

AgentLongBench: A Controllable Long Benchmark For Long-Contexts Agents via Environment Rollouts

Shicheng Fang^{1,2} Yuxin Wang¹ XiaoRan Liu^{1,2} Jiahao Lu^{1,2}
Chuanyuan Tan³ Xinchi Chen¹ Yining Zheng^{1,†} Xuanjing Huang¹
Xipeng Qiu^{1,2,†}

¹Fudan University ²Shanghai Innovation Institute ³Soochow University

Abstract

The evolution of Large Language Models (LLMs) into autonomous agents necessitates the management of extensive, dynamic contexts. Current benchmarks, however, remain largely static, relying on passive retrieval tasks that fail to simulate the complexities of agent-environment interaction, such as non-linear reasoning and iterative feedback. To address this, we introduce **AgentLongBench**, which evaluates agents through simulated environment rollouts based on Lateral Thinking Puzzles. This framework generates rigorous interaction trajectories across knowledge-intensive and knowledge-free scenarios. Experiments with state-of-the-art models and memory systems (32K to 4M tokens) expose a critical weakness: while adept at static retrieval, agents struggle with the dynamic information synthesis essential for workflows. Our analysis indicates that this degradation is driven by the minimum number of tokens required to resolve a query. This factor explains why the high information density inherent in massive tool responses poses a significantly greater challenge than the memory fragmentation typical of long-turn dialogues.

Correspondence: scfang25@m.fudan.edu.cn, ynzheng@fudan.edu.cn, xpqiu@fudan.edu.cn

Repository: <https://github.com/euReKa025/AgentLongBench>

Benchmark: <https://huggingface.co/datasets/ign1s/AgentLongBench>

1 Introduction

The rapid evolution of Large Language Models (LLMs) from static chatbots to autonomous agents demands capabilities that extend far beyond simple conversation. Agents must synthesize vast amounts of historical information to execute complex workflows; failure to do so leads to fragmented reasoning, hallucinations, and planning errors. Although the community has actively expanded context windows and developed retrieval-augmented architectures, evaluation frameworks remain disproportionately focused on passive reading comprehension.

Prevalent benchmarks still prioritize static retrieval, often asking models to locate isolated facts within artificially concatenated documents. This paradigm misses the core of agentic behavior. Real-world problem solving involves dynamic tool usage and non-linear reasoning, creating a context that evolves based on the agent's own decisions. Unlike the static User-AI dialogues found in current datasets, autonomous opera-

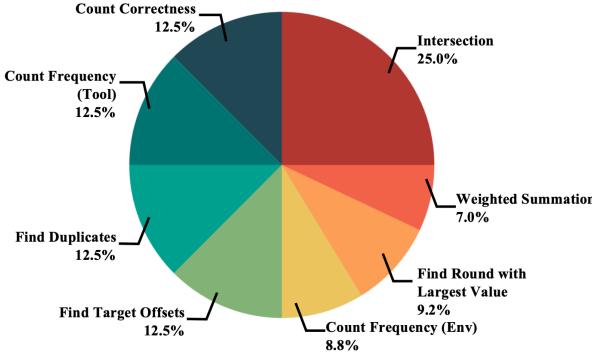


Figure 1 The distribution of distinct question types under the *Knowledge-Intensive* setting with *Concise-Response* formatting in our dataset.

tions generate unique AI-Environment trajectories. These scenarios demand active state tracking through iterative feedback loops, a challenge that fixed, human-authored texts fail to capture.

	Max Length	Evolving Context	Knowledge-Free	Det. Ground Truth	State Tracking	Tool Use Logs	Controllability
NeedleBench[37]	128K		✓	✓	✗	✗	✗
BABILong[34]	10M	✗	✗	✓	✗	✗	✗
LV-Eval[77]	256K	✗	✗	✗	✗	✗	✗
RULER[25]	128K	✗	✓	✓	✓	✗	✓
L-Eval[4]	200K	✗	✗	✗	✗	✗	✗
Michelangelo[58]	128K	✓	✓	✓	✓	✗	✓
Loong[63]	250K	✗	✗	✗	✗	✗	✗
BAMBOO[15]	16K	✗	✗	✓	✗	✗	✗
∞-Bench[78]	200K	✗	✗	✓	✓	✗	✗
LooGLE[36]	80K	✗	✗	✗	✗	✗	✗
NoCha[31]	336K	✗	✗	✓	✗	✗	✗
LongBenchV2[7]	128K	✗	✗	✓	✗	✗	✗
MRCR(OpenAI)[49]	1M	✗	✗	✓	✗	✗	✗
NoLiMa[48]	32K	✗	✗	✓	✗	✗	✗
HELMET[74]	128K	✗	✗	✗	✗	✗	✗
LIFBENCH[65]	128K	✗	✓	✓	✗	✗	✗
LongBioBench[72]	128K	✗	✗	✓	✗	✗	✓
LooGLE V2[23]	2M	✓	✗	✓	✓	✗	✗
LocoMo[47]	16K	✓	✗	✓	✓	✗	✗
LongMemEval[24]	2M	✗	✗	✗	✓	✗	✗
MemoryAgentBench[26]	2M	✗	✗	✓	✓	✗	✗
AgentLongBench (ours)	∞ (4M)	✓	✓	✓	✓	✓	✓

Table 1 Comparison of long-context benchmarks. Our published dataset ends at 4M.

We introduce **AgentLongBench** to evaluate agents through rigorous environment rollouts. True agentic capabilities emerge within evolving contexts that mirror the causality of real-world workflows, rather than in static reading comprehension tasks. Consequently, our setting forces agents to parse high-density, machine-generated tool logs instead of natural text distractors, requiring precise state tracking to manage dynamic information updates. To guarantee validity, we rely on deterministic ground truth derived from the environment’s logic and incorporate a Knowledge-Free setting to eliminate parametric memory bias. Furthermore, the framework emphasizes controllability and extensibility [72] to facilitate fine-grained diagnosis of failure modes. The benchmark comprises 8 tasks in each setting. Figure 1 illustrates the representative task distribution, and we provide full statistics for all settings in Appendix B. Table 1 contrasts our approach with prior benchmarks, highlighting how AgentLongBench uniquely targets the requirements of autonomous operation. A comprehensive review of these related works is available in Appendix 5.

In summary, the main contributions of our work are as follows:

- We introduce **AgentLongBench**, a controllable benchmark built on simulated environment rollouts

