau_i)}\hat{A}_i, \text{clip}(\ldots)\hat{A}_i\right)\right] \tag{5}$$

where $\hat{A}_i$ is the standardized reward advantage.

Reward Formulation. We design a compound reward $R = R_{\text{outcome}} + \lambda R_{\text{process}}$, where $\lambda = 0.1$ balances answer correctness against process quality.

The **outcome reward** measures the token-level F1 between the predicted answer $\hat{y}$ and the ground truth y^*:

$$R_{\text{outcome}} = \frac{2\text{Precision}(\hat{y}, y^*) \cdot \text{Recall}(\hat{y}, y^*)}{\text{Precision}(\hat{y}, y^*) + \text{Recall}(\hat{y}, y^*)} \tag{6}$$

The **process reward** enforces structural compliance with the single-action protocol defined in Section 3.3. It assigns a binary penalty based on whether the agent produces valid XML action tags in each turn:

Dataset	# Examples	Avg # Docs	Avg # Steps
TriviaQA	16853	1	1
HotpotQA	7405	9.94	2.43
2WikiMultihop	12576	10	2.44
Musique	2417	20	2.65

Table 1: Statistics of the Evaluation Datasets. **Avg # Docs** denotes the average number of documents per sample, and **Avg # Steps** represents the average number of supporting facts required to deduce the final answer.

$$R_{\text{process}} = \begin{cases} 1, & \text{if action tags are valid,} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

This term prevents reward hacking behaviors such as generating multiple actions per turn or malformed tags, ensuring that the RL signal remains grounded in well-formed trajectories.

4 Experiment

4.1 Experiment Setup

Dataset. We evaluate GRAM on four question answering benchmarks spanning single-hop and multi-hop reasoning: TriviaQA (Joshi et al., 2017), HotpotQA (Yang et al., 2018), 2WikiMultiHopQA (Ho et al., 2020), and MuSiQue (Trivedi et al., 2021). To simulate incremental information settings, we adapt these datasets by presenting supporting and distractor documents sequentially rather than providing full context at once. As shown in Table 1, TriviaQA serves as a single-hop baseline with well-localized context, while multi-hop datasets like MuSiQue impose substantially greater demands. These benchmarks range from simple factoid retrieval to complex multi-step reasoning, rigorously testing GRAM's ability to maintain coherent graph memory under long-horizon retrieval scenarios.

Evaluation Metrics. For answer quality evaluation, we use the *F1 Score*, which measures the average word overlap between the prediction and the groundtruth.

For cost-effectiveness evaluation, we track the *Average Interaction Turns (AIT)* to evaluate efficiency not by absolute turn counts alone, but by how well the agent allocates its interaction budget relative to task complexity, avoiding both redundancy on simple queries and premature termination on complex ones.

Method	Backbone	Size	TriviaQA	HotpotQA	2Wiki	Musique
Zero-shot	Qwen2.5	3B	0.288	0.149	0.244	0.020
	Qwen2.5	7B	0.408	0.183	0.250	0.031
RAG	Qwen2.5	3B	0.544	0.255	0.226	0.047
	Qwen2.5	7B	0.585	0.299	0.235	0.058
CoT (Wei et al., 2022)	Qwen2.5	3B	0.185	0.092	0.111	0.022
	Qwen2.5	7B	0.032	0.021	0.021	0.002
IRCoT (Trivedi et al., 2023)	Qwen2.5	3B	0.312	0.164	0.171	0.067
	Qwen2.5	7B	0.478	0.133	0.149	0.072
Search-R1 (Jin et al., 2025)	Qwen2.5	3B	0.545	0.324	0.319	0.103
	Qwen2.5	7B	0.610	0.370	0.414	0.146
Mem1 (Zhou et al., 2025)	Qwen2.5	3B	0.767	0.638	0.301	0.129
	Qwen2.5	7B	**0.819**	**0.709**	0.321	0.146
Ours	Qwen2.5	3B	0.792	0.637	**0.528**	**0.316**
	LLaMA3.2	3B	0.728	0.605	0.459	0.274

Table 2: Evaluation results on our datasets. All baselines use the Qwen2.5-Instruct series; GRAM is also evaluated on LLaMA-3.2-3B-Instruct to validate cross-family generalization. Best in **Bold** and second best in Underline.

Baselines. We compare GRAM against a range of baselines, from direct prompting to advanced agentic frameworks. The baselines fall into three categories: i) direct generation methods (Zero-shot and CoT (Wei et al., 2022)), which test the model's parametric knowledge without any retrieval; ii): retrieval-augmented generation methods (Standard RAG and IRCoT (Trivedi et al., 2023)), which ground the model in external document chunks; iii): agentic methods (Search-R1 (Jin et al., 2025) and MEM1 (Zhou et al., 2025)), which give the model active control over its information-gathering process. Note that all methods use Qwen2.5 as the backbone LLM to ensure a fair comparison. We exclude offline graph-augmented methods (GraphRAG (Edge et al., 2024), LightRAG (Guo et al., 2024), HippoRAG (Jimenez Gutierrez et al., 2024)) from the main comparison, as their offline two-stage pipeline is fundamentally incompatible with our incremental acquisition setting where documents arrive sequentially. Please refer to the appendix for more implementation details, e.g., Appendix A for detailed baseline description and training setups and Appendix D for used prompts.

4.2 Overall Performance

Table 2 presents the comparative performance of GRAM against state-of-the-art baselines across four benchmarks.