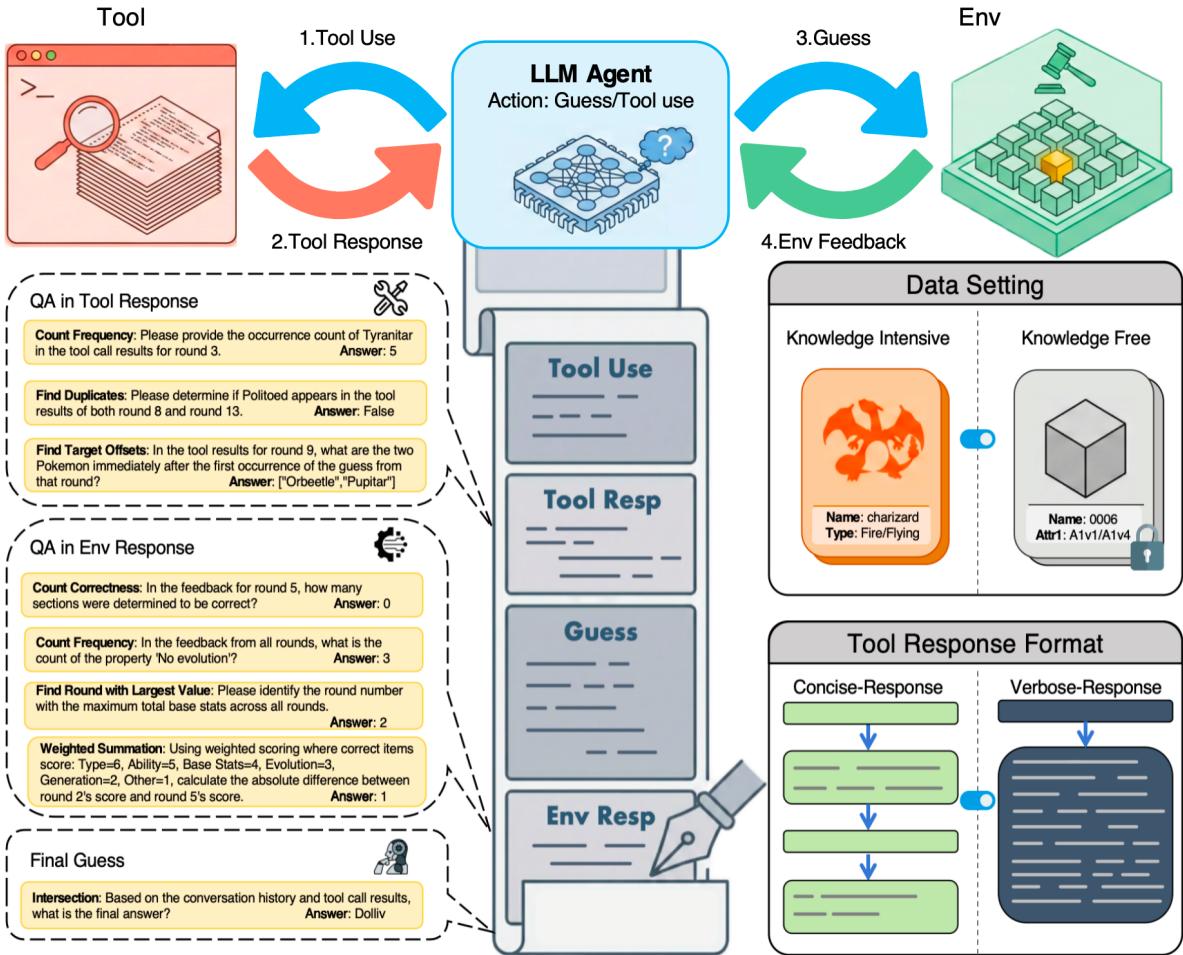


Figure 2 Overview of the Data Construction Pipeline for AgentLongBench. The dataset is constructed by simulating Environment Rollouts (Top), which capture the iterative interaction logs between an LLM agent, tools, and environmental feedback. These trajectories are then used to derive three categories of QA tasks (Left): QA in Tool Response, QA in Environment Response, and Final Guess. The construction process incorporates two data settings (Right Top) to distinguish between *Knowledge-Intensive* and *Knowledge-Free* scenarios, and two tool response formats (Right Bottom)—*Concise* vs. *Verbose*—to simulate different context densities and noise levels.

that generates dynamic interaction trajectories for evaluating long-horizon consistency and planning.

- We propose a comprehensive evaluation taxonomy with **32 distinct question types**, spanning 2 settings, 2 interaction formats, and 8 tasks, and covering context lengths **from 32K to 4M tokens**, with 800 samples in each length.
- Through extensive evaluations on state-of-the-art LLMs and memory frameworks, we reveal fundamental failure modes in long-horizon agentic reasoning: (i) a strong reliance on parametric knowledge in Knowledge-Free settings; (ii) a trade-off between long-turn interaction trajectories and dense single-turn outputs; and (iii) a substantially higher reasoning burden for high-density tool logs, captured by the notion of a minimum token requirement.

2 AgentLongBench

AgentLongBench shifts the evaluation paradigm from static text processing to dynamic interaction through simulated environment rollouts, with an overview shown in Figure 2. Instead of relying on concatenated documents, this framework captures the continuous exchange between an agent and a reactive system. By simulating the temporal evolution of context, we preserve the causal dependencies inherent in real-world applications, which are often lost in static reading comprehension tasks.

The foundation of this framework is a Lateral Thinking Puzzle environment [2], selected for its rigorous demands on iterative inquiry and logical deduction. As the agent hypothesizes and receives feedback, the context expands procedurally based on the environment’s deterministic rules. This generation mechanism ensures that the resulting long-context trajectories are verifiable and logically consistent, avoiding the artifacts common in benchmarks constructed via arbitrary document insertion.

We structure the benchmark around two orthogonal dimensions, creating four distinct experimental configurations. To decouple reasoning skills from parametric memory, the first dimension contrasts Knowledge-Intensive with Knowledge-Free scenarios. Simultaneously, we examine the trade-off between temporal span and information density by varying the interaction format between Concise responses and Verbose responses. This cross-dimensional design ensures that performance degradation can be traced directly to either memory retention failures or information overload.

2.1 Lateral Thinking Puzzle Environment

The core testbed utilizes Lateral Thinking Puzzles, where agents must reconstruct a hidden state by satisfying a series of logical constraints. This iterative inquiry process contrasts sharply with static QA, serving as a rigorous proxy for the complex, investigative workflows typical of autonomous agents.

2.1.1 Puzzle Formulation

We formulate the puzzle as a target identification process under a closed-world assumption. The environment initializes a finite set of items, each defined by a unique vector of attributes ranging from categorical properties (e.g., Type, Abilities) to numerical statistics. One item is designated as the hidden target. In the Knowledge-Intensive setting, we instantiate this item set using the Pokémon[1] dataset (pre-July 2025), ensuring that no two items share identical attribute profiles. The agent operates as an investigator, engaging in a goal-oriented dialogue to bridge the information gap between its current belief state and the ground truth. The puzzle unfolds as the agent continuously queries the environment to isolate the target.

2.1.2 Environment Response

The environment functions as a deterministic oracle that holds the ground truth. To simulate rigorous agentic constraints, it parses natural language inquiries and returns precise feedback rather than open-ended narrative descriptions. Responses are typically limited to binary validation (Yes/No) or relational operators for numeric values. Crucially, upon an incorrect guess, the environment generates a comprehensive attribute-wise evaluation. It returns the full profile of the hypothesized item, explicitly annotating the relationship between each attribute and the ground truth—confirming categorical matches while providing directional constraints for numerical discrepancies. This feedback mechanism enforces strict state tracking, as the agent must update its history of valid constraints to iteratively narrow the search space.

2.1.3 Tool Response

Beyond direct interaction with the environment, the agent is equipped with auxiliary tools to aid in state refinement. The *Tool Response* represents the output from these external function calls. We provide two search tools corresponding to the two formatting strategies described in Section 2.3.2. The context generated here differs from the Environment Response; it often contains structured, noisy, or verbose text that the agent must parse, filter, and integrate into its working memory.

2.2 Data Construction

The dataset is constructed through automated environment rollouts governed by a rule-based simulation. The generation process begins with the random selection of an initial item to trigger the feedback loop. For subsequent rounds, we generate a sequence of [Tool use, Tool Response, Guess, Environment Response] for each interaction step. To achieve scalable context lengths, we parametrically adjust the granularity of puzzle constraints or sequentially chain related interaction sessions. This methodology ensures that the expanded context remains causally linked and logically coherent, avoiding the disjointed nature of random document concatenation.

2.3 Task Description

We decompose the evaluation into specific cognitive dimensions to pinpoint the mechanisms of agentic failure.

2.3.1 Two Settings

We differentiate the evaluation based on the semantic nature of the information processed. The **Knowledge-Intensive** setting constructs trajectories using real-world entities, instantiated here with the Pokémon dataset. Although the evaluation answers are theoretically derivable solely from the context history, the presence of familiar entities triggers the model’s parametric memory. This design mimics realistic domain-specific tasks where models may hallucinate based on prior knowledge—such as predicting a type based on a name rather than tool output—or conversely, benefit from domain familiarity.

To rigorously evaluate pure in-context reasoning, we employ a **Knowledge-Free** setting via fully symbolic masking. Unlike previous benchmarks that merely perform entity substitution (e.g., changing “Newton” to “John”) while retaining semantic structures, we map all entities and attributes to abstract tokens. Specifically, item names are mapped to IDs (e.g., Item_84), and attributes are mapped to abstract codes (e.g., Attr_1 with value A1V1). This approach eliminates semantic cues, forcing the model to rely exclusively on the logical constraints defined within the interaction history. This provides an unbiased measurement of state tracking and memory retention, free from the interference of pre-trained knowledge.

2.3.2 Two Formats

To investigate how information distribution impacts performance, we apply two distinct interaction formats. While both are controlled to maintain comparable total context lengths, they present fundamentally different challenges regarding information density.

The **Concise-Response** format prioritizes turns extension. Here, the tool returns only the pre-calculated intersection of candidate items that satisfy the queried attributes. To accumulate a total context length comparable to the Verbose format, this setting involves a massive number of interaction turns (e.g., hundreds of rounds). This design evaluates whether agents can maintain consistent state tracking over hundreds of rounds without losing early constraints.

Conversely, the **Verbose-Response** format tests the capacity to handle information overload. In this setting, tools return full, unfiltered candidate lists for each queried attribute. A query for three attributes results in three extensive lists, creating a trajectory with fewer turns but high-density blocks of structured text. The agent is thus forced to perform logical intersections internally and extract key information from massive, noisy inputs within a single step.

2.3.3 Task Taxonomy

To pinpoint the specific cognitive mechanisms behind agentic failures, we classify the eight tasks into three dimensions (visualized in Figure 2; see Appendix D for detailed definitions).

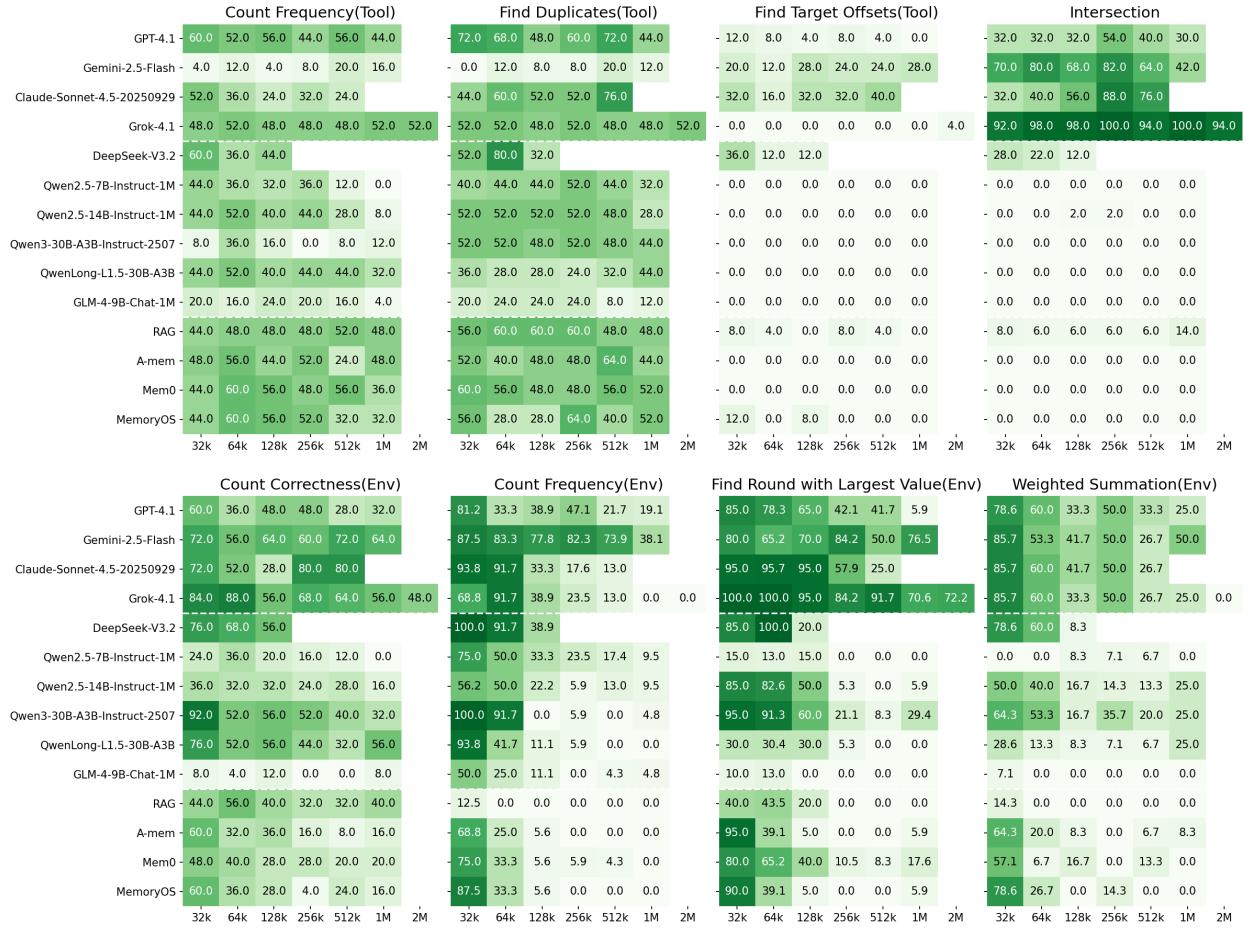


Figure 3 Main Results on Knowledge-Intensive & Concise-Response Setting. The heatmap visualizes model performance across varying context lengths (32K to 2M). Green indicates higher accuracy.

QA in Tool Response evaluates the robustness of parsing machine-generated logs. Tasks such as *Find Duplicates* measure the ability to extract precise details from structured noise, explicitly testing resilience against information overload.

QA in Environment Response targets the capacity to track evolving states and interpret historical feedback constraints, exemplified by the *Weighted Summation* task. This dimension assesses how well an agent maintains a coherent belief state across long, iterative interactions, isolating the impact of memory fragmentation.

Final Guess (Intersection) serves as the ultimate test of global understanding. It requires the agent to perform logical set operations across the entire context trajectory to deduce the target, thereby integrating retrieval with deductive reasoning.

This dimensional breakdown allows us to distinguish whether performance degradation stems from local retrieval errors, calculation deficits, or a fundamental breakdown in logical consistency.