Performance Comparison against Baselines. GRAM consistently outperforms traditional retrieval (RAG), linear reasoning (IRCoT), and agentic baselines, demonstrating its most significant advantage on complex multi-hop datasets. On the highly challenging Musique benchmark, GRAM-3B achieves an F1 score of 0.316, reflecting a 6.7× improvement over standard RAG (0.047) and substantially outperforming Search-R1-3B (0.146). Similarly, it surpasses Search-R1 by over 11 points on 2Wiki. These gains highlight how GRAM's active memory management and explicit graph structure effectively mitigate the "lost-in-the-middle" phenomenon and "reasoning drift" inherent to passive context stuffing, successfully preserving relational bridges across fragmented evidence.

Parameter Efficiency and Structural Fidelity. Despite using a compact 3B backbone, GRAM achieves performance competitive with considerably larger models. On TriviaQA, GRAM-3B (0.792) is comparable to 7B-scale Mem1 (0.819), indicating that structured graph representations retain the fine-grained information necessary for precise fact extraction, a property that rolling summary approaches tend to compromise. On HotpotQA, GRAM substantially narrows the gap against larger or more specialized models, suggesting that equipping smaller LLMs with a persistent, dynamic belief state is an efficient route to strong multi-hop reasoning without proportional increases in computational cost.

Cross-Family Generalization. To rule out the possibility that GRAM's gains are tied to Qwen-specific inductive biases, we train and evaluate GRAM on LLaMA-3.2-3B-Instruct under an iden-

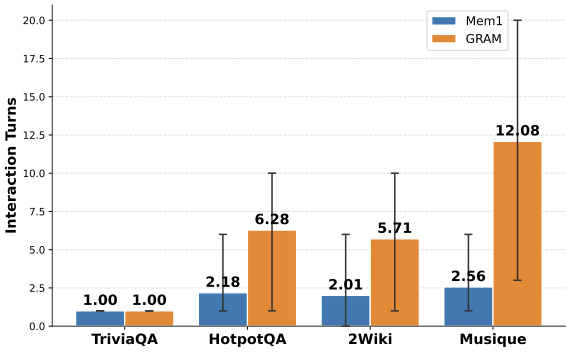

Figure 3: Comparison of Average Interaction Turns across different benchmarks. GRAM adapts its trajectory length based on task complexity, demonstrating efficiency on simple tasks and persistence on complex multi-hop queries.

Setting	TriviaQA	HotpotQA	2Wiki	Musique
w/o Update	0.763	0.628	**0.592**	**0.447**
w/ Update	**0.792**	**0.637**	0.528	0.316

Table 3: Ablation study on the impact of the Graph Update mechanism. w/o Update denotes an insert-only strategy.

Setting	F1 Score	Token Consumption
w/o Graph	0.568	11,240
w/ Graph	**0.637**	**6,450**

Table 4: Ablation Study on Memory Structure. Comparison between a linear text buffer (*w/o Graph*) and graph memory (*w/ Graph*).

tical framework and training pipeline. As reported in Table 2, GRAM-LLaMA achieves 0.728, 0.605, 0.459, and 0.274 on TriviaQA, HotpotQA, 2WikiMultiHopQA, and MuSiQue respectively, outperforming every Qwen2.5-3B baseline on the multi-hop tasks and remaining competitive with 7B-scale methods. On MuSiQue, GRAM-LLaMA (0.274) nearly doubles Search-R1-7B and Mem1-7B (both 0.146), despite using a different model family with fewer than half the parameters. The consistency of these gains across two architecturally distinct backbone families confirms that the performance advantage originates from GRAM's graph-structured memory and RL-trained governance policy rather than from the capability of any single backbone. We note a moderate gap relative to GRAM-Qwen, which we attribute to occasional format-compliance issues observed during LLaMA's RL training. An SFT warm-up stage largely mitigates this problem, as discussed in Appendix B.5.

Adaptive Interaction Efficiency. Beyond accuracy, we examine agent behavior through Average Interaction Turns (AIT), illustrated in Figure 3. GRAM's reasoning depth scales naturally with task complexity. On single-hop tasks such as TriviaQA, it matches the efficiency of summary-based baselines with an average of 1.00 turn, showing that graph maintenance does not introduce unnecessary overhead for simple factual queries. On complex multi-hop tasks such as MuSiQue, GRAM invests substantially more turns (12.08) compared to Mem1 (2.56). This gap is not a sign of inefficiency but rather reflects a qualitative difference in reasoning strategy. Mem1 tends to terminate early by committing to an answer as soon as its rolling summary appears sufficient, which often leads to premature closure when intermediate evidence is incomplete. GRAM, by contrast, continues to chain insert and search operations until a complete evidence path is constructed in the graph, and only then issues the final answer. This persistence directly accounts for its superior F1 on multi-hop benchmarks and suggests that the RL-trained policy has learned to trade additional interaction steps for higher answer reliability when the task demands it.

4.3 Ablation Studies

We ablate two core design choices of GRAM on all four benchmarks using Qwen2.5-3B-Instruct.

Impact of the Update Mechanism. We compare the full model against an append-only variant (*w/o Update*) that disables the `Memory_Update` action (Table 3). Enabling Update improves fact-retrieval tasks (TriviaQA +2.9%, HotpotQA +0.9%), where correcting outdated or conflicting entries in the graph directly benefits answer precision. However, on deeper multi-hop benchmarks (2WikiMultiHopQA, MuSiQue), the append-only variant performs better, with Update causing a −13.1% drop on MuSiQue. We attribute this to the structural role of intermediate nodes: in multi-hop reasoning chains, seemingly redundant entities often serve as bridges connecting disjoint evidence, and aggressive pruning can break these paths. This reflects a fundamental trade-off between memory consistency and structural preservation rather than a deficiency of the mechanism itself. A detailed analysis of the conditions under which Update helps versus harms is provided in Appendix B.1.

Query: *"Who is the spouse of the Green performer?"*	**Ground Truth:** Miquette Giraudy

Step 1 [Doc 1: Grant's First Stand] "...debut album by American jazz guitarist **Grant Green**..."
Agent: "Grant Green" is a *surname*, not the album titled "Green". Irrelevant to the query. → `Skip`

Step 2–4 [Docs about Al Green, Green Party, etc.] All contain the keyword "Green" but refer to unrelated entities.
Agent: Correctly identifies each as a distractor. → `Skip` ×3

Step 5 [Doc 5: Green (Steve Hillage album)] "Green is the fourth studio album by **Steve Hillage**, released in 1978..."
Agent: First relevant hit — "Green" is an album, and its performer is Steve Hillage.
→ `<memory_insert> [Steve Hillage] -[performer of]-> [Green (album)]`

Step 6 [Doc 6: Miquette Giraudy] "best known for her work in Gong and with her **partner Steve Hillage**..."
Agent: New clue connects Giraudy to Hillage, but needs to verify Hillage = "the Green performer" via graph before answering.
→ `<memory_search>` Steve Hillage Green

Step 7 [Memory Search Results]: `[Steve Hillage] -[performer of]-> [Green (album)]`
Agent: Graph traversal confirms the two-hop chain: *Green* $\xrightarrow{\text{performer}}$ *Steve Hillage* $\xrightarrow{\text{partner}}$ *Miquette Giraudy*.
→ `<answer>` Miquette Giraudy ✓

Table 5: Reasoning trajectory of GRAM on a HotpotQA example (Qwen2.5-3B). The case illustrates four capabilities: noise rejection of semantically similar distractors (Steps 1–4), graph construction from relevant documents (Steps 5–6), active retrieval for hypothesis verification (Step 6), and multi-hop answer synthesis via graph traversal (Step 7).

Impact of Memory Structure. We replace the graph memory with a flat text buffer (*w/o Graph*) while keeping the same RL pipeline and action interface (Table 4). The graph variant improves F1 by 6.9 points *and* reduces average token consumption by 42.6%. The accuracy gain can be attributed to the graph's topological awareness: subgraph retrieval surfaces multi-hop relational paths that flat retrieval over text chunks cannot reconstruct. The efficiency gain stems from two complementary properties — entity-level deduplication consolidates redundant mentions across documents into canonical nodes, and structured retrieval returns only the relevant relational paths rather than entire passages, eliminating the token noise that inflates linear-buffer contexts.

4.4 Case Study

Table 5 presents a representative reasoning trajectory of GRAM on a multi-hop question from HotpotQA. The agent first demonstrates noise robustness by correctly rejecting four distractor documents (Steps 1–4) that share the keyword "Green" but refer to unrelated entities. Upon encountering the relevant album entry at Step 5, the agent inserts a structured triplet linking Steve Hillage to the album "Green". At Step 6, after discovering that Miquette Giraudy is described as the partner of Steve Hillage, the agent does not immediately produce an answer. Instead, it issues a `Memory_Search` to verify that Hillage is indeed the performer of "Green", a fact stored two steps earlier. The final answer at Step 7 is derived through explicit graph traversal, chaining *Green* → *Steve Hillage* → *Miquette Giraudy*, a two-hop path that never appeared in any single document but emerges from the structured composition of separately inserted facts. We present additional cases, including failure mode analysis, in Appendix C.

5 Conclusion

In this paper, we propose GRAM, a reinforcement learning framework that equips LLM agents with an actively managed graph-structured memory for incremental knowledge acquisition from sequential document streams. The agent governs its memory through three explicit cognitive actions: Insert, Update, and Search, that enable it to construct, revise, and query a dynamic knowledge graph as a persistent belief state. We further employ the GRPO algorithm to train the agent to master these memory-governance behaviors, allowing it to resolve knowledge conflicts and maintain relational precision. Experiments across four QA benchmarks of increasing multi-hop complexity show that GRAM substantially outperforms both conventional RAG systems and recent agentic memory baselines. Ablation studies further reveal a trade-off between memory consistency and structural preservation in the u·pdate mechanism, and cross-family evaluation confirms that the gains are architecture-driven rather than backbone-specific. These results suggest that effective long-horizon reasoning requires agents to not only retrieve information but also strategically retain, revise, and discard it.

Limitations

While GRAM demonstrates significant advantages, our in-depth ablation studies reveal an important trade-off between memory consistency and structural preservation. Although belief revision is essential for maintaining a concise and accurate memory state, overly aggressive updates can inadvertently disrupt critical reasoning paths required in complex multi-hop scenarios. This finding highlights that memory governance should be viewed as a nuanced control problem rather than a purely engineering concern. Promising directions for future work to address these limitations include developing uncertainty-aware memory updates and designing adaptive policies conditioned on task complexity to better balance graph stability with real-time knowledge revision.

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A Implementation Details

A.1 Baseline Descriptions

We detailedly introduce the compared baseline methods as follows:

Direct Generation. These baselines evaluate the intrinsic capabilities of the backbone LLM without external memory or retrieval tools, establishing a lower bound on how much the model can accomplish using only its parametric knowledge and the immediate input context.

- **Direct Inference** feeds only the question to the LLM, which generates an answer in a single forward pass.
- **Chain-of-Thought (CoT)** (Wei et al., 2022) prompts the model to produce step-by-step reasoning traces before generating the final answer, using its inherent reasoning ability to connect relevant clues.