3 Experiments

3.1 Implementations

We evaluate a diverse array of state-of-the-art Large Language Models (LLMs), encompassing both proprietary and open-weight systems. On the proprietary front, our analysis includes GPT-4.1 [49], Gemini-2.5-

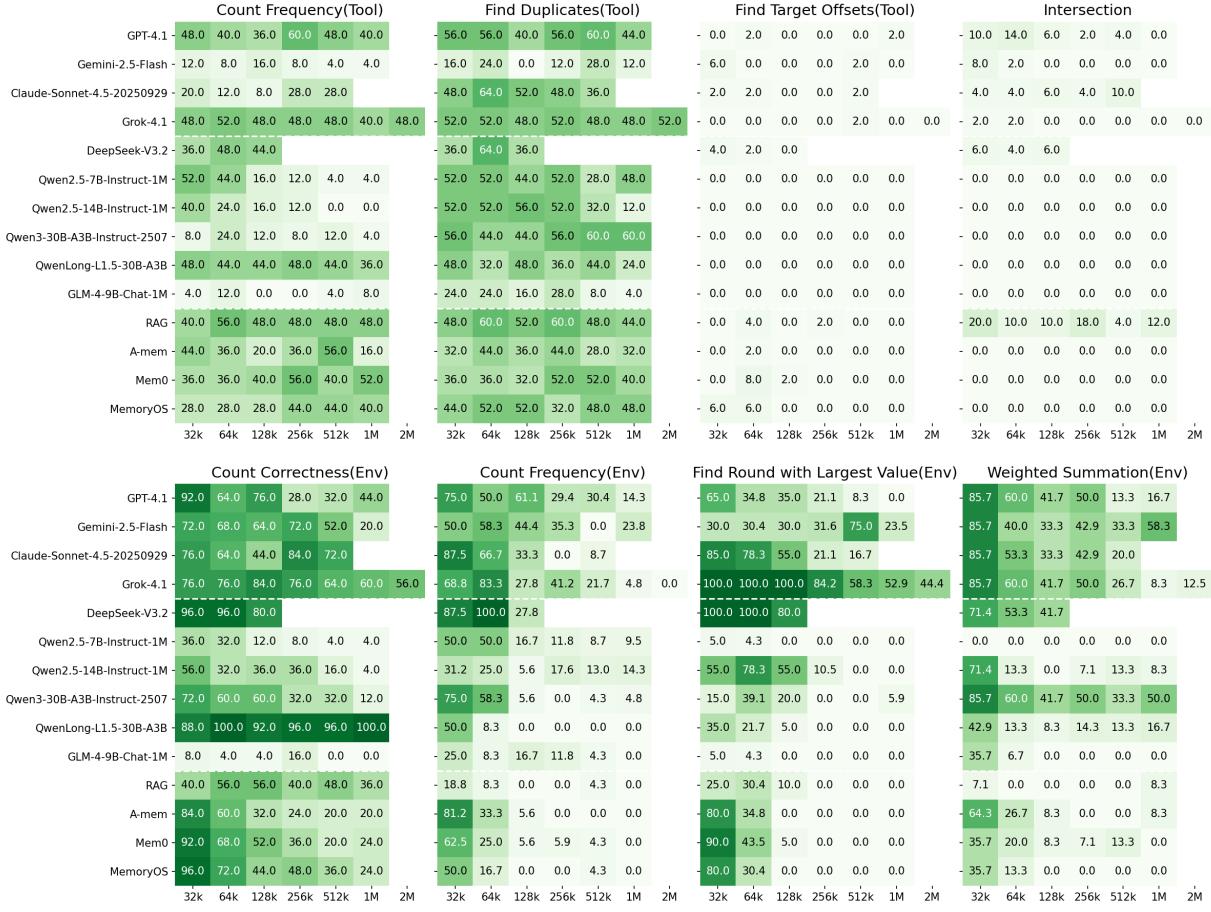


Figure 4 Main Results on Knowledge-Free & Concise-Response Setting.

Flash [12], Claude-Sonnet-4.5 [5], and Grok-4.1 [66]. These models are generally assessed at context lengths up to 1M tokens, with the exception of Grok-4.1, which is evaluated up to 2M tokens. For open-source models, we select representative long-context checkpoints, including DeepSeek-V3.2 [42], the Qwen series (specifically Qwen2.5-7/14B [71] and Qwen3-30B-A3B [70]), QwenLong-L1.5-30B-A3B [55], and GLM-4-9B-Chat-1M [18].

Beyond native long-context models, we also benchmark external memory architectures. We implement standard RAG [35] alongside specialized agentic memory systems such as A-Mem [68], Mem0 [11], and MemoryOS [30]. To control for reasoning variance and isolate the contribution of the memory mechanism, all such frameworks employ **Qwen3-30B-A3B-Instruct-2507** as a unified backbone. For reproducibility, we adhere to standard public configurations for these frameworks, with full implementation details provided in Appendix E.

3.2 Main Evaluation Results

Here, we present the performance heatmaps for all settings from Figures 3 to 6.

Model Performance across Context Lengths. Figure 7 reveals a distinct performance gap between proprietary frontiers and open-weight models (see Figures 3 and 4 for detailed heatmaps). Grok-4.1 demonstrates remarkable resilience, maintaining scores above 50.0 even as the context extends to 2M tokens. Conversely, while Gemini-2.5-Flash and GPT-4.1 display strong initial reasoning, their performance decays significantly beyond the 256k token threshold, dropping below 40.0 and 30.0 respectively at 1M tokens. Open-source

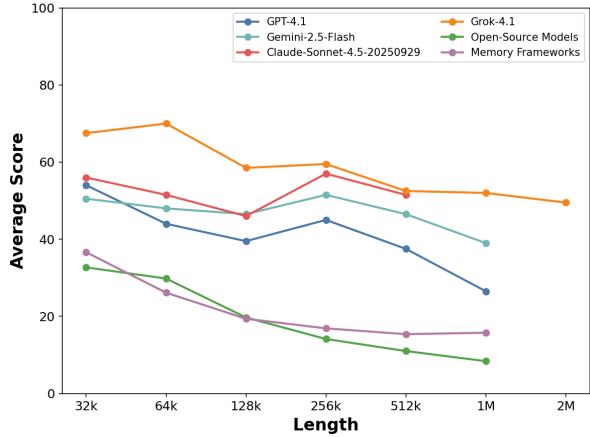


Figure 7 Average score trends across context lengths. Performance comparison of Proprietary models, aggregated Open-Source models, and Memory Frameworks.

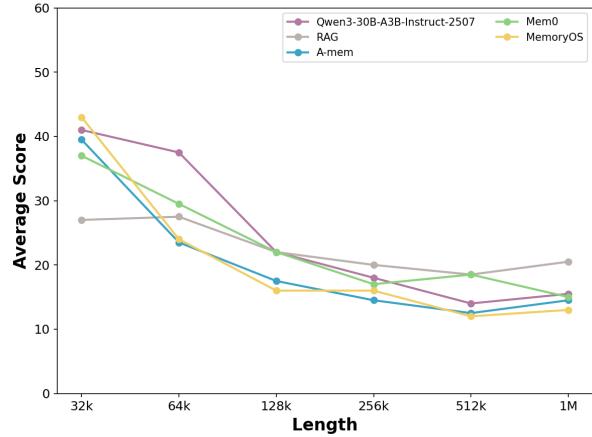


Figure 8 Comparison of Memory Frameworks vs. Base Model. Evaluation of RAG and specialized memory agents on the Qwen3-30B backbone.

long-horizon interaction.

4.2 Concise-Response vs. Verbose-Response

We analyze how the response format reshapes difficulty by comparing the *Concise-Response* setting (Figure 3) with the *Verbose-Response* setting (Figure 5). The key difference is not simply whether responses are “more informative,” but how information that is irrelevant to the queried target is distributed across an episode.

For tasks that query Environment Response (e.g., *Count Frequency (Env)*), the Verbose format often yields higher accuracy. This improvement does not come from richer tool outputs—the tool content is largely incidental for these queries. Instead, verbose responses reduce the number of interaction turns. Under the concise format, episodes become much longer, and the model must maintain the evolving state across many steps even though most tool-return tokens are not needed for answering. This makes long-horizon state tracking the dominant bottleneck, and performance degrades accordingly.

The trend reverses for tasks that query Tool Response (e.g., *Find Duplicates*). Here the tool-return content is the evidence. The Verbose format concentrates a large amount of machine-generated text into fewer turns, which increases the density of distractors and the cost of locating the relevant fields within a single response. In contrast, the Concise format spreads tool outputs across more turns, but each turn is smaller and easier to scan, which can make evidence localization and comparison more manageable for these tasks.

Overall, the two formats trade off where the difficulty lies: Concise increases episode length and long-range state maintenance, while Verbose increases within-turn density when the answer must be extracted from tool logs.

4.3 Environment Response vs. Tool Response and Adequate Context Length

Across all four settings, we observe a consistent gap between tasks that query Tool Response and those that query Environment Response. In Figure 3, tool-response tasks (top row) are uniformly harder than environment-response tasks (bottom row), even when the total context length is matched.

To account for this gap, we introduce **Adequate Context Length (ACL)**. ACL is a property of the input trajectory: it measures how many tokens a model must traverse to locate and assemble the evidence needed for a single query. Importantly, ACL is computed from the episode text alone and does not depend on model outputs or prediction correctness.

For environment-response tasks such as *Count Frequency (Env)*, models generally favor the Verbose format. This advantage stems from the experimental design rather than the content itself: Verbose trajectories inherently comprise significantly fewer interaction steps than their Concise counterparts. Crucially, since the answers to these tasks are derived solely from environmental feedback, the voluminous tool outputs in the Verbose format serve merely as distractors which do not aid reasoning. The results suggest that models find it easier to bypass this dense, irrelevant noise within a single turn than to maintain a coherent state across the hundreds of fragmented turns characteristic of the Concise format.

The pattern reverses for tasks that query tool logs, such as QA in Tool Response (e.g., *Find Duplicates*). Here, Verbose responses often hurt. Consolidating tool outputs into a single turn yields long, dense, machine-generated text where relevant fields are mixed with large amounts of irrelevant structure. This creates information overload: the model must extract and align specific values from the verbose block.

Table 2 quantifies this difference. Even with identical total context lengths, tool-response tasks impose a much larger ACL, which increases the difficulty of evidence localization and aggregation and is associated with substantially lower accuracy.

Format	Query target	ACL (tokens)	Acc.(128k)
Concise	Env response	2044.1	47.3%
	Tool response	3040.8	36.0%
Verbose	Env response	535.8	68.2%
	Tool response	11439.6	25.3%

Table 2 Performance and adequate context length. We report GPT-4.1 accuracy at a 128k context window. ACL is measured in tokens and computed from the input trajectory only, independent of model outputs. Within each format, tool-response queries have substantially larger ACL and lower accuracy than environment-response queries, consistent with the intuition that evidence localization becomes harder as the required span grows.

5 Related works

Benchmarks for Long Contexts. The evaluation of long-context LLMs has evolved from adapting traditional NLP tasks to designing complex, synthetic reasoning scenarios. However, the majority of these efforts focus on the static context with no close relation with one target, showing less reality in agent scenerios..

General Understanding and Retrieval. Initial benchmarks, such as [53, 54] and [6], established the foundation by aggregating datasets like NarrativeQA [33] and GovReport [27]. These were further standardized by suites like L-Eval [4] and LongBenchV2 [7] to assess general capabilities across varying lengths. A major focus has been strictly testing retrieval limits, popularized by the “Needle-In-A-Haystack” paradigm [29]. This approach has expanded into comprehensive suites like RULER [25] and NeedleBench [37], covering multi-needle retrieval [49, 52], citation evaluation [40, 74], and instruction following stability [65]. Recent studies have also utilized these setups to investigate phenomena like “Lost-In-the-Middle” [19, 44] and the impact of demonstration quality in long in-context learning [3, 8, 28, 38, 61].

Reasoning, Logic, and Domain Specifics. To evaluate deeper cognitive functions beyond passive retrieval, recent works have introduced tasks requiring logic, mathematics, and code understanding. ∞ -Bench [78] and BAMBOO [15] target complex reasoning across diverse domains, while others focus on repository-level code [43] and mathematical noise filtering [62]. A critical direction involves testing long-range dependencies and robustness. Benchmarks like LooGLE [23, 36] and BABILong [34] challenge models to trace multi-hop evidence or comprehend native long texts such as novels [60, 69, 73]. Concurrently, works like LV-Eval [77] and NoCha [31] probe model robustness against confounding facts. Other efforts emphasize data synthesis and controllability: Michelangelo [58] and HoloBench [46] test structure discernment, while Ada-LEval [59] and LongBioBench [72] utilize generated content to decouple reasoning from parametric memory. Loong [63] further pushes density by ensuring every document is crucial.

Agentic and Memory Evaluations. As LLMs evolve into agents, evaluating their ability to maintain history is critical. LocoMo [47] and LongMemEval [24] assess memory retention across long conversational histories, while MemoryAgentBench [26] reconstructs long benches and focuses on memory recall accuracy.

Long LLMs. Recent advancements in large language models have substantially extended their context window, with state-of-the-art models claiming to support up to 128K or even 2M tokens [5, 12, 20, 41, 49, 66]. Meanwhile, various efforts have been made to extend models’ context length and enhance their long-dependency capabilities. These include more efficient attention mechanisms [13, 67, 76], scalable training strategies such as test-time training and parameter-efficient fine-tuning [10, 57], and length-extrapolatable positional encodings [14, 51, 56]. Together, these innovations reduce computational overhead while preserving the model’s ability to retain distant information, thus enabling more effective reasoning over extended contexts.

RAG and Memory Systems. The concept of augmenting language models with external knowledge retrieval has gained significant traction. Early work on Dense Passage Retrieval (DPR) [32] demonstrated the effectiveness of dense vector representations, leading to the proposal of Retrieval-Augmented Generation (RAG) [35] and subsequent developments [17, 39]. To enhance retrieval quality, LightRAG [21] employs a dual-level system, while structure-based methods like GraphRAG [16] and others [9, 22, 45] utilize fine-grained entities or links. **Agentic Memory Agents** introduce an iterative, decision-driven framework. Unlike single-pass retrieval, these agents dynamically process queries through multiple reasoning cycles. Examples include MemGPT [50] and other recent systems [11, 30, 64, 68, 75, 79].