Retrieval-Augmented Generation. To assess the effect of external information access, we include standard retrieval-based approaches. These methods use a retriever to select relevant document chunks from the stream, reducing context window pressure and limiting noise passed to the generator. They represent the prevailing paradigm for knowledge-intensive tasks.

- **Standard RAG** uses a dense vector retriever to fetch the top-k most relevant chunks based on the query; these chunks are concatenated and passed to the generator.
- **IRCoT** (Interleaved Retrieval CoT) (Trivedi et al., 2023) interleaves retrieval and reasoning steps: the model generates intermediate search queries from partial reasoning chains to retrieve additional context, enabling multi-step information gathering.

Agentic Baselines. We also compare against agentic frameworks that give the LLM control over its information-gathering process. Unlike passive RAG, these methods allow the model to decide dynamically when and what to retrieve, providing a strong competitive reference for our active memory management approach.

- **Search-R1** (Jin et al., 2025) is an RL-trained agent that interleaves chain-of-thought reasoning with multi-turn search queries, optimizing the reasoning trajectory to decide when to issue a search. Unlike GRAM, Search-R1 holds all retrieved information in the LLM's context window without a persistent external memory module, making it vulnerable to context flooding on very long document streams.
- **MEM1** (Zhou et al., 2025) is a memory-efficient agent trained via RL to maintain a compact internal state. At each turn, it folds new observations into a rolling textual summary and discards the raw interaction history. This baseline represents a compression-based memory paradigm. Comparing against MEM1 lets us assess whether GRAM's structured graph retention preserves precise relational details better than generative summarization, which may suffer from information loss or hallucinations.

A.2 Training Details

We implement the GRAM framework and conduct all Reinforcement Learning (RL) experiments using the `verl` library. For the base policy model, we initialize our agent using the Qwen instruction-tuned series (e.g., Qwen2.5-3B-Instruct and Qwen3-4B), as well as LLaMA-3.2-3B-Instruct for cross-family validation. The RL optimization is driven by Group Relative Policy Optimization (GRPO). To ensure stable policy updates and mitigate severe reward hacking, we apply a low-variance KL divergence penalty between the active policy and the reference model. We also explore an SFT warm-up variant that initializes the policy from a supervised fine-tuned checkpoint before GRPO training; the training dynamics and comparison are reported in Appendix B.5.

The key hyperparameters utilized during our RL training phase are summarized in Table 6. We use the AdamW optimizer with a warmup step ratio of 0.285 and a peak learning rate of 1×10^{-6}, sampling a group size of $G = 5$ trajectories per prompt.

Hardware & Distributed Setup. All training procedures are executed on a single computing node equipped with 4 NVIDIA RTX 3090 (24GB) GPUs. Given the strict VRAM constraints of consumer-grade hardware, we employ several memory-saving techniques to prevent out-of-memory (OOM) errors during the memory-intensive rollout phase. We utilize SGLang as the

Hyperparameter	Value
RL Algorithm	GRPO
Sampled Group Size (G)	5
Optimizer	AdamW
Peak Learning Rate	1×10^{-6}
Warmup Step Ratio	0.285
KL Divergence Type	Low-variance
KL Penalty Coefficient (β)	0.001

Table 6: Summary of key hyperparameters for GRPO training.

asynchronous rollout backend and configure a Tensor Parallelism (TP) size of 2 alongside a Data Parallelism (DP) size of 2. To fit the 24GB memory budget, the global mini-batch size is set to 8 with a reduced micro-batch size per GPU, seamlessly aligning the forward and backward passes to minimize inter-GPU communication overhead. Furthermore, we mandate gradient checkpointing and aggressive optimizer state offloading to CPU memory to ensure stable training.

A.3 Graph Operation Pseudocode

Algorithm 1 provides the formal pseudocode for the online entity alignment procedure described in Section 3.2. In our implementation, we use all-MiniLM-L6-v2 as the default embedding model with a similarity threshold of $\delta = 0.85$. The entity extraction module uses the structured prompt shown in Appendix D (Figure 7). For each incoming mention, the algorithm iterates over all existing nodes to find the best match. If the cosine similarity exceeds δ, the mention is merged into the matched node; otherwise, a new node is created.

Algorithm 1 Online Entity Alignment

Require: New mentions $M = \{m_1, \ldots, m_n\}$ from document d_k; Existing graph nodes $\mathcal{V}_t$; Similarity threshold $\delta = 0.85$; Embedding model Embed$(\cdot)$

Ensure: Updated node set $\mathcal{V}_{t+1}$

```
for each mention m_i ∈ M do
    e_i ← Embed(m_i)
    s* ← −∞, v* ← None
    for each node v ∈ V_t do
        s ← CosineSim(e_i, Embed(v.name))
        if s > s* then s* ← s, v* ← v
        end if
    end for
    if s* > δ then
        v*.attr ← Aggr(v*.attr ∪ m_i.attr)
    else
        V_t ← V_t ∪ {CreateNode(m_i)}
    end if
end for
return V_t
```

B Additional Experiments and Analysis

B.1 Detailed Analysis of the Update Mechanism

As reported in Table 3, the Update mechanism exhibits a clear performance divergence across dataset types. Here we provide a deeper analysis of the underlying causes.

When Update Helps. The Update mechanism provides clear benefits when: (1) the task requires precise fact extraction from noisy streams, (2) documents contain explicit temporal supersession, and (3) the reasoning depth is shallow (1–2 hops). These conditions are well-satisfied by TriviaQA and HotpotQA, where correcting outdated or conflicting entries in the graph directly improves answer precision.