6 Conclusion

We introduced **AgentLongBench**, a long-context benchmark built around agent–environment interaction rather than static document retrieval. Using automated rollouts, AgentLongBench generates verifiable trajectories at scale and supports evaluation over extended horizons.

Experiments on frontier LLMs and memory-augmented agents reveal a sharp drop in accuracy as episodes grow longer and tool use becomes more involved. The failures are not explained by context length alone. Models often rely on parametric shortcuts when semantic cues are available, but struggle when they must track and update discrete states over many steps. They also degrade when the answer is embedded in dense tool logs, where extracting and aligning the relevant fields becomes difficult even at the same total context length. Overall, current RAG and memory mechanisms do not reliably support long-horizon state tracking and high-ACL evidence localization, suggesting that robust tool-grounded reasoning remains an open bottleneck for long-context agents.

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Appendix

Appendix Contents

A Ethics Statement	19
A.1 Scientific Artifacts	19
A.2 Budget	19
B Dataset Distributions and Statistics	19
B.1 Knowledge-Intensive Setting	19
B.2 Knowledge-Free Setting	19
C Trajectory Generation Details	22
C.1 Base Engine and Simulation Logic	22
C.2 Trajectory Variants: Concise vs. Verbose	22
C.3 Behavioral Control Parameters	22
C.4 Post-Processing and Task Construction	23
C.5 Knowledge-Free Adaptation	23
D Detailed Tasks Taxonomy	23
D.1 QA in Tool Response	23
D.2 QA in Environment Response	23
D.3 Final Guess	24
E Baselines and Implementation Details	24

A Ethics Statement

A.1 Scientific Artifacts

License: The following are the names of the licenses corresponding to the scientific artifacts we use.

- MIT: DeepSeek-V3.2, A-Mem
- Apache-2.0: LLMs from the Qwen series (Qwen2.5-7/14B-Instruct-1M, Qwen3-30B-A3B-Instruct-2507, QwenLong), Mem0, MemoryOS
- glm-4: GLM-4-9B-Chat-1M

Intention of Usage: Our use of existing artifacts is consistent with their intended use. As for the artifact we create (AgentLong), it is intended solely for research purposes such as the development of Long-Contexts Agents, and shall not be used for any other purposes, including commercial profit-making activities.

Documentation: For all LLMs we used, please refer to the corresponding model cards or technical reports. For all memory frameworks we used, they are designed for long-contexts agents and are theoretically applicable to any language.

A.2 Budget

In the experiment, the total cost incurred from API calls is about 15632.96 USD.

B Dataset Distributions and Statistics

In this section, we provide a detailed breakdown of the dataset distribution across different settings. We ensure a balanced evaluation by maintaining a consistent number of samples across varying context lengths. The following tables and figures illustrate the distribution of distinct question types for each of the four experimental configurations: *Knowledge-Intensive* vs. *Knowledge-Free*, and *Concise-Response* vs. *Verbose-Response*.

B.1 Knowledge-Intensive Setting

In the Knowledge-Intensive setting, tasks involve real-world entities (Pokémon). We visualize the proportion of question types for both formatting strategies in Figure 9 and Figure 10, allowing for a direct comparison between the two structures. Table 3 and Table 4 provide the exact sample counts per context length.

B.2 Knowledge-Free Setting

In the Knowledge-Free setting, all entities are masked with abstract tokens to eliminate parametric bias. Figure 11 and Figure 12 show the task proportions, while Table 5 and Table 6 detail the sample counts across varying context lengths.

Question Type	32K	64K	128K	256K	512K	1M	2M	4M	Total
Count Frequency (Tool)	25	25	25	25	25	25	25	25	200
Find Duplicates	25	25	25	25	25	25	25	25	200
Find Target Offsets	25	25	25	25	25	25	25	25	200
Count Correctness	25	25	25	25	25	25	25	25	200
Count Frequency (Env)	16	12	18	17	23	21	16	17	140
Find Round with Largest Value	20	23	20	19	12	17	18	19	148
Weighted Summation	14	15	12	14	15	12	16	14	112
Intersection	50	50	50	50	50	50	50	50	400
Total	200	1600							

Table 3 Dataset distribution for Knowledge-Intensive & Concise-Response. Values represent sample counts.

Question Type	32K	64K	128K	256K	512K	1M	2M	4M	Total
Count Frequency (Tool)	25	25	25	25	25	25	25	25	200
Find Duplicates	24	25	25	25	25	25	25	25	199
Find Target Offsets	26	25	25	25	25	25	25	25	201
Count Correctness	25	25	25	25	25	25	25	25	200
Count Frequency (Env)	21	24	20	21	13	17	20	21	157
Find Round with Largest Value	13	13	16	15	20	18	24	17	136
Weighted Summation	16	13	14	14	17	15	6	12	107
Intersection	50	50	50	50	50	50	50	50	400
Total	200	1600							

Table 4 Dataset distribution for Knowledge-Intensive & Verbose-Response. Values represent sample counts.

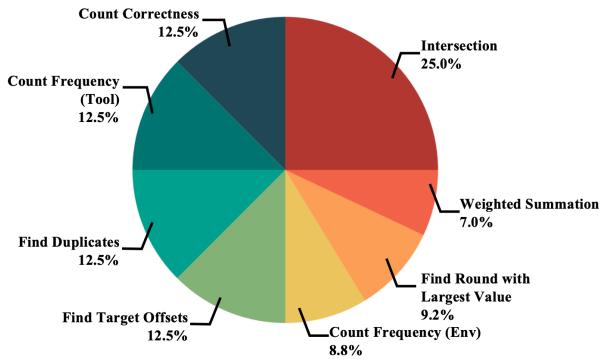


Figure 9 Distribution for Knowledge-Intensive & Concise-Response.

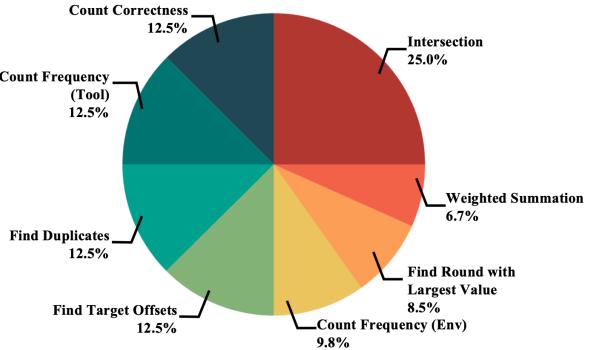


Figure 10 Distribution for Knowledge-Intensive & Verbose-Response.

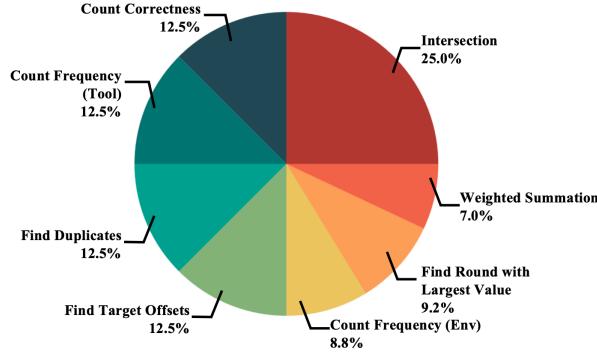


Figure 11 Distribution for *Knowledge-Free & Concise-Response*.

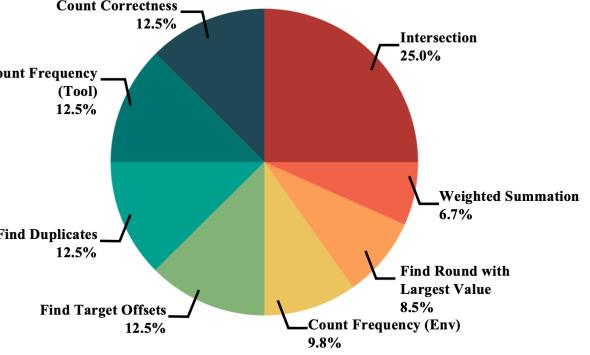


Figure 12 Distribution for *Knowledge-Free & Verbose-Response*.

Question Type	32K	64K	128K	256K	512K	1M	2M	4M	Total
Count Frequency (Tool)	25	25	25	25	25	25	25	25	200
Find Duplicates	25	25	25	25	25	25	25	25	200
Find Target Offsets	25	25	25	25	25	25	25	25	200
Count Correctness	25	25	25	25	25	25	25	25	200
Count Frequency (Env)	16	12	18	17	23	21	16	17	140
Find Round with Largest Value	20	23	20	19	12	17	18	19	148
Weighted Summation	14	15	12	14	15	12	16	14	112
Intersection	50	50	50	50	50	50	50	50	400
Total	200	200	200	200	200	200	200	200	1600

Table 5 Dataset distribution for Knowledge-Free & Concise-Response.

Question Type	32K	64K	128K	256K	512K	1M	2M	4M	Total
Count Frequency (Tool)	25	25	25	25	25	25	25	25	200
Find Duplicates	24	25	25	25	25	25	25	25	199
Find Target Offsets	26	25	25	25	25	25	25	25	201
Count Correctness	25	25	25	25	25	25	25	25	200
Count Frequency (Env)	21	24	20	21	13	17	20	21	157
Find Round with Largest Value	13	13	16	15	20	18	24	17	136
Weighted Summation	16	13	14	14	17	15	6	12	107
Intersection	50	50	50	50	50	50	50	50	400
Total	200	200	200	200	200	200	200	200	1600

Table 6 Dataset distribution for Knowledge-Free & Verbose-Response.

C Trajectory Generation Details

The data construction pipeline of AgentLongBench is designed to generate scalable, controllable, and logically rigorous interaction logs. The pipeline transforms raw game logic into structured datasets suitable for LLM evaluation. The process consists of four main stages:

C.1 Base Engine and Simulation Logic

The core of the generation is a deterministic game engine that manages the ground-truth state. The simulation follows an iterative loop:

1. **Tool Call:** The agent queries specific attributes via the tool API.
2. **Tool Result:** The tool returns data based on the formatting strategy (see Section C.2).
3. **Model Guess:** The simulated agent proposes a candidate item.
4. **Engine Feedback:** The environment compares the guess with the hidden target and provides differential feedback.

C.2 Trajectory Variants: Concise vs. Verbose

We generate two distinct interaction histories from the same underlying game engine to isolate the effects of memory fragmentation versus information density. Figures 13 and 14 provide side-by-side examples of the raw JSON logs used in these configurations.

Concise-Response. As illustrated in Figure 13, the tool in this setting functions as a logic filter, returning only the intersection of items that satisfy all queried attributes. By abstracting away per-section candidate lists, this format maintains a low token density per turn. Consequently, interaction histories can extend to hundreds of rounds, shifting the cognitive burden to long-term state tracking and testing the model’s resilience against memory fragmentation.

Verbose-Response. Conversely, the Verbose format (Figure 14) mimics raw database outputs where the tool returns independent, unfiltered candidate lists for each queried condition. This approach preserves all raw evidence but floods the context window with high-density structured noise. Although this results in fewer interaction rounds for a given token budget, it compels the agent to perform logical intersections internally, thereby strictly testing its capacity to handle information overload within a single reasoning step.

C.3 Behavioral Control Parameters

To ensure the generated trajectories mimic realistic and imperfect agent behaviors rather than optimal searches, we introduce several control parameters into the simulator:

history_window: Defines a rolling window size representing the agent’s active working memory. Conditions outside this window may be dropped.

forget_history_prob: The probability that older conditions outside the current batch are “forgotten” by the simulated agent. Higher values simulate an agent with poorer long-term retention, necessitating redundant queries.

mask_prob & max_mask_sections: Parameters that randomly hide specific sections or conditions in the tool query, simulating partial attention or incomplete information gathering.

epsilon (Exploration Rate): The probability of “relaxing” constraints. Instead of strictly querying the intersection, the agent may explore broader attributes. This prevents the trajectory from converging too quickly, allowing for longer contexts.

C.4 Post-Processing and Task Construction

Token-Length Truncation Raw histories are essentially infinite. We truncate and bucket these trajectories into fixed context lengths (32K, 64K, ..., 4M). Crucially, this process preserves **whole rounds only** to ensure logical integrity.

Final Guess Specialization For the *Intersection* task in concise-response scene, simple truncation is insufficient because the final answer must be logically deducible from the remaining context. We employ a strict filtering process for this task:

- Ensure the intersection of all tool responses in the history yields exactly the unique target item.
- Verify that every round’s intersection list is sufficiently large to maintain task difficulty before the final convergence.

QA Dataset Generation The final benchmark samples are created by selecting specific target rounds from the processed histories. For each sample, we assemble the full ‘messages’ list (System, User, Assistant, Tool) up to the target point and attach the corresponding question (e.g., “Find Duplicates”) and the deterministic ground-truth answer.

C.5 Knowledge-Free Adaptation

The *Knowledge-Free* setting is derived directly from the pipeline above. We apply a symbolic mapping layer where all semantic entities (e.g., Pokémon names, types, ability names) are replaced with abstract tokens (e.g., `Item_29A`, `Attr_B`). This ensures that the structural complexity and logical dependencies of the dataset remain identical to the *Knowledge-Intensive* version, while strictly isolating the model’s reasoning capabilities from its parametric knowledge.

D Detailed Tasks Taxonomy

We design three categories of tasks comprising eight distinct question types. These tasks allow us to isolate specific cognitive failures in long-context agents.

D.1 QA in Tool Response

This category evaluates the agent’s ability to recall specific details from tool execution outputs, testing robustness in parsing machine-generated data.

- **Count Frequency:** Count the frequency of a specific item appearing in the tool return values for a specific round. Unlike simple retrieval, the “needle” here is embedded in structured tool noise.
- **Find Duplicates:** Determine whether a specific item appears in the tool return values of **both** Round i and Round j . This evaluates retrieval across temporal distances.
- **Find Target Offsets:** Identify the two items immediately following the first occurrence of a specific item in the tool return list for Round i . This tests positional matching ability.

D.2 QA in Environment Response

This category focuses on the interaction history with the Host, testing the agent’s ability to track the *State* and “Yes/No” constraints.

- **Count Correctness:** Determine how many attribute sections were guessed correctly in a specific round based on feedback.
- **Count Frequency:** Count how many times a specific attribute value has appeared across the feedback of **all** rounds.

- **Find Round with Largest Value:** Identify which round’s feedback contained the highest specific numeric attribute value.
- **Weighted Summation:** Calculate the absolute difference between the weighted scores of Round i and Round j . The score is calculated based on a weighted scheme assigning points to different attribute categories (e.g., Type: 6, Ability: 5, Base Stats: 4, etc.), testing both retrieval and computational reasoning.