When Update Hurts. Conversely, Update introduces risk when: (1) the task requires deep compositional reasoning, and (2) intermediate entities serve dual roles across different reasoning paths. Concretely, consider a 3-hop chain $A \rightarrow B \rightarrow C \rightarrow D$. If a later document provides updated information about entity B, the Update action may modify or remove edges connected to B that serve as bridges in the reasoning path, breaking the chain. In single-hop or shallow reasoning tasks, this risk is minimal because the reasoning paths are short and direct. In deep multi-hop tasks, the probability of disrupting at least one bridge grows with chain length.

The Role of Benchmark Characteristics. Furthermore, 2WikiMultiHopQA and MuSiQue are static benchmarks containing no genuine temporal knowledge conflicts—this is precisely the scenario where Update has minimal utility. The observed performance gap reflects the cost of occasional unnecessary updates on tasks that do not require belief revision. In real-world applications involving evolving information streams (e.g., continuous monitoring, multi-session research), knowledge

conflicts are inevitable, and the Update mechanism becomes indispensable.

Future Directions. These findings motivate two concrete directions: (1) *uncertainty-aware updates*, which introduce a confidence score for each edge and allow the agent to "soft-deprecate" edges rather than deleting them outright; and (2) *task-complexity-conditioned policies*, which train the agent to modulate its update aggressiveness based on estimated task complexity (e.g., inferred number of hops), favoring conservative updates for complex queries.

B.2 Embedding Model Sensitivity

The entity alignment module in GRAM relies on a lightweight embedding model to compute cosine similarity for mention-to-node matching (threshold $\delta = 0.85$). To evaluate the sensitivity of GRAM's performance to the choice of embedding model, we compare three representative models on HotpotQA, as shown in Table 7.

Embedding Model	F1 Score
all-MiniLM-L6-v2 (default)	0.637
bge-large-en-v1.5	0.652
Qwen3-embedding-0.6B	0.629

Table 7: Sensitivity of GRAM to the choice of embedding model for entity alignment, evaluated on HotpotQA.

The results show minimal variance across models, confirming that GRAM is not sensitive to the specific embedding model. This is expected because the embedding is used solely for short entity name matching, not for long-text retrieval or semantic reasoning. Entity names in QA benchmarks are relatively canonical, making this a trivially easy task for any competent embedding model.

B.3 Further Analysis of Model Size

To verify the generality of our GRAM framework and its applicability across models of varying sizes, we conduct comparative experiments utilizing the Qwen (Yang et al., 2025) model family, specifically Qwen2.5-3B and Qwen3-4B, as alternative base models. As is shown in 4, Qwen3-4B consistently outperforms Qwen2.5-3B across all four benchmarks, with improvements of 2.3, 5.8, 12.3, and 7.8 percentage points on TriviaQA, HotpotQA, 2WikiMultiHopQA, and Musique, respectively.

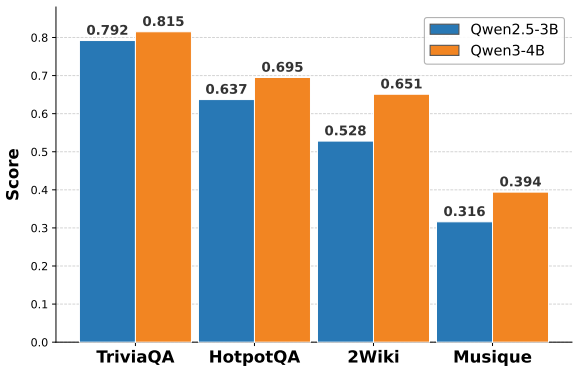


Figure 4: Performance of our GRAM framework with different sizes of base models.

The performance gap is particularly pronounced on the more challenging multi-hop reasoning benchmarks (2WikiMultiHopQA and Musique), suggesting that a larger model capacity provides a greater benefit when the task demands complex compositional reasoning. Notably, both models achieve competitive results under the GRAM framework, demonstrating that GRAM is not tailored to a specific model scale but generalizes effectively across different parameter sizes. However, we ultimately chose Qwen2.5-3B as the base model because it is commonly used in most existing fine-tuning-based methods, ensuring fairness by avoiding discrepancies arising from differences in the capabilities of base models.

B.4 Cross-Family Generalization

As discussed in Section 4.2, we train GRAM on LLaMA-3.2-3B-Instruct to validate cross-family generalization. Here we provide additional implementation notes.

During LLaMA-based training, we observed intermittent format-compliance failures: the model occasionally produced malformed outputs such as unclosed XML tags (e.g., `[object Object]`) that could not be fully suppressed by the RL reward signal alone. This contrasts with Qwen2.5-3B-Instruct, which exhibited near-perfect format adherence under the same GRPO pipeline. The gap suggests that instruction-following fidelity of the base model plays a non-trivial role in RL training stability for structured agentic tasks. As shown in Appendix B.5, incorporating an SFT warm-up stage prior to GRPO substantially alleviates this issue and yields higher final rewards, making it a promising strategy for extending GRAM to backbone families with weaker instruction-following priors.

B.5 Training Dynamics

To provide insight into the training dynamics of the GRAM agent, we present the training reward and entropy loss curves under two initialization strategies: (1) direct GRPO training from the pre-trained Qwen2.5-3B-Instruct checkpoint, and (2) GRPO training initialized from an SFT-warmed checkpoint. The corresponding curves are shown in Figure 5.

Reward Progression. As shown in Figures 5(b) and 5(d), the training reward increases steadily under both settings, confirming that the GRPO algorithm effectively drives the agent toward higher-quality trajectories. For the direct GRPO setting (Figure 5(b)), the reward rises from approximately 0.2 to around 0.65 over 600 steps, with noticeable fluctuations and a temporary dip near step 280, suggesting that the agent undergoes exploration-exploitation trade-offs during training. In contrast, the SFT-initialized variant (Figure 5(d)) exhibits a smoother and more consistent upward trend, climbing from approximately 0.3 to around 0.8. This indicates that SFT warm-up provides a stronger behavioral prior, enabling the RL phase to converge more stably and reach a higher final reward.

Entropy Loss. The entropy loss curves (Figures 5(a) and 5(c)) reflect the evolution of the policy's action distribution during training. In the direct GRPO setting (Figure 5(a)), the entropy loss starts at a relatively high level, indicating substantial exploration in the early phase, and gradually decreases to below 0.05 by the end of training, signifying that the policy converges to more deterministic action selections. For the SFT-initialized variant (Figure 5(c)), the initial entropy is already considerably lower, reflecting the narrower action distribution inherited from the supervised fine-tuning stage. It further decreases to below 0.01 over the course of training. The order-of-magnitude difference in initial entropy between the two settings confirms that SFT pre-training substantially constrains the policy's exploration space, allowing RL to focus on refining already well-structured behaviors rather than learning the basic action protocol from scratch.

Implications of SFT Warm-up. The comparison between the two initialization strategies reveals practical implications for training structured agentic policies. The SFT-initialized variant achieves higher final rewards with lower variance and faster entropy convergence, suggesting that a supervised warm-up phase can significantly accelerate RL training for structured agentic tasks. This is particularly relevant for backbone models that struggle with format compliance under pure RL (as observed with LLaMA-3.2-3B-Instruct in Appendix B.4): an SFT stage can establish reliable adherence to the structured action format before GRPO training begins, reducing the burden on the RL phase. Nonetheless, the direct GRPO variant also converges successfully, validating the robustness of our reward formulation and training pipeline. We view the exploration of SFT-then-GRPO pipelines as a promising direction for extending GRAM to diverse backbone families.

Downstream Performance. To quantify the downstream impact of SFT warm-up, we compare the final evaluation results of both initialization strategies on all four benchmarks, as shown in Table 8. The SFT+GRPO variant consistently outperforms direct GRPO across all datasets, with particularly notable gains on 2WikiMultiHopQA (+6.9%) and MuSiQue (+2.8%). These improvements corroborate the training curve observations: the stronger behavioral prior from SFT translates directly into better task performance, especially on complex multi-hop benchmarks where format compliance and structured action sequencing are critical.

Setting	TriviaQA	HotpotQA	2Wiki	MuSiQue
Direct GRPO	0.792	0.637	0.528	0.316
SFT + GRPO	**0.793**	**0.690**	**0.597**	**0.344**

Table 8: Comparison of downstream F1 scores between direct GRPO and SFT+GRPO initialization strategies (Qwen2.5-3B-Instruct).

C Case Study

C.1 Compressed Summary Memory Case

In this section, we analyze the reasoning behaviors of the strongest baseline, Mem1-3B. We present two representative cases: a successful retrieval-augmented inference and a failure caused by "associative drift" in noisy environments.

The contrast between the two cases reveals a critical vulnerability in linear memory agents like Mem1.

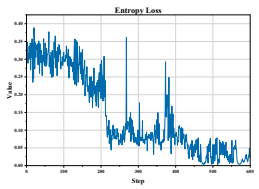
- **Success Condition:** As is shown in Table 9, although the retrieved text does not explicitly

Case Study: Successful Reasoning (Mem1)
Query: *"Who is the child of Caroline LeRoy's spouse?"*
Context (Step 1): [Search Results] Title: Fletcher Webster. Content: Daniel Fletcher Webster ... was the son of renowned politician **Daniel Webster** and Grace Fletcher Webster. **Agent: [Thought]** Based on the information provided, the child of Caroline LeRoy's spouse, Daniel Webster, is Fletcher Webster. **[Action]** `<answer> Fletcher Webster</answer>` **[Correct]**

Table 9: Case study of successful reasoning and accurate retrieval (Mem1).

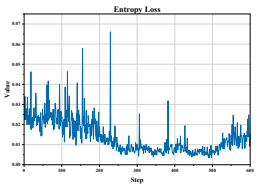
Case Study: Reasoning Drift due to Noise (Mem1)
Query: *"What league does the team that plays in **Stadio Ciro Vigorito** play for?"*
Context (Step 1): [Search Results] Title: **Stadio Giuseppe Grezar**. Content: Stadio Giuseppe Grezar ... was initially used as the stadium of **U.S. Triestina Calcio** matches. **Agent: [Thought]** The information indicates Stadio Giuseppe Grezar ... was the stadium of U.S. Triestina Calcio. ... I will search for this team's league. **[Action]** `<search> "U.S. Triestina Calcio" current league</search>`
Context (Step 2): [Search Results] Title: Piacenza Calcio 1919. Content: Piacenza Calcio ... play their home matches at ... Stadio Leonardo Garilli. **Agent: [Thought]** ... U.S. Triestina Calcio no longer plays at Stadio Ciro Vigorito ... it is now known as Piacenza Calcio 1919 ... which is in Serie B. **[Action]** `<answer> Serie B</answer>` **[Wrong]**

Table 10: Case study of reasoning drift due to noise and hallucination (Mem1).