D.3 Final Guess

This predictive category requires the agent to generate the final answer based on the global understanding of the context.

- **Intersection:** The agent must compute the intersection of candidate items based on the provided tool responses.
 - In the **Concise-Response** format, since the tool returns pre-filtered results, this effectively requires intersecting constraints across the entire history to deduce the final target.
 - In the **Verbose-Response** format, this requires identifying the intersection of attribute lists within a specific round’s tool response.

This task evaluates the agent’s ability to perform logical set operations and synthesize information, determining whether it understands the evolving state rather than merely retrieving facts.

E Baselines and Implementation Details

Our experimental evaluation covers a comprehensive spectrum of proprietary frontiers, open-weight models, and specialized memory architectures. All inference tasks were executed using the VLLM framework to ensure high-throughput processing. We maintained a consistent sampling temperature of 0.7 across all runs to balance generation diversity with instruction adherence.

Proprietary Models We accessed proprietary systems via their official APIs. To ensure fair comparison, we utilized the standard chat templates and default system prompts recommended by the respective vendors, without specific prompt engineering for context compression.

Open-Source Models For open-weight baselines, we deployed the official Instruct versions of the Qwen series (Qwen2.5, Qwen3) and GLM-4 on a cluster of NVIDIA H200 GPUs. In cases where models support multiple system prompt configurations, we unified the evaluation under a standardized prompt to isolate the model’s intrinsic context processing capabilities.

Memory and RAG Frameworks For Retrieval-Augmented Generation (RAG) and dedicated agentic memory systems (A-Mem, Mem0, MemoryOS), we adhered strictly to their public default configurations to reflect standard usage patterns. We standardized the retrieval hyperparameter across all memory-augmented baselines, setting the top- k retrieved chunks to 5 ($k = 5$). This setting provides a consistent context window for the backbone model (Qwen3-30B-A3B) to synthesize the final response.

Trajectory Variant A: Concise-Response (Intersection Only)

```
{
  "messages": [
    {
      "role": "system",
      "content": "You are playing a guess-the-Pokemon game... [System prompt truncated]..."
    },
    {
      "role": "user",
      "content": "Round 1: Guess Kakuna (#0014)\nSections:\n - Type: Bug (wrong); Poison (wrong)... [Attributes Omitted]...\nResult: wrong\nRemaining rounds: 2009"
    },
    {
      "role": "assistant",
      "content": "<think>Thinking and calling query_pokemon.</think>",
      "tool_calls": [
        {
          "id": "call_3",
          "type": "function",
          "function": {
            "name": "query_pokemon",
            "arguments": "{\"conditions\": [{\"type\": \"value\", \"section\": \"Abilities\", \"values\": [\"Shed Skin\"], \"exclude\": true}, {\"type\": \"value\", \"section\": \"Type\", \"values\": [\"Bug\", \"Poison\"]}, \"exclude\": true}]}"
          }
        }
      ]
    },
    {
      "role": "tool",
      "tool_call_id": "call_3",
      "name": "query_pokemon",
      "content": "{\"intersection\": [\"Abomasnow\", \"Abra\", ..., \"Zygarde\"]}"
      // Concise: The tool executes the logic and returns ONLY the intersection list.
    },
    {
      "role": "assistant",
      "content": "<answer>Thwackey</answer>"
    },
    ... [Rounds 2-10 omitted for brevity] ...
    {
      "role": "user",
      "content": "Round 11: Guess Kirlia (#0281)\nSections:\n - Type: Psychic (wrong); Fairy (wrong)\nBase Stats: 278 (wrong, too low)...\nResult: wrong\nRemaining rounds: 1999"
    },
    {
      "role": "assistant",
      "content": "<think>Filtering based on new constraints...</think>",
      "tool_calls": [
        {
          "id": "call_43",
          "type": "function",
          "function": {
            "name": "query_pokemon",
            "arguments": "{\"conditions\": [{\"type\": \"value\", \"section\": \"Type\", \"values\": [\"Psychic\", \"Fairy\"], \"exclude\": true}, {\"type\": \"numeric\", \"section\": \"Base Stats\", \"comparator\": \">\", \"threshold\": 278}]}"
          }
        }
      ]
    },
    {
      "role": "tool",
      "tool_call_id": "call_43",
      "name": "query_pokemon",
      "content": "{\"intersection\": [\"Abomasnow\", \"Absol\", ..., \"Zweilous\"]}"
    },
    {
      "role": "assistant",
      "content": "<answer>Darkrai</answer>"
    }
  ]
}
```

Figure 13 Concise-Response Trajectory Example.

Trajectory Variant B: Verbose-Response (Full Candidate Lists)

```
{
  "messages": [
    {
      "role": "system",
      "content": "You are playing a guess-the-Pokemon game... [System prompt truncated]..."
    },
    {
      "role": "assistant",
      "content": "<answer>Seedot</answer>"
    },
    {
      "role": "user",
      "content": "Round 1: Guess Seedot (#0273)\nSections:\n - Type: Grass (correct)\n ... [Attributes Omitted]\nResult: wrong\nRemaining rounds: 259"
    },
    {
      "role": "assistant",
      "content": "<think>Thinking and calling query_pokemon.</think>",
      "tool_calls": [
        {
          "id": "call_3",
          "type": "function",
          "function": {
            "name": "query_pokemon",
            "arguments": "{\"conditions\": [{\"type\": \"value\", \"section\": \"Type\", \"values\": [\"Grass\"]}, {\"type\": \"numeric\", \"section\": \"Base Stats\", \"comparator\": \">>\", \"threshold\": 220}, {\"type\": \"numeric\", \"section\": \"Generation\", \"comparator\": \"==\", \"threshold\": 3}]}"
          }
        }
      ]
    },
    {
      "role": "tool",
      "tool_call_id": "call_3",
      "name": "query_pokemon",
      "content": {
        "per_section": [
          {
            "section": "Type",
            "conditions": [{"type": "value", "values": ["Grass"]}],
            "candidates": [
              "Abomasnow", "Amoonguss", "Appletun", "Applin", "Arboliva", ... [138 items omitted] ..., "Zarude"
            ]
          },
          {
            "section": "Base Stats",
            "conditions": [{"type": "numeric", "comparator": ">", "threshold": 220}],
            "candidates": [
              "Abomasnow", "Abra", "Absol", "Accelgor", "Aegislash", ... [850 items omitted] ..., "Zygarde"
            ]
          },
          {
            "section": "Generation",
            "conditions": [{"type": "numeric", "comparator": "==", "threshold": 3}],
            "candidates": [ ... [135 items omitted] ... ]
          },
          {
            "section": "Abilities",
            "candidates": [ ... [Huge list omitted] ... ]
          }
        ]
      }
    }
  ],
  // Verbose: The tool returns SEPARATE lists for each condition. The agent must mentally intersect these hundreds of items to find the target.
  {
    "role": "assistant",
    "content": "<answer>Lileep</answer>"
  },
  ...
  [Rounds 2-3 omitted] ...
  {
    "role": "user",
    "content": "Round 4: Guess Palossand (#0770)\nSections:\n - Type: Ghost (wrong); Ground (wrong)\n - Base Stats: 480 (wrong, too high)...\nResult: wrong\nRemaining rounds: 256"
  }
]
}
```

Figure 14 Verbose-Response Trajectory Example.