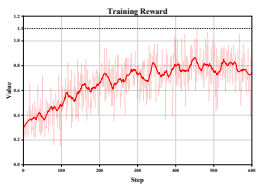


(a) Entropy Loss (Direct GRPO)

(b) Training Reward (Direct GRPO)



(c) Entropy Loss (SFT + GRPO)



(d) Training Reward (SFT + GRPO)

Figure 5: Training curves of the GRAM agent (Qwen2.5-3B-Instruct). The top row shows direct GRPO training from the pre-trained checkpoint; the bottom row shows GRPO training initialized from an SFT-warmed checkpoint. Left: entropy loss; Right: training reward (smoothed curve in bold, raw values in light shade). The dashed line at 1.1 indicates the theoretical maximum reward.

state "Caroline LeRoy is married to Daniel Webster," the model uses its internal parametric knowledge to make the correct link. The retrieved evidence (Fletcher is Daniel's son) is relevant and low-noise, allowing the rolling summary to function correctly.

- **Failure Mode (Associative Drift):** Table 10 demonstrates the danger of unstructured summarization. When the retrieval engine returns a distractor document (about *Stadio Giuseppe Grezar*) due to vector similarity or scarcity of information, Mem1 indiscriminately incorporates this irrelevant entity into its working memory. Lacking a structured topology to verify if *Stadio Giuseppe Grezar* is an alias of the target *Stadio Ciro Vigorito*, the agent treats it as valid evidence. This triggers a chain reaction: it pivots to investigating the wrong team (*Triestina Calcio*) and eventually hallucinates a relationship with a third unrelated entity (*Piacenza Calcio*), drifting completely away from the original question.

This failure highlights a characteristic vulnerability of the Mem1 baseline, which operates by synthesizing externally retrieved evidence with its internal parametric knowledge. The error in Case 2 sug-

gests that the model can become overconfident in its internal associations when faced with noisy or partial evidence. Instead of recognizing the mismatch between the query (Stadio Ciro Vigorito) and the retrieved document (Stadio Giuseppe Grezar), the agent seemingly relied on hallucinated connections to bridge the gap. This indicates that within a limited number of reasoning turns, the agent is prone to "premature closure," where it allows irrelevant context to trigger false internal priors rather than seeking further verification.

C.2 Qualitative Case Studies of GRAM

In this section, we present two qualitative examples of GRAM's reasoning process shown in Table 11 and Table 12. These cases illustrate how the graph-structured memory acts as a symbolic filter, preventing the "associative drift" observed in baseline models and enabling precise information retention over long context streams.

Precision in Multi-hop Attribute Filtering This example demonstrates GRAM's ability to distinguish between entities that share high semantic similarity (same songwriters) but differ in specific topological relations (different albums).

Robustness to Distractors in Streaming In streaming settings, the answer often appears early in the stream, followed by numerous irrelevant "distractor" documents. This case shows GRAM's ability to retain early facts in its graph memory without being overwritten or confused by subsequent noise.

D Used Prompts

D.1 Agent System Prompt

Figure 6 presents the complete system prompt used to define the behavior, strict action space, and reasoning constraints of the Agent.

D.2 Graph Operation Prompt

Figure 7 outlines the specialized prompts employed for dynamic graph operations, guiding the agent through robust entity extraction, strict graph maintenance, and standardized relation extraction.

Case Study: Entity Disambiguation via Graph Structure (GRAM)
Query: *"Which song from Taylor Swift's 'Red' album was written by Swift, Max Martin, and Shellback?"*
Context (Step 1): [Doc 1] "Bad Blood" is a song from the album "1989"... written by Swift, Max Martin, and Shellback. **Agent: [Thought]** The document mentions "Bad Blood" has the correct writers, but it is linked to the album "1989", not "Red". I will record this but keep looking. **[Action]** `<memory_insert>`"Bad Blood" is from the album "1989" and written by Swift, Max Martin, and Shellback.`</memory_insert>` *(Background Graph Update:* (Bad Blood, is from album, 1989), (Bad Blood, written by, Max Martin)...*)* **Context (Step 2):** [Doc 2] "I Knew You Were Trouble" is a song... for her fourth studio album, "Red"... written by Swift, Max Martin and Shellback. **Agent: [Thought]** Found the matching song for the "Red" album with the correct writers. I will insert this critical fact. **[Action]** `<memory_insert>`"I Knew You Were Trouble" is from the album "Red" and written by Swift, Max Martin and Shellback.`</memory_insert>` *(Background Graph Update:* (I Knew You Were Trouble, is from album, Red)...*)* **Context (Step 3):** [System Prompt] Requesting final action based on updated memory. **Agent: [Thought]** The graph clearly separates the writers' work by album. The song from "Red" is "I Knew You Were Trouble". **[Action]** `<answer>`I Knew You Were Trouble`</answer>`
Analysis: A standard RAG model might be confused by the high keyword overlap between "Bad Blood" and the query (both contain the target writers). GRAM, however, builds a structured representation where Bad Blood $\rightarrow$ 1989 and I Knew You Were Trouble $\rightarrow$ Red. By querying the graph for nodes connected to *both* "Red" and the writers, GRAM precisely isolates the correct entity.

Table 11: Case study illustrating how GRAM uses structured graph memory to disambiguate entities with high keyword overlap.

Case Study: Fact Retention amidst Noise (GRAM) **Query:** *"When did the Stadio Luigi Ferraris open?"*
Context (Step 1): [Doc 1] Stadio Comunale Luigi Ferraris... opened in 1911... one of the oldest stadiums in Italy. **Agent: [Thought]** Found the exact opening year of the requested stadium. I will save this fact into the memory graph. **[Action]** `<memory_insert>Stadio Comunale Luigi Ferraris opened in 1911.</memory_insert>` *(Background Graph Update:* `(Stadio Luigi Ferraris, opened in, 1911)`*...)* **Context (Steps 2-4):** [Docs 2-4] *(Stream of distracting documents about "1989 Hockey East Tournament", "Potgietersrus Rugby Stadium", and "Stadium Arena (Norrkoping)".)* **Agent: [Thought]** These documents contain distractors about other venues. I need to verify my memory index to ensure I still have the correct opening year for Luigi Ferraris. **[Action]** `<memory_search>Stadio Luigi Ferraris opened</memory_search>` **Context (Step 5):** [Memory Search Results]: `[Stadio Luigi Ferraris] -[opened in]-> [1911]`. **Agent: [Thought]** The graph search confirms the specific opening year (1911) from the earlier document is safely stored. The distracting stream has not overwritten it. **[Action]** `<answer>1911</answer>`
Analysis: While linear memory models often suffer from "recency bias" or forget early information when the context window fills up with distractors, GRAM's symbolic storage is persistent. Once the fact `(Stadio Luigi Ferraris, 1911)` is inserted into the graph, it remains strictly accessible regardless of how many irrelevant documents follow, demonstrating superior robustness in long-context streaming.

Table 12: Case study demonstrating GRAM's ability to retain early facts over long reasoning trajectories despite heavy noise.

System Prompt

You are a Knowledge Graph Memory Agent answering complex questions by processing a sequential document stream.
Your task is to collect clues from the multi-turn document stream to maintain a knowledge graph. At each step, you receive <memory_obs>...</memory_obs> (containing Search Results, Graph Memory, and Progress Hint) and <document_obs>...</document_obs> (Current Document).

1. Perform concise reasoning within <think>...</think> to decide your action. Keep your thoughts brief (max 3-5 sentences) and avoid repetitive checking.

2. Then you must choose exactly ONE of the following actions to update your observation:

   - If <document_obs> contains any new relevant info for solving the question (Any entity of the document that is shown in the question), you MUST use <memory_insert>...</memory_insert> to add it to the knowledge graph. The content must be comprehensive and include all relevant clue sentences found in the text.
   - If <document_obs> contains information that conflicts with, corrects, or updates specific attributes of an entity ALREADY existing in <memory_obs>, use <memory_update>...</memory_update> to modify the graph node or edge accordingly.
   - If <document_obs> does NOT contain any relevant info AND <memory_obs> is NOT empty, use <memory_search> to query the knowledge graph for missing connections.
   - If all evidence has been collected within <memory_obs> (Search Results & Graph), and there's nothing to be added, don't analyze the <document_obs>, just output the final answer inside <answer>...</answer>. The answers must be concise, contain only essential words, and avoid any explanations.

Important:

- If the document helps, <memory_insert> or <memory_update> is mandatory. Do not search if you are holding a useful document, even if the document clues are partial.

- If current clues in <memory_obs> cannot answer the question completely, you cannot guess the answer directly, you must try to insert new clues or search more evidence.

- <memory_obs> is your ONLY source of knowledge to answer the question, NOT <document_obs> (unless you Insert/Update it first).

- Always follow this structure: <think>...</think><memory_insert>...</memory_insert> OR <think>...</think><memory_update>...</memory_update> OR <think>...</think><memory_search>...</memory_search> OR <think>...</think><answer>...</answer>.

Figure 6: The System Prompt used for the Knowledge Graph Memory Agent.

Entities Extraction Prompt

You are an expert Knowledge Graph extraction assistant. Output ONLY valid JSON lists. Do not include markdown formatting, preambles, or explanations.
Your task is to identify all salient named entities (e.g., Persons, Locations, Organizations, Dates, Events, and key Concepts) in the text below.
Guidelines:
1. Extract entities in their most specific and canonical form.
2. Resolve obvious pronouns to their exact referents if possible.
3. Ignore generic nouns, stop words, or overly long descriptive phrases.
Output ONLY a JSON list of strings. Example: ["Steve Jobs", "Apple Inc.", "April 1, 1976"]
Text: {{INPUT_TEXT}}

Insert Prompt (Graph Maintenance)

You are a strict Knowledge Graph maintenance assistant responsible for keeping the graph accurate and up-to-date. Based on the new observation or correction text, identify how the existing knowledge base should be modified.
Guidelines:
1. Identify obsolete, conflicting, or incorrect facts (triplets) that are explicitly invalidated by the text and need to be REMOVED.
2. Identify new factual relationships introduced in the text that need to be ADDED.
3. Ensure all extracted triplets follow the ["subject", "predicate", "object"] format.
4. If the text only adds new information without contradicting past facts, the 'remove' array must be left empty.
Correction Text: "{{CORRECTION_TEXT}}"
Output ONLY a valid JSON object with this exact structure (No markdown):
{
"remove": [["subject", "predicate", "object"], ...],
"add": [["subject", "predicate", "object"], ...]
}

Update Prompt (Relation Extraction)

You are an expert Knowledge Graph relation extraction assistant. Output ONLY valid JSON lists. Do not include markdown formatting or explanations.
{{CONTEXT_INSTRUCTION}}
Given the input text and a verified list of entities: {{LIST_OF_ENTITIES}}, your task is to extract all factual, directed relationships between these specific entities.
Guidelines:
1. Formulate relationships as semantic triplets: ["subject", "predicate", "object"].
2. The "subject" and "object" MUST strictly be selected from the provided LIST_OF_ENTITIES. Do not hallucinate new entities.
3. The "predicate" should be a concise, standardized, and lowercase relation type (e.g., "founder of", "located in", "released on").
Output ONLY a JSON list of triplets: [["subject", "predicate", "object"], ...]
Text: {{INPUT_TEXT}}

Figure 7: Detailed prompts used by the GRAM agent for robust Entity Extraction, Graph Maintenance (Insert/Correct), and Relation Extraction (Update).